UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

ALEŠ ZEBEC

THE RELATIONSHIP BETWEEN ARTIFICIAL INTELLIGENCE ADOPTION AND ORGANIZATIONAL PERFORMANCE

DOCTORAL DISSERTATION

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AUTHORSHIP STATEMENT

The undersigned Aleš Zebec, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title The relationship between artificial intelligence adoption and organizational performance, prepared under supervision of prof. Mojca Indihar Štemberger, Ph.D.

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SUMMARY

There is an increasing uptake of artificial intelligence in business, but there remain concerns that organizations fail to realize the full value of their investments. Despite extensive research on AI, not enough empirical studies have explored how AI can create business value. This study extends the literature by contextualizing the integrative model of IT business value, using a resource-based view to examine the relationship between AI and organizational performance. We employ the dynamic capabilities approach and a knowledge-based view and propose several variables as mediating this relationship: automation–augmentation, process innovation, organizational learning, decision-making performance, and process performance. We analyze 448 EU organizations using artificial intelligence in their business operations using structural equation modeling. The results validate the proposed serial multiple-mediation model, according to which artificial intelligence capabilities should boost decision-making processes and process transformation activities to yield business value.

Keywords: Artificial intelligence, Resource-based View, Business Process Management, Business Value, Automation, Augmentation, Organizational Learning, Business Process Innovation, Incremental improvement, Radical improvement, Decision-making Performance, Business Process Performance, Organizational Performance, Firm Performance

POVZETEK

Uvajanje umetne inteligence v poslovanje doživlja rast, kljub temu pa ne gre prezreti pomislekov. Mnoge organizacije ne realizirajo ali izkoristijo vseh prednosti, ki jih prinašajo naložbe v umetno inteligenco. Pretekle raziskave so le v manjši meri podale empirične rezultate o ustvarjanju poslovne vrednosti z umetno inteligenco. Pričujoča študija razširja dosedanja dognanja s kontekstualizacijo integrativnega modela poslovne vrednosti IT (angl. IT Business Value) in z uporabo pogleda na osnovi virov (angl. Resource-Based View) nudi izboljšanje razumevanja razmerja med umetno inteligenco in organizacijsko uspešnostjo. Na podlagi teorij pogleda dinamičnih zmogljivosti (angl. Dynamic Capabilities View) in na znanju temelječe perspektive (angl. Knowledge-based View) predlagamo avtomatizacijo in avgmentacijo, procesno inovacijo, organizacijsko učenje, uspešnost odločanja in uspešnost izvajanja procesov kot spremenljivke mediacije. Z uporabo strukturnih modelov smo analizirali 448 organizacij iz EU, ki uporabljajo umetno inteligenco v svojem poslovanju. Rezultati potrjujejo predlagani model zaporedne večkratne mediacije (angl. serial multiple-mediation model), po katerem zmogljivosti umetne inteligence pozitivno vplivajo na procese odločanja in aktivnosti transformacije procesov, s tem pa spodbujajo poslovno uspešnost oziroma podpirajo ustvarjanje poslovne vrednosti.

Ključne besede: umetna inteligenca, teorija na temelju virov, management poslovnih procesov, poslovna vrednost, avtomatizacija, avgmentacija, organizacijsko učenje, inovacije poslovnih procesov, postopne izboljšave, radikalne izboljšave, učinkovitost odločanja, učinkovitost poslovnih procesov, uspešnost poslovanja

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sl. – Slovene

AGFI – (sl. prilagojeni indeks skladnost); Adjusted goodness-of-fit index

AGI – (sl. splošna umetna inteligenca); Artificial General Intelligence

AI – (sl. umetna inteligenca); Artificial Intelligence Technology

AIGO – (sl. skupina strokovnjakov za umetno inteligenco pri OECD); OECD's AI Experts Group

ANI – (sl. ozka umetna inteligenca); Artificial Narrow Intelligence

ASI – (sl. umetna super inteligenca); Artificial Super Intelligence

AVE – (sl. povprečna izražena variance); Average Variance Extracted

BA – (sl. poslovna analitika); Business Analytics

BDA – (sl. analitika velepodatkov); Big Data Analytics

BI – (sl. poslovna inteligenca); Business Intelligence

Big Data – (sl. velepodatki); extremely large and complex data sets

BPA – (sl. avtomatizacija poslovnih procesov); Business Process Automation

BPI – (sl. inovacije poslovnih procesov); Business Process Innovation

BPII – (sl. inovacije poslovnih procesov – postopne); Business Process Innovation – Incremental

BPIR – (sl. inovacije poslovnih procesov – radikalne); Business Process Innovation – Radical

BPM – (sl. management poslovnih procesov); Business Process Management

BPMM – (sl. zrelost managementa poslovnih procesov); BPM Maturity

BPP – (sl. učinkovitost poslovnih procesov); Business Process Performance

CA – (sl. kognitivna avtomatizacija); Cognitive Automation

CBPA – (sl. kognitivna avtomatizacija poslovnih procesov); Cognitive Business Process Automation

CDA – (sl. kognitivna podpora odločanju); Cognitive Decision Assistance

CE – (sl. kognitivna vključenost); Cognitive Engagement

CFA – (sl. potrdilna faktorska analiza); Confirmatory Factor Analysis

CFI – (sl. primerjalni indeks prileganja); Comparative fit index

CI – (sl. kognitivni vpogled); Cognitive Insight

CLF – (sl. skupni latentni faktor); Common Latent Factor

CMV – (sl. variance skupne metode); Common Method Variance

CR – (sl. kompozitna zanesljivost); Composite Reliability

CRM – (sl. upravljanje odnosov s strankami); Customer Relationship Management

CT – (sl. kognitivne tehnologije); Cognitive Technologies

CX – (sl. upravljanje uporabniške izkušnje); Customer Experience Management

DACQ – (sl. pridobivanje in predhodna obdelava podatkov); Data Acquisition and Preprocessing

DCV – (sl. teorija na temelju dinamičnih zmožnosti); Dynamic Capabilities View

DDC – (sl. podatkovno vodena kultura); Data-Driven Culture

DL – (sl. globoko učenje); Deep Learning

DM – (sl. digitalna zrelost); Digital Maturity

DMP – (sl. učinkovitost odločanja); Decision-Making Performance

DOI – (sl. teorija širjenja inovacij); The Diffusion of Innovations Theory

DV – (sl. odvisna spremenljivka); Dependent Variable

EFA – (sl. pojasnjevalna faktorska analiza); Exploratory Factor Analysis

GAI – (sl. generativna umetna inteligenca); Generative Artificial Intelligence

GDPR – (sl. splošna uredba o varstvu podatkov); General Data Protection Regulation

GFI – (sl. indeks ustreznosti prileganja); Goodness-of-fit index

GPT – (sl. generativni vnaprej-izurjeni pretvornik); Generative Pre-trained Transformer

IoT – (sl. internet stvari); Internet of Things

IPA – (sl. inteligentna avtomatizacija procesov); Intelligent Process Automation

IS – (sl. informacijski sistem); Information System

IT – (sl. informacijska tehnologija); Information Technology

IV – (sl. neodvisna spremenljivka); Independent Variable

KBV – (sl. pogled temelječ na znanju); Knowledge-based View

KD – (sl. odkrivanje znanja); Knowledge Discovery

KiPs – (sl. procesi z visoko intenzivnostjo znanja); Knowledge-intensive Processes

KM – (sl. upravljanje z znanjem); Knowledge Management

KMT – (sl. teorija upravljanja z znanjem); Knowledge Management Theory

LLM – (sl. veliki jezikovni model); Large Language Model

MaxR(H) – (sl. maksimalna statistična zanesljivost); Maximum Reliability

MIS – (sl. management informacijski sistemi); Management Information Systems

ML – (sl. strojno učenje); Machine Learning

MSV – (sl. maksimalne skupne kvadratne variance); Maximum Shared Squared Variance

NFI – (sl. normiran indeks prileganja); Normed fit index

NLP – (sl. obdelava naravnega jezika); Natural Language Processing

NNFI – (sl. nenormiran indeks ujemanja); Non-normed Fit Index

OC – (sl. organizacijska kultura); Organizational Culture

OL – (sl. organizacijsko učenje); Organizational Learning

OP – (sl. uspešnost poslovanja); Organizational Performance

PCFI – (sl. indeks za primerjalno ustreznost z upoštevanjem parsimonije); Parsimony-adjusted comparative fit index

RBV – (sl. teorija na temelju virov); Resource-Based View

RDBMS – (sl. sistem za upravljanje relacijskih zbirk podatkov); Relational Database Management System

RMSEA – (sl. koren povprečne kvadrirane napake približka); Root mean square error of approximation

RPA – (sl. robotska avtomatizacija procesov); Robotic Process Automation

SCADA – (sl. nadzor, kontrola, alarmiranje in zbiranje podatkov); Supervisory Control And Data Acquisition

SEM – (sl. modeliranje strukturnih enačb); Structural Equation Modeling

SLR – (sl. sistematični pregled literature); Systematic Literature Review

SRMR – (sl. standardizirani kvadratni koren povprečne kvadratne napake); Standardized Root Mean Squared Residual

TLI – (sl. Tucker-Lewisov indeks); Tucker-Lewis Index

TOE – (sl. ogrodje tehnologija-organizacija-okolje); The technology-organization-environment framework

VRIN – (sl. vredno, redko, neponovljivo in nenadomestljivo); Valuable, Rare, Inimitable, and Non-Substitutable

1 INTRODUCTION

While artificial intelligence (AI) technology emerged in the 1960s, it has only recently gained traction due to its potential business applications (Warwick, 2013). Vast amounts of data (Big Data), cloud computing, data management, programming frameworks, AI models, and AI services have contributed to and provided a platform for the resurgence of this technology. Over the past several years, organizations have turned to AI to realize business value through sustained competitive advantage in intra- and inter-organizational business processes (Wamba, 2022). AI has quickly been developed to the point where it can undergo transformations that enable intelligent automation and augmentation, creating opportunities for ongoing digital innovation (Abbad, Jaber, AlQeisi, & Eletter, 2021).

1.1 Motivation

AI technologies have demonstrated immense potential in revolutionizing business operations and decision-making, creating new value propositions and customer experiences (Mondal, Das, & Vrana, 2023; Trivedi & Patel, 2020). AI has become a key driver of innovation and competitive advantage by enhancing efficiency and automation and improving the data analysis and predictive capabilities of businesses (Akter, Michael, Uddin, McCarthy, & Rahman, 2022; Brem, Giones, & Werle, 2021a; Dash, McMurtrey, Rebman, & Kar, 2019; Wamba-Taguimdje, Wamba, Kamdjoug, & Wanko, 2020b). In today's rapidly changing business environment, organizations from a range of industries acknowledge the importance of utilizing AI to stay competitive (Peyravi, Nekrošienė, & Lobanova, 2020). AI promises to unlock valuable insights from vast data, enabling organizations to make data-driven decisions and optimize their operations.

Despite this promise, organizations still struggle to adopt and leverage AI technologies and realize performance gains (Fountaine, McCarthy, & Saleh, 2019; Mishra & Pani, 2020). The question then arises, "Why do some organizations do so much better than others?" The literature on this topic is still underdeveloped, and there is a need for research on the underlying relationships through which AI can improve organizational performance (Enholm, Papagiannidis, Mikalef, & Krogstie, 2021).

Although several studies (Table 1) focus on the interaction of individual strategic constructs and their impact on AI implementation and its success, there is a gap in the literature and a need for studies that confirm the impact of AI on organizational performance through the concurrent effects of AI-enabled automation and augmentation. We intend to empirically validate the impact of AI on organizational performance and identify the underlying mechanisms, mediating factors, and contextual influences that shape this relationship. Understanding these interactions provides an initial base for organizational strategy, resource allocation, risk management, and informed decisions regarding AI adoption and utilization, from developing AI capabilities to deploying end-to-end organizational processes to generate and capture the full potential of AI technology in terms of business value.

Gaining insight into AI's impacts on organizational performance allows organizations to develop appropriate frameworks, policies, and practices to maximize the value derived from these technologies while minimizing the risks associated with their investments. Empirical research on the impact of AI adoption on organizational performance is crucial to guiding organizations operating in a dynamic and technology-driven business environment. With these findings, organizations can leverage AI more effectively, adapt to changing market dynamics, and gain a competitive edge in the era of digital transformation.

1.2 Purpose of the Study

This research investigates the new challenges arising from the adoption of AI in business operations and focuses on several key aspects. Most importantly, the adoption of AI is highly dependent on data and domain knowledge. As Chui (2017) notes, the effectiveness and performance of AI systems rely heavily on high-quality data and a comprehensive understanding of the specific domain to which they are applied. Obtaining and managing the required data and knowledge can pose significant challenges for organizations and may hinder the seamless integration of AI into existing processes. Furthermore, there is a notable lack of knowledge regarding how to apply AI technologies to business problems. Many organizations struggle to understand how AI can be effectively leveraged to solve complex business challenges (Mishra & Pani, 2020). The scarcity of expertise in AI implementation makes it difficult to align AI initiatives with existing business processes and objectives, often leading to uncertainty and presenting a significant obstacle to businesses (Davenport & Ronanki, 2018). An investigation of application domains is thus needed to identify use cases and guidelines for effectively incorporating AI into business operations.

Using AI technologies can also significantly impact an organization's internal decision-making processes (Davenport & Mahidhar, 2018). AI can transform conventional decision-making, and these can be augmented and even replaced by automated algorithms and predictive models, as Duan, Edwards, and Dwivedi (2019) highlight. Investigating the impact of AI on decision-making processes is crucial for organizations to ensure the efficient and effective use of AI technologies. In addition, the adaptation of AI technologies is significantly influenced by organizational culture (Duan et al., 2019). Understanding how the organizational context shapes AI implementation is crucial to developing strategies that encourage the acceptance and integration of AI technologies.

1.3 Formulation of the Research Question

AI is a distinct kind of technology because it can perform the cognitive tasks usually performed by humans (Collins, Dennehy, Conboy, & Mikalef, 2021). AI is built around the idea of an intelligent agent, and although there is no single definition of this technology, we understand AI as a *simulation* of *human cognitive functions* using *intelligent agents*. The machine is able to perform these functions, exhibiting intelligent human behavior, including the ability to perceive, reason, learn, interact, and adapt to changing environments (Russell & Norvig, 2020). Intelligent agents are agents that can receive percepts from the environment and perform actions; that is, an agent is anything that perceives its environment through sensors and acts upon that environment through actuators. Action is what an intelligent agent does to change its environment or to achieve its goals (Russell & Norvig, 2020). In this sense, an agent’s choice of action (behavior) at any given instant depends on its built-in knowledge and the observed percept sequence but not on anything not perceived.

An agent’s behavior is defined by its agent function, which maps any given perception sequence to an action and is implemented by an agent (software) program (Russell & Norvig, 2020). Agents can be classified into two categories: physical entities, such as robots using sensors and actuators, and software programs functioning within virtual environments. A major objective of AI is to develop and enhance intelligent agents to perform complex tasks and interact effectively with humans and their environment. AI is recognized as a general-purpose technology (Cockburn, Henderson, & Stern, 2018), characterized by pervasiveness, inherent potential for technical improvements, and innovational complementarities (Bresnahan & Trajtenberg, 1995).

Despite extensive research on information technology (IT) business value (De Haes, Van Grembergen, Joshi, & Huygh, 2020), the literature contains no coherent understanding of how AI technologies create business value (Enholm et al., 2021). Existing studies posit that the adoption of AI has a partial indirect influence on performance; the relationship is mediated by the organizational capabilities of creativity and agility (Chen, Esperança, & Wang, 2022; Mikalef & Gupta, 2021; Wamba, 2022). However, these studies do not consider the role of business process management (BPM) in AI’s creation of value. BPM is recognized as one of the most central and sustainable management approaches (Rosemann, De Bruin, & Hueffner, 2004). The structured and strategic approach of BPM complements the innovative capabilities of AI (Ng, Chen, Lee, Jiao, & Yang, 2021b), and there have been several investigations of AI adoption in a BPM context. Wamba-Taguimdje, Wamba, Kamdjoug, and Wanko (2020a) examine the mediating effect of process-oriented dynamic capabilities and emphasize the process-level impact on performance (Wamba-Taguimdje et al., 2020b). Nevertheless, the ways that AI generates business value, specifically via BPM capabilities, have not received sufficient attention (Ahmad & Van Looy, 2020).

This research adds to the conversation in the literature (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020a; Wamba, 2022) to answer the overarching research question: “How do AI technologies create business value, and what form of business value can be expected?” This question is designed to generate dialogue on the specific topic of advancing the concept of IT business value.

Responding to this question requires a comprehensive understanding of the value-generation process at the organizational level. This study considers the relationship between AI adoption and organizational performance by identifying the mediating variables that positively leverage AI technology. We conduct a comprehensive analysis to highlight the outcomes that managers can anticipate as a result of adopting AI in day-to-day business operations and how businesses may benefit from AI-enabled automation or augmentation. We further the organizational context, moderators, and control variables influencing the outcome of AI adoption.

1.4 Objectives and Contributions

We address the research question by first comprehensively defining a concept that captures all components of AI adoption at an organizational level in the context of BPM. This concept is an essential and foundational element supporting and enhancing the efforts to measure the impact and value of AI technology.

Our proposed extended AI business value framework includes AI applications as components of AI adoption, mediating organizational capabilities (incorporating the AI-enabled strategies of automation and augmentation), and the impacts at the process and organizational level. Existing studies recognize duality in using AI to augment and automate human capabilities to create value (Brynjolfsson & McAfee, 2014; Daugherty & Wilson, 2018; Davenport & Kirby, 2016; Dellermann, Ebel, Söllner, & Leimeister, 2019; Raisch & Krakowski, 2021; Schroder, Constantiou, Tuunainen, & Austin, 2022).

In this context, automation is the process or system by which a machine takes over a human task, and augmentation is the close collaboration between humans and machines to perform a task (Raisch & Krakowski, 2021). We include an automation–augmentation perspective to explore how the impact of AI adoption on performance is mediated. In addition, we draw connections between organizational learning and ambidexterity based on the ability of AI to impact the exploration and exploitation of process innovation. (Mishra & Pati, 2020). We expect that the specific ability of AI to create intelligent agents capable of self-learning and decision-making can produce significant performance gains (Wamba-Taguimdje et al., 2020b). We deconstruct the outcomes into lower- and higher-order effects to better understand how AI can boost performance, representing impacts at the process and organizational level. We offer a more detailed understanding of the value-generation process by considering the mediating effect of lower-order measures examining operational and market performance via process and decision-making performance.

We contextualize the integrative IT business value model (Melville, Kraemer, & Gurbaxani, 2004), and examine the impact of AI adoption at the process and organizational levels, considering complementary organizational resources and a competitive environment. This allows us to bridge the gap between business, AI, and human workers using the concept of BPM. The resource-based, dynamic capabilities and knowledge-based views provide an appropriate theoretical basis to identify resources and operational and dynamic AI-enabled capabilities that comprise the focal construct of AI adoption.

We define AI adoption as *the implementation*[1], *deployment, and use of AI resources (data, AI infrastructure, skills, competencies) in business processes*[2]. An organization's level of AI adoption is measured by its AI-enabled capabilities (components of AI adoption), which represent *the organization's ability to mobilize AI resources for specific business needs through the implementation, deployment, and use of AI applications, tools, or technologies*. We conduct exploratory interviews and a literature review and, based on these, operationalize and measure the concept of AI adoption and, in turn, assess the impact and value of AI technology.

We follow the guidelines established in MacKenzie, Podsakoff, and Podsakoff (2011); Podsakoff, MacKenzie, and Podsakoff (2016) for the concept, scale development, and validation commonly used in the management information systems literature. The content validity, scale purification, and refinement are based on a pilot study and confirmed by an expert panel. In addition, we assess dimensionality, reliability, convergent, discriminant, and nomological validity. This conceptualization and measure development procedure is also used for cognitive business process automation (CBPA) because there is, as yet, no comprehensive model or measurement instrument. Finally, the measures that we develop for AI adoption and CBPA are merged with existing measures in a structured questionnaire that represents the operationalized research model. The questionnaire is applied in an EU-wide research study with a sample of 448 organizations using AI technology in their business processes.

1.5 Outline

The remainder of the thesis is structured as follows. In Chapter 2, we introduce the theoretical basis and elaborate on our hypotheses and the proposed AI business value framework. In Chapter 3, we describe the conceptualization procedure and the implications of a component-based view of AI adoption and its dimensions. In Chapter 4, we describe the procedure by which we conceptualize and operationalize the CBPA construct and the results of our analysis. We then present our empirical research methodology (Chapter 5) and our results (Chapter 6). Finally, we present our discussion (Chapter 7) and conclusions (Chapter

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[1] Implementation is the process of taking an idea from concept to reality, whereas deployment is the process of putting it into use. The term "use" refers to the actual application or utilization of something by the end user.
[2] An organization can be described as a set of business processes (Melão & Pidd, 2000) representing an organization's core (Willaert, Van den Bergh, Willems, & Deschoolmeester, 2007). Our research is based on a process oriented model of IT business value (Mooney, Gurbaxani, & Kraemer, 1996). We theorize that organizations derive business value from IT through its impacts on business processes (Kohlbacher, 2010). Measuring the level of AI adoption via implementation, deployment, and use in business processes is therefore appropriate.

8), the study's theoretical contributions, managerial implications, limitations, and future research suggestions.

2 THEORETICAL BACKGROUND AND HYPOTHESES

Considering the vast transformative potential of AI (Enholm et al., 2021; Gruetzemacher & Whittlestone, 2022), we start from the premise that a multi-theory framework is needed to better understand the link between AI and organizational performance. We aim to discern the various mechanisms and variables by which this relationship is mediated and moderated. The resource-based view serves as the foundation of our study to ensure alignment with prior research on AI adoption (as seen in Table 1). We further enrich this framework by incorporating insights from the dynamic capability and knowledge-based views.

Table 1: Selected Empirical Studies on AI and Firm Performance

Author	Scope	Theory	Findings
Mikalef et al. (2023)	Survey, 168 public organizations	RBV	(+) AI capability → Process Automation, Cognitive Insight, Cognitive Engagement, Organizational performance
Mikalef and Gupta (2021)	Survey, 143 senior US firm managers	RBV, DCV	(+) AI capability → Organizational Creativity & Organizational performance
Wamba (2022)	Survey, 205 US firm managers	RBV, DCV	(+) AI assimilation → Organizational agility, Customer agility, Firm performance
Wamba-Taguimdje et al. (2020a)	150 AI-related case studies	RBV, DCV	(+) AI capability → Process-driven Dynamic Capabilities, Firm performance
Chen, Esperança, et al. (2022)	Survey, 394 e-commerce entrepreneurs	RBV, DCV	(+) AI capability → Firm creativity, AI Management, AI driven decision making, Firm Performance
Rammer, Fernández, and Czarnitzki (2022)	Germany Community Innovation Survey (CIS) 2018		(+) AI → Innovation Performance
Bag, Gupta, Kumar, and Sivarajah (2021)	306 senior executives in South Africa	KMT	(+) Big data powered artificial intelligence → Knowledge Management Process, Decision Making Style, Firm Performance
Mishra, Ewing, and Cooper (2022)	10-K data from US firms		(+) AI Focus → Firm Perfromance
Kim, Park, and Kim (2022)	395 US-listed firms using AI between 2000-2018		(+) AI adoption → Firm Performance, (+) AI adoption → Automation
Lui, Lee, and Ngai (2022)	62 US-listed firms between 2015–2019		(−) AI adoption announcements → Firm market value (−) AI adoption announcements → Abnormal market returns
Joseph and Falana (2021)	159 firms from Nigeria		(+) AI → Firm Performance
Panduro-Ramirez et al. (2022)	80 interviews from the UK		(+) Integrated AI technology → Firm Performance and Profitability
Chetty (2019)	Survey, 190 participants from South Africa	RBV	(+) AI moderates Big Data Analytics Capability → Firm Performance
Yang (2022)	5,257 Taiwanese companies that have filed at least one AI patent during the period 2000 - 2019		(+) AI technology → Productivity and employment
Lyu and Liu (2021)	US Energy Sector Compustat data during the period 2010–2019		(+) AI adoption → Productivity
Chatterjee, Chaudhuri, Kamble, Gupta, and Sivarajah (2022)	62 US-listed firms during the period 2015–2019	DCV	(+) Adoption of AI based application → Firm performance
Naz, Ul Haq, and Nasir (2022)	Survey, 240 firms from Pakistani food manufacturing	DCV, Contingency Theory	(+) Entrepreneurial orientation, Big Data Analytics Capabilities, and Artificial Intelligence Capabilities → Firm Performance
Ho, Gan, Jin, and Le (2022)	AI-related global Bloomberg stock market index from 2019 to 2020		(+) Adoption of AI based applications → Sustainable perfromance in challenging environments

To be continued

Table 1: Selected Empirical Studies on AI and Firm Performance (cont.)

Author	Scope	Theory	Findings
Jain (2019)	An online survey in India, 50 respondents		(+) AI → Manage technology-related challenges (+) AI → Economic growth of businesses (enhance business operations: productivity, operating efficiency, business expansion)
Alekseeva, Gine, Samila, and Taska (2020)	Compustat Online US job postings during the period 2010–2018		(+) AI → Sales growth, capital expenditure, EBITDA margin, R&D investments (+) AI → Total factor productivity
Babina, Fedyk, He, and Hodson (2021)	Job postings from the US during the period 2010–2018		(+) AI → Sales growth, product innovation, employment, market valuations; control variable: larger firms benefit more from AI investments
Fotheringham and Wiles (2022)	Event study on US stock market postings during the period 2016–2019; 153 announcements	Market-based Asset Theory	(+) AI investment announcements (chatbots) → Abnormal stock returns
Sullivan and Wamba (2022)	Survey, 107 business and IT executives from UK and France	DCV, Organizational Information Theory	(+) AI Use → Firm Resilience, Firm Performance

Note. (+) Positive impact; (−) Negative impact; ( ) No impact. RBV = Resource-Based View. DCV = Dynamic Capabilities View. KMT = Knowledge Management Theory.

Source: Own work.

The resource-based view dominates the strategic management literature (Newbert, 2007; Wu, 2010) as a way to explain performance differences among organizations in the same industry (Zott, 2003). Accumulating valuable, rare, inimitable, and non-substitutable resources (assets, capabilities, organizational processes, organizational attributes, data, information, and knowledge) to enhance competitive advantage has become fundamental academic and managerial strategic thinking. The resource-based view has been applied extensively in past research in the broader information systems domain. It is positioned as a central theoretical perspective in understanding how IT resources produce value and enable performance gains (Bharadwaj, 2000; Patas, Bartenschlager, & Goeken, 2012; Wade & Hulland, 2004).

The existing research shows that the resource-based view is valuable in measuring organizational performance diversity. IT resources are conceptualized in different ways (Wade & Hulland, 2004). It is common for IT resource conceptualizations to equate potentially heterogeneous investment allocations across organizations by measuring total IT intensity (Aral & Weill, 2007). Measuring investments and organizational capabilities is crucial to avoid the common mistake of equating resources with capabilities. Organizations can better understand the capabilities required and make more informed decisions regarding IT investment. We thus understand AI resources as a combination of AI-related IT investment allocations (among infrastructure, transactional, informational, and strategic assets) and a mutually reinforcing system of competencies and practices. According to Aral and Weill (2007), investments in specific IT asset classes will boost performance only if aligned with the strategic objective or purpose of the assets.

In an increasingly digital business environment, data is one of the key resources that an organization must harness to understand its business operations and improve and adapt to the environment (Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019). According to Amit and Schoemaker (1993), an organization's resources are its tradable and non-specific assets, while its capabilities are the non-tradable organization-specific abilities that it employs to integrate, deploy, and utilize resources. It is important to note that, depending on privacy regulations, contractual agreements, intellectual property rights, and industry practices, data may be tradable or non-tradable and non-specific or specific. Data that are considered tradable can be bought, sold, or exchanged between organizations. For example, aggregated or anonymized data sets are used for market research, analytics, targeted advertising, or machine learning applications. This type of data is typically not tied to any specific organization and can be used across applications and industries.

Other types of data are not tradable or specific. Examples of such data include proprietary or confidential data unique to an organization that cannot be shared or traded with others for reasons of legality, ethics, or competitiveness, such as customer databases, internal research findings, and trade secrets. Therefore, data can serve as a source of competitive advantage; legal access to data and access to large volumes of data can be particularly advantageous since vast amounts of data are needed to train large AI models.

AI is primarily concerned with data as a core resource that is exploited and explored through AI capabilities and AI-enabled capabilities. AI capabilities (from which additional value is derived) and AI-enabled capabilities (that enhance existing capabilities) are how organizations create or extend a set of organizational, personal, and AI resources for creating and capturing business value from data (Wamba-Taguimdje et al., 2020a). The theoretical perspective discussed here has immense significance in our framework since an organization wishing to leverage its AI investments (or investment in AI-related IT assets) must first identify the AI and AI-enabled capabilities that must be developed.

The findings in the literature show that the resource-based view serves as an appropriate theoretical lens for studying organizations in dynamic and turbulent environments, relying on complementarity organizational resources to explain performance variation. Studies that apply the resource-based view note that, in addition to the IT assets and competencies (technical and managerial skills) needed for AI implementation, deployment, and utilization, various complementary organizational resources are also required to leverage investments (Mikalef & Gupta, 2021). We draw from Melville et al. (2004), who combine these perspectives in an integrative model, arguing that the application of the resource-based view enables researchers to construct empirically testable propositions. Subsequent evaluation of these propositions advances our understanding of the significance of diverse IT resources and their impact on organizational performance.

Relevant to our study, the resource-based view is used to explain organizational phenomena and is an appropriate tool to understand if and how an organization's parts affect the whole.

It also makes a valuable distinction between IT and information systems. The former is asset-based, while the latter consists of a mix of assets and capabilities concerned with the productive use of IT (Wade & Hulland, 2004).

The resource-based view is an appropriate theoretical foundation for our framework, given that our objective is to determine the essential organizational resources (including assets and capabilities) that facilitate the successful adoption of AI technology (including implementation, deployment, and utilization), which is hypothesized to lead to improved performance.

To expand upon the resource-based theoretical framework, we incorporate the extended dynamic capability view (Teece, Pisano, & Shuen, 1997). The dynamic capabilities approach is viable for explaining how organizations create and capture business value in a dynamic environment. It is one of the most influential theoretical perspectives for understanding the foundations of firm-level competitive advantage (Kurtmollaiev, 2020). It emphasizes an organization's ability to sense and seize emerging business opportunities and create, extend, and reconfigure its resource base to adapt to shifting market conditions and sustain competitive advantage (Teece, 2007). On this view, performance differences across organizations within a given industry with a similar resource base (Leemann & Kanbach, 2022) are explained in terms of differences in dynamic capabilities. The expected outcomes include creating and modifying operating routines and significantly improving organizational effectiveness (Leemann & Kanbach, 2022; Wamba, 2022).

Studies taking this approach have classified various organizational capabilities to determine the superior level of organizational performance. The categories include ordinary, operational, or zero-order capabilities and dynamic or high-order capabilities (Kurtmollaiev, 2020; Teece, Peteraf, & Leih, 2016). As Wade and Hulland (2004) suggest, IS resources may have many of the attributes of dynamic capabilities and might be particularly useful for organizations operating in rapidly changing environments. Researchers confirm that leveraging IT to enable dynamic capabilities allows organizations to enhance their capacity for innovation and streamline their internal processes for agility; these are key components of competitive advantage (Mikalef & Pateli, 2016).

As is the case with IT resources, AI can enable or enhance the underlying processes that comprise an organization's dynamic capabilities and impact its performance (Chen, Esperança, et al., 2022; Mikalef, Conboy, & Krogstie, 2021; Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020a; Wamba, 2022). AI can assist organizations in automating their processes. By leveraging insights from previously unattainable data, organizations can sense and seize business opportunities, respond to threats, improve engagement with key customers, and quickly adapt to internal and external changes in the business environment (Bag, Pretorius, Gupta, & Dwivedi, 2021; Davenport & Ronanki, 2018; Mikalef et al., 2021). This BPM-focused study explores how AI adoption can optimize operations through process-level improvements and by fostering dynamic capabilities. This is achievable using a dynamic capabilities approach as it helps identify the core BPM capabilities that benefit from AI.

We further develop the resource-based theoretical framework by integrating the knowledge-based view, which reconceptualizes organizations as heterogeneous, knowledge-bearing entities (Zheng, Zhang, & Du, 2011). According to Zheng et al. (2011), the fundamental function of the organization is to integrate and use knowledge. Organizations' resource bases increasingly consist of knowledge-based assets (i.e., information with an applied interpretation process). Knowledge assets underpin all organizational capabilities and core competencies, which are understood as fundamental strategic tools for fostering continuous innovation (Marr, Schiuma, & Neely, 2004). According to the resource-based view, research efforts should target the unique features of intangible resources, particularly knowledge, as these are key to achieving a sustainable competitive advantage (Curado & Bontis, 2006). Knowledge assets are essential to ensuring that this competitive advantage is sustainable since they are difficult to imitate and are the foundation for sustainable differentiation (de Camargo Fiorini, Seles, Jabbour, Mariano, & de Sousa Jabbour, 2018; Wiklund & Shepherd, 2003).

Knowledge management theory concerns the operational and tactical aspects of managing knowledge. Knowledge management is a popular strategy employed by organizations to enhance their competitive position. It primarily focuses on organizational design, operational principles and processes, and organizational structures, applications, and technologies that help knowledge workers leverage their creativity and deliver business value (Abubakar, Elrehail, Alatailat, & Elçi, 2019; de Camargo Fiorini et al., 2018).

de Camargo Fiorini et al. (2018) argue that knowledge management theory (i.e., theories and practices for creating, sharing, using, and managing knowledge within organizations) is useful in investigating the various aspects of large data adoption that are inherently linked to AI. Knowledge management has been significantly affected by technology. For instance, IT and AI support knowledge management activities, including database decision support, management information, expert, resource planning, and knowledge management (i.e., lessons learned) systems (Al Mansoori, Salloum, & Shaalan, 2020; Castaneda, Manrique, & Cuellar, 2018). AI and knowledge management are inherently linked, and the extent to which AI can play a role in knowledge management is widely discussed (Baskerville & Dulipovici, 2006). Categories of AI that enhance knowledge management practices include artificial neural networks and intelligent agents (Al Mansoori et al., 2020).

Since IT underpins most knowledge work in organizations, it is helpful to explore the impact of AI on knowledge management activities (Sanzogni, Guzman, & Busch, 2017). We acknowledge the importance of knowledge and analyze the impact of AI on knowledge management by employing the knowledge-based view as a key theoretical lens in developing our research framework.

Each theory we employ focuses on different aspects of an organization's resources and capabilities. The resource-based view emphasizes the static qualities (i.e., valuable, rare, inimitable, and non-substitutable) of resources, the dynamic capabilities view focuses on dynamic adaptation capabilities, and the knowledge-based view considers knowledge as an essential resource. These theories are complementary rather than mutually exclusive. We use a multi-theoretical approach to uncover nuanced relationships that might be overlooked when using a single theory, thereby providing a more comprehensive perspective. This approach acknowledges the complexity of the current business environment and serves as a rich theoretical base from which to examine the impact of AI on performance. This integrated approach can lead to more robust, innovative, and relevant research outcomes.

2.1 AI and Firm Performance

We understand AI as a simulation of human cognitive functions using intelligent agents. According to (Russell & Norvig, 2020), an intelligent agent perceives its environment and takes action to achieve goals rationally. This broader definition of AI encompasses the entire field of AI and its objective to replicate human cognitive processes. However, when we refer to a specific implementation of AI, i.e., AI system, we use the definition: “a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment.” (OECD, 2024).

This definition highlights that an AI system is a concrete application designed to perform specific tasks by processing inputs to produce valuable outputs. The extent of an AI system's autonomy and ability to adapt post-deployment can vary, reflecting the diversity in AI applications and their capabilities. Articulated by the OECD's AI Experts Group, this definition has gained broad consensus among experts and it has been accepeted as an accurate and comprehensive description of AI by various organizations and governments. The concept of AI adoption developed and operationalized for this study, grounded in the definition of an AI system, is as follows: the implementation, deployment, and use of AI resources (data, AI infrastructure, skills, capabilities) in business processes. The development process is described in detail in Chapter 3.

Researchers have shown that by developing a strong IT capability an organization can effectively leverage its IT investments and improve organizational and process performance (Santhanam & Hartono, 2003). This idea has been adapted for technologies such as business analytics, business intelligence, and Big Data analytics (Krishnamoorthi & Mathew, 2018; Mikalef, Krogstie, Pappas, & Pavlou, 2020; Shanks & Bekmamedova, 2012). Recent empirical research suggests that AI adoption impacts dynamic capabilities and can improve performance (Table 1).

These studies position dynamic capabilities as the mediators that link AI and organizational performance. Examples of dynamic capabilities include organizational creativity and agility, customer agility, process-oriented dynamic capabilities, and innovation (Breznik & D. Hisrich, 2014). Other dynamic capabilities relate to Big Data analytics and knowledge management processing. These studies describe the dynamic capabilities of an organization as its AI-enabled potential to initiate and create frame-breaking change, solve business problems based on the disposition to sense opportunities and threats, make timely and market-oriented decisions, and change its resource base (Bratnicka & Bratnicki, 2013). Other studies consider the direct impact of AI, emphasizing productivity and efficiency as outcomes (Alekseeva et al., 2020; Babina et al., 2021; Jain, 2019; Joseph & Falana, 2021; Kim et al., 2022; Lui et al., 2022; Lyu & Liu, 2021; Mishra et al., 2022; Panduro-Ramirez et al., 2022; Yang, 2022).

In most existing studies (see Table 1), AI is viewed as an enabler, as technology incorporated into a system or process to enhance its capabilities or functionalities. Collectively, these studies emphasize AI's role in improving organizational performance and innovation through advanced tools and technologies that augment human abilities, streamline processes, and generate insights from large volumes of data (Mikalef & Gupta, 2021; Mikalef et al., 2023; Panduro-Ramirez et al., 2022). AI enhances efficiency, productivity, and innovation across sectors by leveraging data and automation (Joseph & Falana, 2021; Wamba, 2022). Additionally, the information-processing capabilities that AI introduces enable organizations to adapt or disrupt the market, innovate in their operations and strategies, improve decision-making, achieve sustainability, and navigate uncertainties in the supply chain (Chatterjee et al., 2022; Jain, 2019; Lui et al., 2022; Sullivan & Wamba, 2022; Wamba-Taguimdje et al., 2020a).

By contrast, in "AI-driven" systems or processes, AI plays a central and dominant role in decision-making, automation, or optimization. For example, AI-driven recommendation engines or chatbots provide real-time personalized recommendations without requiring human involvement by analyzing user behaviors and preferences. Several studies offer comprehensive insights into how AI can drive organizational performance and effectiveness across various dimensions. Mishra et al. (2022) show how AI can directly influence firms' operational performance and efficiency metrics. (Kim et al., 2022) find that AI adoption drives firm transformation, affecting value, profit, and operational dynamics. Studies consider the direct impact of AI on productivity and employee profiles (Yang, 2022), and its transformative effects in the energy sector (Lyu & Liu, 2021) and in manufacturing (Naz et al., 2022).

However, other studies focus on AI as an enabler, emphasizing its impact on Big Data analytics. For example, Babina et al. (2021) highlight AI's transformational effect on innovation and economic growth and Fotheringham and Wiles (2022) demonstrate how AI, particularly chatbots, impact value across the organization by influencing the response of investors. These studies provide evidence of the importance of AI as a driver of organizational change, innovation, and performance improvement.

AI's role as a mediator of organizational performance is considered in several studies. Bag, Gupta, et al. (2021) find that AI mediates the relationship between Big Data technology and knowledge creation in business-to-business marketing, impacting decision-making and organizational performance. Similarly, Joseph and Falana (2021) consider AI as a mediator in the relationship between technological innovation and performance and find that it facilitates improvements in operational efficiency. Chetty (2019) emphasizes that AI mediates the relationship between Big Data analytics, organizational capabilities, and performance by enabling advanced data analysis. Ho et al. (2022) show that AI mitigates the adverse effects of the COVID-19 pandemic on performance, serving as a resilient, crucial driver for sustainable performance in challenging environments. Finally, Alekseeva et al. (2020) demonstrate that AI skills and expertise within the organization facilitate outcomes, such as growth, productivity, and investment decisions. These studies collectively underscore AI's pivotal role as a mediator in shaping the relationships between factors such as capabilities, technology adoption, external shocks, and organizational performance, but at the same time, underline AI's role as an enabler.

Following the literature review, we consider how AI facilitates dynamic capabilities and its transformative effects. The transformative changes enabled by AI are often powered by the adoption and utilization of AI technologies, which play a central role in driving innovation. We posit that AI-specific abilities to create intelligent agents facilitating automation–augmentation of decision-making and transformation (redesign) of business processes can unlock organizational performance gains (Wamba-Taguimdje et al., 2020a). In light of the above, we formulate the following hypothesis:

H1: *AI adoption directly positively influences organizational performance.*

Organizations may struggle to leverage AI technologies and realize performance gains (Mishra & Pani, 2020). There is also strong evidence that AI investment can reduce a firm's market value (Lui et al., 2022), and is risky for managers, complicating AI adoption (considering operational and broader contextual factors). Investors can perceive disruptive innovation investments (Lui et al., 2022). Hence, a more complete understanding of the value-generation process is necessary to predict outcomes and reduce the investment risk in AI adoption.

2.2 AI Business Value Model

Empirical studies generally suggest that processes mediate the impact of IT on organizational performance (Bhatt & Grover, 2005; Kim, Shin, Kim, & Lee, 2011; Krishnamoorthi & Mathew, 2018; Marie Burvill, Jones-Evans, & Rowlands, 2018). We adopt the integrative IT business value model (Melville et al., 2004) to study AI adoption in the BPM setting. The model offers a comprehensive perspective on the process of AI business value generation and the integration of AI resources, capabilities, business processes, process performance, organizational performance, and the external environment.

Since the model is process-oriented, one of the central focuses of the analysis is business processes (Melville et al., 2004; Mooney et al., 1996). Although AI technology broadly impacts all business processes, certain types are particularly affected. The analysis especially considers knowledge-intensive processes and decision-making processes. After considering the scope of the BPM context, we identify several organizational capabilities and align these with the IT business value model.

New digital technologies such as AI have become increasingly important in managing business processes (Mendling, Pentland, & Recker, 2020). Prior research (Table 1) shows that particular organizational capabilities mediate the impact of AI. While aligning AI and AI-enabled capabilities (explored in Sections 3.4.1.4, 3.4.1.5, and 3.4.3) with BPM capabilities (Kerpedzhiev, König, Röglinger, & Rosemann, 2020), we identify three capabilities: CBPA, organizational learning (OL), and business process innovation (BPI). CBPA is aligned with Cognitive Decision Assistance (Advanced Process Automation as per Kerpedzhiev et al., 2020), OL with Cognitive Insights, Cognitive Engagement and Cognitive Decision Assistance (core element People as per Kerpedzhiev et al., 2020), and BPI with all AI adoption subdimensions, and (Agile Process Improvement and Transformational Process Improvement as per Kerpedzhiev et al., 2020).

Cognitive business process automation automation – reducing human interaction in operations (Sarker, 2022) – is a strategic BPM capability; it facilitates business transformation and productivity improvements (Baier, Lockl, Röglinger, & Weidlich, 2022; Engel, Ebel, & Leimeister, 2022; Lacity & Willcocks, 2021). According to (Kerpedzhiev et al., 2020) and in line with Cepeda and Vera (2007), it can be considered an operational capability (zero-order: geared toward the operational functioning of an organization). It allows existing processes to be streamlined via the exploitation of automation technologies to assist human participants in performing unstructured tasks and complex decisions or to fully automate such tasks and decisions. However, automation allows AI to be leveraged for adaptability, that is, the context-aware execution and redesign of business processes, and can thus be understood as a dynamic capability (first-order: dedicated to modifying operational capabilities).

The BPM capability framework has several core elements, and in the areas of people and culture, for example, learning and knowledge in different fields is essential (Helbin & Van Looy, 2021; Kerpedzhiev et al., 2020). Organizational learning can thus also be considered a BPM capability.

Digital transformation using new digital technologies enables organizations to improve and innovate business processes (Mendling et al., 2020; Sullivan & Wamba, 2024). Drawing on

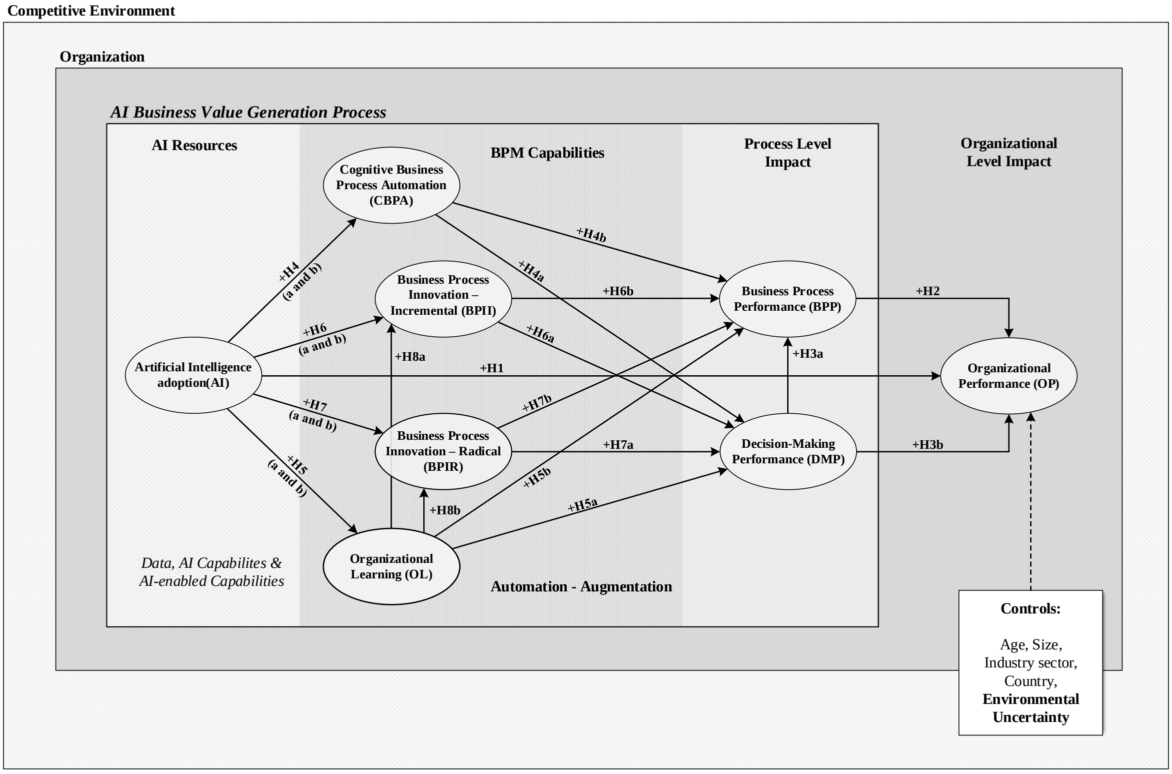
Kerpedzhiev et al. (2020), this perspective integrates the operational capability of fast, iterative, and incremental process improvements (*BPII*) and the dynamic capability of progressive or radical transformational process improvements (*BPIR*), reflecting an ambidextrous innovation view (Belhadi, Mani, Kamble, Khan, & Verma, 2024).

We expand upon prior research (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Enholm et al., 2021; Mikalef et al., 2023) and, ensuring adherence to the IT business value model, we examine outcomes on the process level, considering business process performance (*BPP*) and decision-making performance (*DMP*). We then extend the model to organizational performance. The individual relationships are presented in Figure 1.

We follow the guidelines of Hong, Chan, Thong, Chasalow, and Dhillon (2014) on context-specific theorizing and apply the IT business value-generation process model to the AI technology context. As AI resources are a subset of IT resources and share similarities with these (Deng, Zhang, He, & Xu, 2023; Deng, Zhang, & Xu, 2023; Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020b), we can refer to the existing literature on IT resources and their impact on business processes. We contextualize the established theory of IT business value (Melville et al., 2004) by replacing IT with AI resources following the first level of contextualization (Level 1). For the second level of contextualization (Level 2a), we include BPM capabilities as antecedents of dependent variables, that is, as mediators, to contextualize complementary organization resources. Core components of *BPP* and organizational performance are applied in the context of process and organizational impacts (Level 1 contextualization). In addition, we add *DMP* as an antecedent of the dependent variable of *BPP* (Level 2a). We add contextual variables to capture the competitive and macro environment as controls (moderators) as second-level contextualization (Level 2b).

We also add contextual organizational variables (digital maturity, data-driven culture, BPM maturity, and organizational culture) as moderators. A graphical representation of the procedure is presented in Appendix 3: Contextualization procedure. We position the adoption of AI technology as a central focus of our research. Figure 1 shows the conceptual framework and the nexus of the relationships between the main constructs.

Figure 1: Proposed Research Model



Source: Own work.

2.3 Business Process Performance

The relevant research on IT business value for AI-related technologies (defined in Section 3.3) concerning business analytics, business intelligence, and Big Data analytics (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Garmaki, Boughzala, & Wamba, 2016; Krishnamoorthi & Mathew, 2018; Mikalef et al., 2020; Shanks & Bekmamedova, 2012) offers evidence of its positive impact on process performance. Several authors theorize that AI technology has the same positive impact (Bawack & Wamba, 2019; Enholm et al., 2021; Mikalef et al., 2023; Wamba-Taguimdje et al., 2020b). Drawing from Melville et al. (2004) IT business value model, the proposed research model posits that AI technology's impact occurs via business processes, thereby suggesting that its impact should be evaluated at the process level. We examine the impact on process performance by aligning the key characteristics of the AI value proposition – speed, scale, granularity, learning (accuracy of prediction), problem-solving, and decision-making (Agrawal, Gans, & Goldfarb, 2017; Mikalef, Fjørtoft, & Torvatn, 2019; Roeglinger, Seyfried, Stelzl, & Muehlen, 2018; Zasada, 2019) – with the lead indicators of process efficiency (time, cost), effectiveness (quality), and flexibility (Dumas, La Rosa, Mendling, & Reijers, 2018). We argue that leveraging AI capabilities by establishing (intelligent) agent-oriented business processes should increase process productivity. Next, we theorize about the impact of AI adoption on four dimensions of process performance.

2.3.1 Process Execution Time

The automation of repetitive tasks mainly impacts process execution time (e.g., transferring data for back-office administrative and financial activities, rule-based robotic process automation). These tasks are completed faster and with fewer errors, allowing the processing of vast amounts of structured and unstructured data (data from documents, electronic communication, audio, video or image materials), producing real-time data insights (e.g., fraud detection, targeted marketing, actuarial modeling, credit scoring, behavioral anomaly detection), and event identification and processing (e.g., anomaly detection and risk detection (Davenport & Ronanki, 2018; Plastino & Purdy, 2018; Roeglinger et al., 2018; Zasada, 2019). Waiting or idle time is also reduced by automation, releasing resources (e.g., relieving employees of repetitive routine tasks) and synchronizing related sub or chained processes (e.g., shop floor optimization).

2.3.2 Operational Costs

Operational costs are also decreased by automation. It reduces the labor cost in manufacturing (e.g., through computer vision-guided robotics) or delivering a service (e.g., insurance claim processing, chatbots, virtual assistants, recommendation systems), thereby increasing productivity (Bawack, Fosso Wamba, & Carillo, 2019; Schatsky, Muraskin, & Gurumurthy, 2014). Typical fixed costs of infrastructure and maintenance are decreased with AI-enabled planning, scheduling, and optimization (e.g., resource planning, supply chain optimization, and requirement engineering). It allows the detection of anomalies and deviant behavior (e.g., proactive incident detection, provider–consumer anomaly detection for healthcare systems, threat detection, DevOps monitoring, and smart city applications such as traffic, air quality, water distribution, energy consumption). It is also employed for predictive maintenance (e.g., digital twin, failure prediction, processing and refining maintenance, predictive acoustics maintenance, predictive disaster recovery, smart buildings, infrastructure maintenance, and facilities management; see Prieto, 2019; Schatsky et al., 2014). Automation of marketing and talent management systems can reduce variable costs from sales, supply chain fluctuations, and hires (e.g., demand forecasting, trend identification, and candidate screening automation; see Heimbach, Kostyra, & Hinz, 2015; Todor, 2016; Tussyadiah, 2020).

2.3.3 Process Quality

We examine two aspects of process quality (Dumas et al., 2018). First, with respect to the external quality perceived by customers, AI can generate valuable insights from customer-related data and support data-driven decision-making about products and services. Applications include marketing automation, marketing intelligence, customer relationship management, and customer experience management systems (e.g., self-optimizing campaign design and management, context-aware marketing, account opening, client onboarding, advanced targeting and retargeting; Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Prieto, 2019).

Second, internal quality concerns control over execution and variation (Dumas et al., 2018). AI-enabled process execution management offers several features, such as analysis, prediction, monitoring, control, and optimization (e.g., predictive business process analytics, process model and requirement-discovery automation, process mining and monitoring, and sensor-enabled process intelligence; Zasada, 2019).

2.3.4 Flexibility

In this context, flexibility is the ability to respond to changes and to allow for appropriate response times in event-driven business environments; Dumas et al. (2018) distinguish runtime and build-time flexibility. The learning aspect of AI technology mainly impacts the flexibility of processes. AI systems use inputs to perceive real and/or virtual environments and can abstract these perceptions into models through automated analysis. New inputs (data) are processed automatically, increasing the model's scope and accuracy in predictions, recommendations, or decisions. Business rules, policies, or other analytical models can be mapped to predicted data at runtime to assist decision-making. AI can deal with uncertainty when the process being implemented is based on a loosely or partially specified process model. The full specification is made during runtime and may be unique to each process (Reichert, 2011). At build-time, many processes are only implicit in purpose-built documents, digital exhaust, and system logs. Across the entire spectrum, from structured to unstructured processes, AI can help capture and codify process specifications to facilitate further automation while retaining the requisite flexibility (Hull & Motahari-Nezhad, 2016).

2.4 Organizational Performance

The established connection between IT and value generation (Melville et al., 2004; Patas et al., 2012; Wade & Hulland, 2004; Wiengarten, Humphreys, Cao, & McHugh, 2013) highlights the importance of seamlessly integrating IT into broader organizational and information systems to maximize value creation. As discussed in Section 2.1, empirical studies indicate a link between the adoption of AI and organizational performance that manifests in increased business value and competitive advantage (Bag, Gupta, et al., 2021; Bhatnagar, 2020; Kim et al., 2022; Mikalef & Gupta, 2021; Mishra et al., 2022; Wamba-Taguimdje et al., 2020a; Wamba, 2022). We operationalize organizational performance with reference to the organization's overall productivity, profitability, financial indicators, and market performance; the latter refers to the organization's success in entering and introducing new products or services to the market (Wang, Liang, Zhong, Xue, & Xiao, 2012). In the following section, we explore how AI impacts key dimensions of organizational performance.

2.4.1 Productivity

AI can potentially enhance productivity[3], and represents a key metric of its economic contribution (Yang, 2022).

Organizational performance is often described as the umbrella term for excellence. It includes profitability, productivity, and other non-cost factors of quality, speed, delivery, and flexibility (Rogers & Rogers, 1998; Tangen, 2005). In this research, we measure the organization's performance by comparing its productivity gains to those of competitors (Section 5.5.9). Non-cost factors are the effectiveness and efficiency of the transformation process and are, to some extent, cross-functional. Effectiveness is the degree to which the desired results are achieved, and efficiency is how well resources are utilized in the transformation process. Based on this, we define productivity growth as the net change in output due to efficiency-related and technical changes (Grosskopf, 1993), in this case, the introduction of AI. We introduce a BPP variable to obtain a more detailed view of the AI value-generation process; this measures the effectiveness and efficiency of the transformation process at the process level.

Existing studies show that AI's impact on productivity is primarily driven by non-cost factors related to efficiency and technical change, such as quality, speed, and flexibility. Yang (2022) presents evidence of productivity gains achieved through AI's transformational effect on production methods. AI also allows organizations to identify new ways of combining existing technologies (Agrawal et al., 2017). There are examples of the use of AI in process management systems in manufacturing to improve input efficiency and analyze and adjust equipment performance from sensory data. In automation production programming, engineers are being replaced by machine learning and deep learning, which have been designed to automatically learn production patterns from data (Brynjolfsson & Mitchell, 2017). Computer vision systems are used to reduce error rates or identify defects in visual inspection (e.g., image processing for control and measurement systems). They expands the robot's routine machine actions with various hand-eye coordination tasks (Levine, Finn, Darrell, & Abbeel, 2016).

Lyu Lyu and Liu (2021) present evidence that the use of AI technology itself attracts the most talented and skilled employees, and, in turn, this high-level workforce positively impacts productivity. However, there may be a lag between the deployment of AI technology and any productivity gains (Jovanovic & Rousseau, 2005). This may be attributable to

[3] We follow Tangen (2005) and define productivity as the ratio of output quantity (i.e., the number of products or services provided according to specification) divided by input quantity (i.e., all resources consumed in the transformation process).

adjustment costs, complementary innovations, and organizational changes (Brynjolfsson, Rock, & Syverson, 2017).

2.4.2 Profitability

Like productivity, profitability[4] is a relationship between output and input, specifically, a monetary relationship that includes price factors, allowing price recovery (Tangen, 2005). In the context of profitability, price recovery refers to an organization's ability to recover its costs and generate profits. Tangen (2005) emphasizes that organizations should combine productivity and profitability ratios to clarify the reasons underlying increased profits. However, productivity improvement may not have an immediate impact on profits; rather, it may impact long-term profitability (Tangen, 2005). Productivity and profitability are interdependent but not always correlated. Grünberg (2004) argues that profitability results from operational actions and processes and is not a direct contributor to improvements. We conclude that AI's impact on profitability comes mostly from increased productivity and improved process-level decision-making.

According to Panduro-Ramirez et al. (2022), AI's impact on business decisions and profitability are directly linked. The authors recognize that AI applications play a vital role by creating information from business operations data, and providing reliable and accurate information for decision-making. Alekseeva et al. (2020) present evidence of a positive association between AI adoption and changes in sales volume and various productivity measures and investments. The main drivers of these changes are AI-enabled marketing automation, marketing intelligence, and customer relationship management applications, allowing better targeting to attract more customers and allow higher product prices. It can also improve the precision of forecasts, facilitating better decision-making and cost optimization, for example, reducing the cost of order handling and inventory management. Babina et al. (2021) highlight AI investment's contribution to the growth of sales and market valuation through product innovation, reflected in trademarks, product patents, and product updates.

2.4.3 Market Performance

Researchers present evidence of market-based performance gains created either through new products (product innovation) or optimizing business processes (process innovation; Mishra & Pani, 2020). Essential AI applications in this field include expert decision support systems for new product evaluation projects and knowledge-based systems supporting conceptual

[4] Profitability is defined in various studies as the product of productivity and price recovery, where productivity represents output quantity per input quantity (Alsyouf, 2007; Grifell-Tatjé & Lovell, 2018; Miller, 1984), while Bernolak (1997) and Diewert (2014) state that profitability is the ratio of the value of outputs produced in a period to the total cost of producing those outputs.

design and group decision-making in concurrent engineering (Rao, Nahm, Shi, Deng, & Syamil, 1999).

Automating manual processes frees up human resources with the potential to engage in creative processes, and organizations will be more likely to innovate. Mikalef and Gupta (2021) present evidence of AI's impact on organizational creativity, for example, by augmenting ideas using generative design. Generative design utilizes AI technology to produce high-performing design alternatives from a singular design idea. Engineers provide input data – spatial requirements, materials, manufacturing methods, and cost constraints – and generative design takes these to create hundreds of feasible alternatives to the original design. The AI tests and learns from each successful and unsuccessful iteration, ultimately creating design alternatives.

2.4.4 Customer Relations

AI transformation drives improvements in customer relations and the development of new products and services. These are closely linked in supporting service transformation through innovation and process redesign. Wamba (2022) shows that AI impacts customer relationships and experience management. Customer predictive insights allow the personalization of offers and services, anticipation and reduction of customer churn, and improvement of lead generation and scoring for sales or cross-sales. Extracting customer sentiment and identifying trends by deep mining internal and external data (e.g., social media) supports and facilitates customer interactions for market intelligence, improved customer service, products, and customer experience (Hadjielias, Christofi, Christou, & Drotarova, 2022). AI allows companies to better perceive and respond to changes in the broader external environment in real time and generate intervention strategies for customer-related innovative competitive actions and opportunities (Haftor, Climent, & Lundström, 2021; Liu, Chan, Yang, & Niu, 2018). AI supports evidence-based decisions in marketing, product development, and customer relationship management (Chen & Lin, 2021).

2.5 The Mediating Role of Business Process Performance

Business processes comprise key business operations that must be managed for business growth and success (Mithas, Ramasubbu, & Sambamurthy, 2011). Superior BPP is related to the transformation of organizational productivity, which includes individual and operational efficiency (i.e., doing things right), customer service efficiency, and product/service development (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Tangen, 2005). The aggregated outcomes of various processes directly influence the organization's performance (Bhatt & Grover, 2005). Process performance is also measured by operational effectiveness (i.e., doing the right things and achieving goals and objectives), which is expected to translate into organizational performance (Elbashir, Collier, & Davern, 2008).

BPP indicators should thus be aligned with the organization's goals (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Bisogno, Calabrese, Gastaldi, & Levialdi Ghiron, 2016).

In Section 2.2, we discuss AI resources as a subset of IT resources, including the hardware, software, and data specifically used to implement, train, and run AI applications. The existing literature on IT business value establishes that process performance mediates the link between IT resources and organizational performance. According to Melville et al. (2004), performance comprises business processes and organizational performance. The IT business value framework model adopted here separates the operational efficiency of specific business processes and overall organizational performance. Prior research on IT business value offers a more detailed perspective on the role of BPP in organizational performance (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Elbashir et al., 2008; Gu & Jung, 2013; Hernaus, 2012, 2016; Kohlbacher, 2010). Several authors emphasize that the benefits of business processes are expected to translate into organizational performance (Melville et al., 2004; Tallon, Kraemer, & Gurbaxani, 2000). However, whether performance is impacted also depends on other factors, including the scope of the process in question, the extent to which it is core to the organization, the organization's decision-making process, and its competitive environment (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Dehning & Richardson, 2002; Melville et al., 2004; Subramani, 2004).

Although several studies demonstrate AI's direct impact on organizational performance (Table 1), it is theorized that AI's first-order impacts occur at the operational level (Enholm et al., 2021; Mikalef et al., 2023; Wamba-Taguimdje et al., 2020b). Key performance indicators related to the efficiency and effectiveness of performance improvements at the process level are proposed to monitor an organization's output (Wamba-Taguimdje et al., 2020b). The second-order impacts of AI are broader and are related to the organization's overall performance, strategy, or structure (Enholm et al., 2021). It is necessary to examine AI's impacts at the process (first-order) and organizational levels (second-order).

The first-order impact of AI on process efficiency and effectiveness results from its ability to automate tasks and enhance human intelligence, thereby increasing process productivity indicators such as speed, cost, delivery, quality, and flexibility (Coombs, Hislop, Taneva, & Barnard, 2020; Kirchmer & Franz, 2019).

Automating repetitive routine tasks allows employees to focus on other knowledge-intensive activities (Makarius, Mukherjee, Fox, & Fox, 2020). Even so, organizations can achieve much more when AI is combined with automation to transform and digitalize operations (Tschang & Almirall, 2021). Many organizations report that accurate demand projection and forecasting have enabled them to reduce costs, increase revenue, and optimize the use of their assets, enhancing the efficiency of research and development (R&D) and lowering manufacturing costs. In terms of effectiveness, AI increases the quality of products and services (e.g., improves the error rate and lag times with real-time monitoring, eliminates waste, lowers process cycle times, optimizes robotics and processes, increases safety by automating risky activities, reduces inventory costs with better supply and demand planning). Furthermore, marketing can be automated (e.g., customer targeting, demographics, pricing strategies, and branding), the customer experience improved, and the organizations' throughput increased, particularly in manufacturing (i.e., smart manufacturing) and supply chain operations (Balasundaram & Venkatagiri, 2020; Finch, Goehring, & Marshall, 2017; Tao, Qi, Liu, & Kusiak, 2018). These AI-impacted areas and value-creation processes are significant for gaining a competitive advantage by bringing innovation to the market more quickly (Dash et al., 2019). In short, wherever a process uses digital data, AI can be applied to ensure data are used more effectively and that digital operations, products, and services are more efficient.

AI systems can also enhance human intelligence. Some researchers have adopted the augmentation perspective, highlighting how AI can improve personal productivity (Agrawal, Gans, & Goldfarb, 2018; Daugherty & Wilson, 2018). AI systems tend to augment rather than replace human capabilities by providing assistive systems such as predictive analytics or generative AI productivity tools, resulting in improved (human) intelligence (Jarrahi, Lutz, & Newlands, 2022; Maedche et al., 2019).

Although the adaptive organizational capabilities necessary to increase operational efficiency can be acquired through AI, organizations must maximize the effectiveness of their AI resources to promote strategic flexibility and business value. To realize second-order impacts requires that AI capabilities be optimized to enable the integration of digital transformation alignment (Perifanis & Kitsios, 2023).

In terms of organizational performance, we position the BPP measure to represent the productivity measure's non-cost factors (i.e., quality, speed, delivery, and flexibility), referring to the effectiveness and efficiency of the productivity transformation process, that is business processes (Rogers & Rogers, 1998; Tangen, 2005).

We illustrate this further by considering the well-established balanced scorecard framework (Ferreira & Otley, 2009) which is a management system aimed at translating an organization's strategic goals into a set of organizational performance objectives. As we separate the internal processes from the overall measurement of organizational performance, the mediating role between BPP and organizational performance is revealed (Kaplan, 2009; Van Looy & Shafagatova, 2016). We obtain a more detailed view of the impact of AI adoption at lower (process) and higher-order (organizational) levels (Enholm et al., 2021).

Drawing upon these conclusions, we argue that AI resources help organizations create value through their direct impact on business processes. IT, and by extension, AI, typically provides automated support to business processes and interprocess linkages (Barua, Kriebel, & Mukhopadhyay, 1995; Mukhopadhyay & Kekre, 2002; Subramani, 2004). As such, research on process-level benefits does more than demonstrate that value is created; it also explains how that value is created (Davern & Kauffman, 2000). The second-order impacts of AI at the organizational level are the consequence of the use of AI in operations (Enholm et al., 2021).

Despite the theoretical foundation for the mediating role of BPP, there is limited empirical research on the links between AI adoption and organizational performance that includes BPP. We thus formulate the following hypothesis.

H2: *Business process performance positively influences organizational performance.*

2.6 The Mediating Effect of Decision-Making Performance

DMP concerns the efficiency and effectiveness of organizational decision-making. Although evidence highlights the direct impact of IT on business-process performance, achieving these effects depends on having a robust and efficient decision-making process. IT tools are instrumental in aggregating and analyzing data to offer actionable insights (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Cao, Duan, & Cadden, 2019; Ghasemaghaei, Ebrahimi, & Hassanein, 2018). AI extends this capability even further. In AI adoption, DMP allows firms to systematically collect, evaluate, and analyze the recommendations of AI systems, enhancing decision-making effectiveness (quality) and efficiency (Ashaari, Singh, Abbasi, Amran, & Liebana-Cabanillas, 2021). AI systems replace human decision-makers for structured or semi-structured decisions (automation) or function as a tool to support unstructured decision-making at the process or strategic organizational level (augmentation; Duan et al., 2019; Edwards, Duan, & Robins, 2000; Taylor, 2011). Thus, AI-assisted decision-making can significantly increase operational efficiency and productivity to achieve superior performance (Ashaari et al., 2021; Chatterjee, Rana, Tamilmani, & Sharma, 2021). We examine the impact of DMP on process and organizational performance.

2.6.1 Decision-Making Performance and Business Process Performance

Research on information processing capabilities indicates that organizations proficient in data capture and management can integrate insights into their business processes and operations, enabling them to make data-driven decisions (Cao et al., 2019; Chen, Preston, & Swink, 2015; Günther, Mehrizi, Huysman, & Feldberg, 2017; Kiron, Prentice, & Ferguson, 2012; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

Making decisions based on relevant data and metrics enables organizations to identify opportunities for process improvement and implement changes that enhance efficiency. Decisions based on intuition or without data often fail to address the underlying causes of process issues (Korherr, Kanbach, Kraus, & Mikalef, 2022). Effective decision-making can streamline processes, eliminate unnecessary steps, and improve overall workflow, resulting in faster completion times and reduced costs. Agile decision-making ensures continuous process flow and quickly adjusts to market conditions or unforeseen circumstances, essential for sustaining process performance under varying conditions. This capability enables organizations to seize opportunities and mitigate risks (Robert Baum & Wally, 2003). Data-driven decision-making helps optimize resource allocation and utilization, thereby enhancing process efficiency (Strauch, Pidun, & zu Knyphausen-Aufsess, 2019). Conversely, slow or indecisive decision-making can halt progress.

Access to accurate, timely information and effective strategies helps decision-makers optimize business processes for efficiency and productivity. Well-informed decisions minimize errors and delays, enhance overall process quality, and improve customer satisfaction (Janssen, Van Der Voort, & Wahyudi, 2017; Litvaj, Ponisciakova, Stancekova, Svobodova, & Mrazik, 2022).

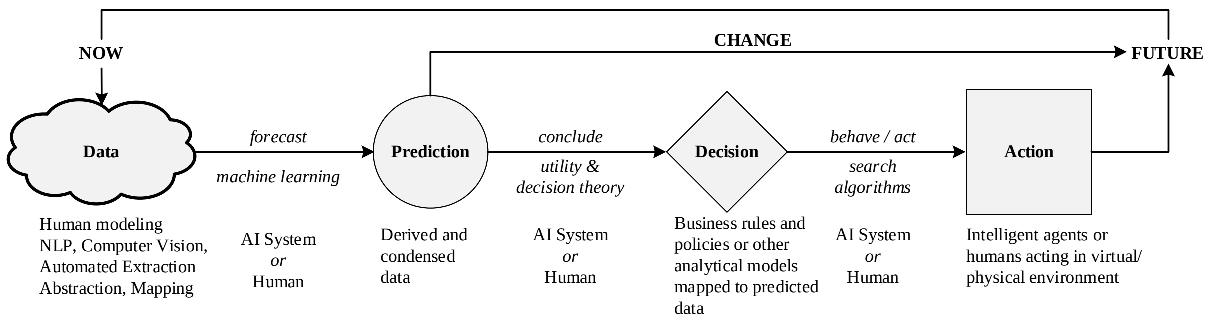
Decisions that promote innovation can improve processes by integrating new technologies and methodologies, leading to better process performance and the development of new products, services, and processes. The likelihood of innovation success is associated with the systematic reduction of decision-making uncertainty as a result of organizational information gathering, diffusion, and processing activities (Van Riel, Lemmink, & Ouwersloot, 2004).

To that end, many organizations increasingly utilize data analytics (information processing capability) to manage Big Data and to improve their decision-making processes (Fernández et al., 2014). Data analytics encompasses a variety of methods and tools, such as predictive analytics, statistics, data mining, artificial intelligence, and natural language processing (Ghasemaghaei et al., 2018; Russom, 2011). These methods are frequently applied to large and sometimes dispersed datasets to derive valuable insights that enhance organizational decision-making (Ertemel, 2015).

Even though making decisions with human actors is complex, it is relatively well understood, and incorporating AI into the process adds a whole new layer of complexity (Von Krogh, 2018). AI, particularly machine learning, can learn from big data to make predictions, but only if the future behaves similarly to the past. The rapid development of AI is driven by its potential to facilitate fast, precise, and cost-effective decision-making processes, approaching the level of human cognitive capability (Agrawal, Gans, & Goldfarb, 2019b). Advancements in AI-enabled machine prediction drive machines' ability to perform cognitive tasks. Next, we explore the impact of these improved predictions on business processes (Shrestha, Ben-Menahem, & Von Krogh, 2019).

Koehler (2018) adopts an abstraction of AI’s impacts on the main activities in a business process (Figure 2). A process uses given data to generate a prediction. The prediction is the basis for deciding how a human or intelligent agent will behave in executing a particular action. The abstraction is consistent with our definition of the intelligence agent making predictions, recommendations, or decisions to influence real or virtual environments (OECD, 2019, 2024). The transitions between activities can be automated or partially performed by humans, augmenting human decision-making. Three key AI technologies drive optimization and the increased quality and flexibility of business processes: machine learning, decision and utility theory, and search algorithms (Koehler, 2018). Deep learning (a subset of machine learning) algorithms, in particular, promise benefits for process decision-making, for example, by assisting employees with information processing and augmenting their analytical capabilities, predictions, or robust patterns using Big Data (Shrestha, Krishna, & von Krogh, 2021). Predictions become more valuable when data are more widely available and accessible. With the expansion of data availability, it is becoming increasingly feasible to make predictions in various tasks (Agrawal et al., 2017).

Figure 2: Common Business Process Design



Source: Adapted from Koehler (2018)

Common business process design can be illustrated with a simple credit score example. A business process is usually triggered by some event, in this case, by a loan application. Data drives the business process toward its goal (Hull & Motahari-Nezhad, 2016; Roeglinger et al., 2018; Zasada, 2019), the loan approval or denial. Many different data sources are integrated, and data are mapped to a model, aggregated, condensed, and analyzed to arrive at an interpretation and assessment to predict the credit score. Based on the prediction, a decision is made, and one or several actions are taken; when the decision is to approve the loan, an account is opened, and the money is transferred.

Decision-making is critical for superior process performance. Organizations prioritizing such capabilities enhance their business process efficiency. AI increases the speed, flexibility, and quality (more data sources, better predictions) of the decision-making process and, in turn, positively impacts BPP. The following hypothesis offers a more general formulation of the relationship:

H3a: *Decision-making performance positively influences business process performance.*

Judgment goes beyond simple prediction in influencing decision-making. Predictions rely on clear information to forecast the future, while judgment incorporates intangible factors like intuition and experience that are difficult to define. These unquantifiable elements are essential for navigating unfamiliar situations. Unlike passive information processing, judgment is an active process demanding thoughtful analysis (Agrawal et al., 2019b). With AI automating decision-making, a critical challenge emerges: should it entirely replace human judgment (automation) or work alongside it to enhance it (augmentation)?

2.6.2 Decision-Making Performance and Organizational Performance

Managers make high-risk decisions in highly unpredictable, ambiguous, time-constrained, and emotionally strained contexts (Baron, 2004; Cao, Duan, Edwards, & Dwivedi, 2021; Shane & Venkataraman, 2000). At an organizational level, the decision-making process involves understanding the trends and patterns in business growth (Amoako, Omari, Kumi, Agbemabiase, & Asamoah, 2021; Keding, 2021). Managers use AI-enabled processing capabilities to learn and augment their decision-making capacity by gaining insights into emerging phenomena, making predictions, and extracting information from Big Data (Ghasemaghaei et al., 2018).

Accurate data are not obtained solely for practical insight; in strategic decision-making, data are also important for implementation. Managerial decision-making is primarily knowledge-based (Wiklund & Shepherd, 2008; Zhang, Liao, & Bellamy, 2020). Therefore, AI-enabled knowledge-based information systems (i.e., decision automation systems, knowledge engineering and expert systems, and decision support systems) are valuable tools, enabling evidence-based decision-making and problem-solving in complex business situations. AI-based applications are already being implemented in many knowledge-based domains (Agrawal, Gans, & Goldfarb, 2019a). Several studies find that AI-based decision-making directly impacts organizational performance (Ashaari et al., 2021; Chen, Esperança, et al., 2022; Keding & Meissner, 2021; Rahman, Hossain, & Fattah, 2021; Yasmin, Tatoglu, Kilic, Zaim, & Delen, 2020). We thus propose the following hypothesis:

H3b: *Decision-making performance positively influences organizational performance.*

2.7 Automation–Augmentation: The Relationship Between AI Adoption, Cognitive Business Process Automation and Organizational Learning

Automation and augmentation are two main use cases for AI technology to increase performance (Davenport & Kirby, 2016; Enholm et al., 2021; Grønsund & Aanestad, 2020; Raisch & Krakowski, 2021; Rouse & Spohrer, 2018; Wilkens, 2020). Automation implies that machines take over a human task, and augmentation means that humans work closely with machines to perform a task. Automation allows organizations to achieve cost efficiencies, establish faster processes, and ensure greater rationality and consistency in information processing. Augmentation generates complementary benefits from the mutual enhancement of human and machine skills. Integrating automation and augmentation leads to additional benefits from synergies between these interdependent activities (Langer & Landers, 2021; Raisch & Krakowski, 2021). The benefits of each suggest that the combination of automation and augmentation generates complementary returns that lead to increased performance (Grønsund & Aanestad, 2020).

The literature on management information systems suggests that capabilities mediate the impact of IT on performance (Krishnamoorthi & Mathew, 2018; Marie Burvill et al., 2018). Each of the mediating factors aids in the development of resources and enhances their performance impact. The mediating factors undergo their own developmental process and impact performance, albeit indirectly. This is especially likely where automation and augmentation are combined; with a higher level of AI adoption and technology exploitation, organizations move from augmentation to automation. The mediating factors influence the resources and each other (Marie Burvill et al., 2018). Next, we examine automation and augmentation with respect to AI-enabled capabilities and how these mediate the impact of AI on performance.

Automation and augmentation are often at either end of the human–machine collaboration spectrum (Raisch & Krakowski, 2021). Automation may vary from fully manual (i.e., human) to fully automatic (Parasuraman, Sheridan, & Wickens, 2000). A four-stage model for applying automation to different functions is proposed by Parasuraman et al. (2000): 1) information acquisition, 2) information analysis, 3) decision and action selection, and 4) action implementation. The model is consistent with common business process design (Agrawal et al., 2017; Koehler, 2018) and is appropriate for examining automation–augmentation in the BPM setting.

Automation can be applied on a continuum and extends from low to high automation, that is, from fully manual to fully automatic. Across this continuum, automation may augment the human performance of a particular task by increasing the capability of humans to approach and comprehend a problem and derive appropriate solutions (Grønsund & Aanestad, 2020). Von Krogh (2018) theorizes that it is in cases of problem-solving (algorithms providing alternative courses of action to resolve a problem) rather than decision-making (conclusions reached by the algorithms based on the data available) that algorithms appear to augment rather than substitute humans in their tasks. Humans outperform machines in dealing with ambiguity, vagueness, and incomplete information; they are better at unstructured problem-solving (Pavlou, 2018). Automated decision-making is often infeasible in business contexts because there is a need for accountability in decision-making, and there is considerable decisional uncertainty (Eberhardt, Bilchik, & Stojadinovic, 2012). In summary, applied to the BPM context, automation is more suitable for structured processes and to augment knowledge-intensive and loosely structured or unstructured processes (Di Ciccio, Marrella, & Russo, 2015; Szelagowski & Lupeikiene, 2020).

2.7.1 The Mediating Role of Cognitive Business Process Automation

Automation is often highlighted as a key characteristic of AI, facilitating higher levels and greater scope of business process optimization (Brás, Pereira, & Moro, 2023). Although extensive theorization exists regarding process automation and IT (Mooney et al., 1996), the specific area of business process automation has not been as thoroughly investigated (Aysolmaz, Joshi, & Stubhan, 2023; Engel et al., 2022). IT has the potential to enhance operational efficiency through automation. It can also improve effectiveness and reliability by integrating processes (Mooney et al., 1996), impacting productivity and profitability (Kromann & Sørensen, 2019). AI-powered (enabled and driven) process automation has established itself in business operations by employing software agents, commonly known as bots. These agents interface with systems to replace human intervention to enhance efficiency, cut costs, and mitigate risks (Brás et al., 2023). Intelligent process automation started by automating simple tasks (previously performed by humans) or strictly transactional processes. With the introduction of AI and cognitive computing, intelligent process automation has become more sophisticated, adding new capabilities to handle more complex tasks. Complex tasks that require judgment, rule-following, decision-making, and navigating unpredictable situations encompass evaluation, reasoning, and compliance with probabilistic and deterministic process requirements in dynamic contexts ("IEEE Approved Draft Guide to Terms and Concepts in Intelligent Process Automation," 2017; "IEEE Guide for Terms and Concepts in Intelligent Process Automation," 2017).

We distinguish two approaches to automation, which is consistent with the OECD (2019): definition of an AI system: 1) Classical AI applies rules-based logic to decide what intelligent action to take; 2) Constructed AI uses ML algorithms to discover patterns from data (Richardson, 2020; Stuart, 2019). Based on this distinction, intelligent process automation (IPA) is a set of new automation technologies (Richardson, 2020; Suri, Elia, Arora, & van Hillegersberg, 2019; Williams, Allen, & McDonough, 2018; Zhang, 2019). The literature, however, distinguishes between IPA and cognitive automation (Marciniak, Moricz, & Baksa, 2020; Ng et al., 2021b; Richardson, 2020; Siderska, 2020; Suri et al., 2019; Zhang, 2019). Some studies treat these as equivalent (Anagnoste, 2018; Kokina & Blanchette, 2019; Naga Lakshmi, Vijayakumar, & Sai Sricharan, 2019; Williams et al., 2018).

2.7.1.1 Intelligent Process Automation

We understand IPA according to the definition given by the IEEE Standards Association Working Group for Intelligent Process Automation ("IEEE Approved Draft Guide to Terms and Concepts in Intelligent Process Automation," 2017, p. 11), as a broad concept encompassing rule-based and inference-based decision-making, that is, “a preconfigured software instance that combines business rules, experience-based context determination logic, and decision criteria to initiate and execute multiple interrelated human and automated processes in a dynamic context. The goal is to complete the execution of a combination of processes, activities, and tasks in one or more unrelated software systems that deliver a result or service with minimal or no human intervention.”

2.7.1.2 Cognitive Automation

We consider cognitive automation as being at the higher end of the automation spectrum. Advances in automation are enabled by AI technology, specifically cognitive technologies, and is operationalized by cognitive computing (further detailed in Section 3.2). Technologies like machine or deep learning, natural language processing, computer vision, automated reasoning, and robotics can perform tasks requiring human intelligence (Viehhauser, 2020; Watson, 2017; Zhang, 2019). Cognitive systems can continuously improve by learning from past experiences (decisions and outcomes). They can make human-like intelligent decisions (Marciniak et al., 2020) and deliver end-to-end automation beyond the rule-based approach by combining complementary technologies to augment business processes. We argue that adopting the cognitive capabilities of AI (sense, comprehend, act, and learn), as Bawack and Wamba (2019) do on a theoretical basis, can enable a higher level of automation.

2.7.1.3 Cognitive Automation in a BPM Context

In BPM context, cognitive process automation is the automation of knowledge-intensive business processes using cognitive technologies, adapting the definitions in Dwarkanhalli, Ananthanarayanan, and Mazumder (2018) and Zasada (2019). The concept is essential in understanding the impact of AI adoption on knowledge-intensive business processes. Cognitive computing underscores a perspective that combines automation and augmentation through innovative problem-solving models. These models aim to replicate human cognitive abilities by autonomously reasoning and learning from incomplete structured and unstructured contextual data. They also facilitate interactions between humans and machines (Hildebrand, Rösl, Auer, & Schieder; Roeglinger et al., 2018).

Domains well-suited for cognitive computing exhibit high uncertainty and involve knowledge-intensive problems with numerous potential solutions (de Almeida Rodrigues Gonçalves, Baiao, Santoro, & Guizzardi, 2023; Roeglinger et al., 2018). Focusing AI adoption efforts on knowledge-intensive processes, as defined in Section 3.2, allows organizations to maximize AI's transformative potential in areas critical for expertise, information value, risk management, and innovation. Evaluating AI's impact within these contexts helps pinpoint processes where implementation, integration, and deployment are most advantageous (i.e., knowledge-intensive business processes).

According to the AI adoption construct (see Section 3.4.3), the primary AI application domains for supporting cognitive automation include Cognitive Insights for AI-driven advanced analytics and predictive insights, Cognitive Engagement to enhance human-computer interaction, and Cognitive Decision Assistance to enhance decision-making processes. These AI application domains align closely with Roeglinger et al. (2018) theoretical insights regarding the impact of cognitive computing on business processes.

According to Kerpedzhiev et al. (2020), CBPA is an operational capability that concerns an organization's ability to perform functional activities using purposefully chosen groups of resources (Protogerou, Caloghirou, & Lioukas, 2012; Saunila, Ukko, Rantala, Nasiri, & Rantanen, 2020). Wu, Melnyk, and Swink (2012) note that operational capabilities are predominantly studied by examining outcomes, including cost, quality, dependability, speed, and flexibility. Our model reflects this by positioning operational capabilities as a factor mediating the relationship between AI and BPP. As a result, we formulate the following hypotheses:

H4b: *Cognitive business process automation mediates the positive impact of AI adoption on business process performance.*

Optimized processes benefit most from automation, which allows cost efficiencies, faster execution, and greater information-processing rationality and consistency (quality; Ansari, Diya, Patil, & Patil, 2019; Berruti, Nixon, Taglioni, & Whiteman, 2017; Forbes Insights, 2019; Raisch & Krakowski, 2021; Rocha, Lacerda, Veit, Rodrigues, & Dresch, 2017). However, some studies are more pessimistic about cognitive automation (Daugherty & Wilson, 2018; Raisch & Krakowski, 2021; Rouse & Spohrer, 2018), claiming a real digital cognitive mediator (full automation), does not yet exist (Rouse & Spohrer, 2018) and that partial automation or augmentation should be prioritized.

We define cognitive business process automation as the organization's ability to automate knowledge-intensive (unpredictable, non-repeatable, highly flexible, and complex) business processes using cognitive technologies; for details on the computational procedure, please refer to Chapter 4). The research centers on business process automation that integrates AI and cognitive computing capabilities (non-deterministic), distinguishing it from traditional rule-based automation (which follows predefined deterministic rules for task execution and decision-making). Cognitive Automation (Section 3.2) targets knowledge-intensive processes and their associated decision-making processes (Section 4.1.3). These processes, more complex and less readily automated than structured ones, are enhanced by cognitive capabilities aimed at problem-solving and decision-making.

We focus on two dimensions: the level of automation (manual, decision support, decision selection, supervisory control, or full automation; Sindhgatta, ter Hofstede, & Ghose, 2020a; Vagia, Transeth, & Fjerdingen, 2016) and the extent of automation (structured, structured with ad hoc exceptions, unstructured with predefined fragments, loosely structured and unstructured processes; Di Ciccio et al., 2015; Szelagowski & Lupeikiene, 2020).

According to the theorizing of Raisch and Krakowski (2021), Daugherty and Wilson (2018), and Karan, Safa, and Suh (2021), we can expect a moderate level of automation of the decision and action-selection function and less automation of the action implementation function (Parasuraman et al., 2000) for structured and semi-structured processes (Rouse & Spohrer, 2018). Considering this, we argue that AI adoption will impact decision-making effectiveness and efficiency. We thus formulate the following hypotheses:

H4a: *Cognitive business process automation mediates the positive impact of AI adoption on decision-making performance.*

2.7.2 The Mediating Role of Organizational Learning

Research has shown that organizational learning mediates the impact of IT (e.g., big data analytics, industry 4.0 technologies, IT capability) on organizational performance (Al-Omoush, Garcia-Monleon, & Iglesias, 2024; Bahrami, Kiani, Montazeralfaraj, Zadeh, & Zadeh, 2016; Khan, Zhang, & Salik, 2020; Lai, Lin, Lin, Wang, & Huang, 2009; Real, Leal, & Roldán, 2006; Tippins & Sohi, 2003; Tortorella, Vergara, Garza-Reyes, & Sawhney, 2020) and innovation (Husain, Dayan, & Di Benedetto, 2016; Obeso, Hernández-Linares, López-Fernández, & Serrano-Bedia, 2020). Given this, we argue that AI capabilities can significantly enhance organizational learning, which in turn mediates AI's impact (Robey, Boudreau, & Rose, 2000). Machine and deep-learning AI systems can transform knowledge resources into new capabilities that facilitate organizational learning by recognizing complex patterns and performing analytics (Jarrahi, Kenyon, Brown, Donahue, & Wicher, 2022). For example, deep learning models, especially large language models, can analyze unstructured text in contracts, invoices, medical documents, and point-of-sales data to flag erroneous charges and detect fraud, making audit processes more cost and time-efficient (An, 2024; Cruz, 2024; Davenport & Mahidhar, 2018; Feng et al., 2023).

2.7.2.1 Organizational Learning

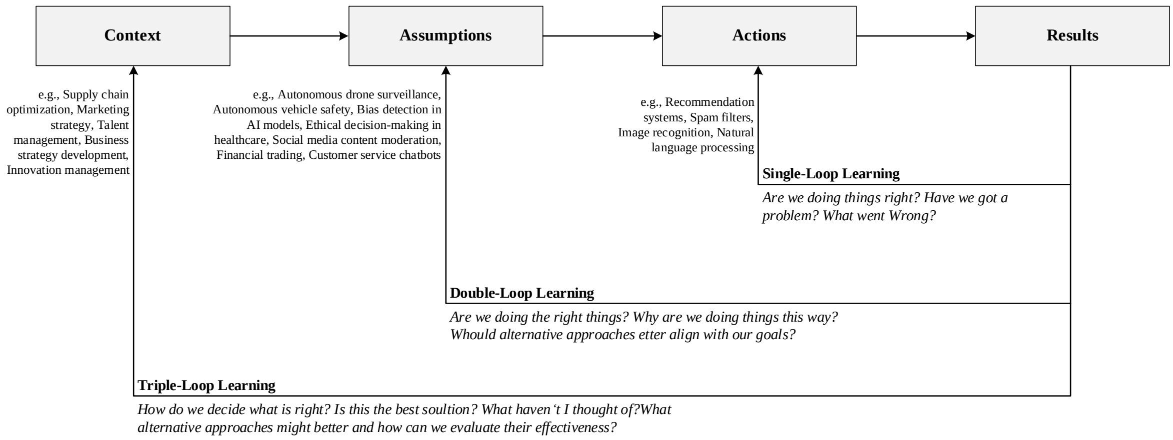
Organizational learning can be understood as “acquiring, creating, integrating, and distributing information and knowledge” (Huber, 1991; Templeton, Lewis, & Snyder, 2002; Wang & Ellinger, 2011). Several BPM capabilities in the areas of people and culture require learning and knowledge in different fields (Helbin & Van Looy, 2021; Kerpedzhiev et al., 2020), and organizational learning can thus also be considered a BPM capability. Given AI’s significant and growing impact on how organizations function and compete, we argue that the definition of organizational learning should encompass the creation and utilization of knowledge through technology, as suggested by Banasiewicz (2021). Regarding machine and deep learning, AI has a high potential to explicate the organizational knowledge base as long as that knowledge base is represented in Big Data. Organizational learning is institutionalization from practices to routines that define and expand the organizational knowledge base (Crossan, Lane, & White, 1999; Wijnhoven, 2022). Where there is a transfer from individual behavior (captured in data) to institutionalized organizational practices, it is the underlying organizational learning processes that support learning on an individual and organizational level. This process can be characterized as triple-loop learning, which involves questioning and modifying the governing variables and the foundations of organizational practices. Triple-loop learning is a critical component of organizational learning that enables organizations to adapt, improve, and transform at a fundamental level (Tosey, Visser, & Saunders, 2012). It connects to organizational learning by providing the deepest layer of reflection and change, ensuring that learning processes lead to actual and sustainable transformation (Flood & Romm, 2018). Next, using triple-loop learning as a theoretical lens, we examine how AI impacts organizational learning's different aspects (i.e., distinct learning loops of triple-loop learning). This broader scope helps us better understand how AI can enhance organizational learning.

2.7.2.2 Triple-Loop Learning

Triple-loop learning is a concept for reflecting on and improving organizational learning processes. In this context, organizational learning can be improving (i.e., single-loop learning) or introducing innovation (i.e., double-loop learning). Creating knowledge requires establishing norms, rules, and conditions (deuteron or institutional learning; Asawo & Ogbonda, 2022). These knowledge-creation processes transform intuitive or tacit insights into more explicit knowledge that can be integrated into the existing knowledge base (Nonaka & Lewin, 1994) and from there, into business operations. Triple-loop learning is a powerful tool for organizations to profoundly and meaningfully transform their practices, strategies, and values (Asawo & Ogbonda, 2022).

There are three distinct but interconnected learning loops, building on each other to facilitate more profound and transformative change and a willingness to challenge deeply held beliefs. Argyris and Schön (1997) identify a typology of learning, which includes single-loop, double-loop, and deutero-learning. Organizations can efficiently innovate in dynamic environments if they develop a capability to efficiently learn from their resources, increasing their competencies and capabilities (Tamayo-Torres, Gutiérrez-Gutiérrez, Llorens-Montes, & Martínez-López, 2016). A learning loop in the AI context comprises human and machine learning, including single-loop, double-loop, and triple-loop learning, that is, the integration of machine learning outcomes with human learning (Seidel, Berente, Lindberg, Lyytinen, & Nickerson, 2018).

Figure 3: Triple-Loop Learning



Source: Adapted from Argyris and Schön (1997)

Single-loop learning involves identifying and correcting errors in existing strategies or actions (Figure 3). This most basic form of learning is focused on fixing problems within the current system. Single-loop learning involves incremental improvements in existing ways of doing things (Asawo & Ogbonda, 2022). This type of learning occurs within a given frame of reference and involves minimum disruptions to the organization’s structures (Easterby-Smith & Lyles, 2011). Organizations engaged in such learning solve problems by doing things differently but not by doing different things (Berthoin Antal & Krebsbach-Gnath, 1998). This level of learning is unsuitable for a constantly changing business environment that requires creativity and radical changes. In the context of AI, reinforcement learning is a type of machine learning often associated with single-loop learning in which feedback from previous experiences is used to adjust actions and improve performance (e.g., recommendation systems, spam filters, image recognition, natural language processing).

Double-loop learning involves questioning the underlying assumptions and values that inform the first loop. In this form of learning, an organization examines its purpose, goals, and values and rethinks its underlying assumptions. Instead of refining current skills, the organization questions what is being done (Asawo & Ogbonda, 2022). Double-loop learning entails doing new things, not merely doing things differently (Berthoin Antal & Krebsbach-Gnath, 1998) Decisions are based on rethinking existing competencies and methods that have proved inadequate and challenging existing knowledge (Eskildsen, Dahlgaard, & Norgaard, 1999). A core part of the process is redefining the organization’s governing variables to meet new challenges (Figure 3) by questioning, challenging, and changing the organization’s frame of reference (Easterby-Smith & Lyles, 2011). Many organizations ignore the radical change arising from interrogating the governing variables. Nevertheless, double-loop learning is a prerequisite for making informed decisions in a rapidly changing and uncertain business environment (Asawo & Ogbonda, 2022).

In the AI context, adversarial learning, a type of machine learning is similar to double-loop learning in that it involves questioning the underlying assumptions and values that drive the development of machine learning models and making changes to address any biases or vulnerabilities (e.g., autonomous drone surveillance, autonomous vehicle safety, bias detection in AI models, ethical decision-making in healthcare, social media content moderation, financial trading, customer service chatbots).

In *triple-loop* or deuteron learning, assumptions and values underlying the first two loops are questioned and potentially changed through organizational processes and structures. Triple-loop learning involves questioning and rethinking the very nature of the organization and how it creates and sustains its assumptions and values (Figure 3). A hypercompetitive environment requires organizations to move beyond single- and double-loop learning and to *learn how to learn* (Pemberton & Stonehouse, 2000). Organizations must learn about previous learning contexts and seek an understanding of past ability or inability, a process that results in new strategies for learning (Othman & Hashim, 2003). This learning level is required when existing knowledge is no longer adequate to achieve business objectives (Eskildsen et al., 1999). The learning process is based on a change in the organization's principles and values and a profound transformation of the organizational action framework. In the context of AI, triple-loop learning can be facilitated by using machine learning techniques to question underlying assumptions and values that guide the organization's decision-making processes (e.g., supply chain optimization, marketing strategy, talent management, business strategy development, innovation management).

2.7.2.3 Knowledge Creation

Organizational learning represents a constant effort to create organizational knowledge and contributes to an organization's ability to adapt effectively to changes in its business environment (Bohanec, Robnik-Šikonja, & Borštnar, 2017). It can involve developing new, incremental knowledge or updates to existing knowledge. We draw on the knowledge-based perspective, which implies knowledge can create competitive advantage (Grant, 1996b) and impact performance. This perspective directs attention to learning as a core organizational action through which knowledge resources are transformed into core competencies (Jarrahi, Kenyon, et al., 2022). We argue that implementing new AI capabilities can augment and enhance learning and knowledge creation.

The following are examples of use cases by function. The knowledge creation function is useful for forecasting sales probabilities and discovering organization inefficiencies by analyzing customer relationship management records. Knowledge storage and retrieval capabilities allow for the organization and summarization of legal precedents and the retrieval of dispersed nuggets of information for troubleshooting. Knowledge sharing includes facilitating feedback and peer review on communication systems and real-time smart sharing between marketing channels and the sales pipeline. Examples of the knowledge application function include finding and applying question-answer pairs in online manuals to manage service knowledge and provide more human-centred and accessible applications of knowledge through chatbots (Jarrahi, Askay, Eshraghi, & Smith, 2022).

2.7.2.4 Organizational Learning and AI

The ultimate purpose of organizational learning is to enhance informational efficacy in decision-making (Banasiewicz, 2021). To remain competitive in a knowledge-driven economy, organizations must develop and deploy robust methods of creating and leveraging decision-guiding knowledge (Banasiewicz, 2021; Samek, Wiegand, & Müller, 2017). We can exploit AI opportunities, including analytic data techniques and codified knowledge, to increase or augment the intelligence of human decision-makers (intelligence amplification). These techniques do not replace decision-makers but may help organizations make complex decisions through well-designed human-AI system learning interactions (Wijnhoven, 2022).

Grønsund and Aanestad (2020) and Seidel et al. (2018) emphasize the importance of a human-in-the-loop pattern. The work of AI and humans is complementary, with AI augmenting the work of auditing (i.e., the generation of ground truth and assessment of the algorithmic output against that) and through altering the algorithm and data acquisition architecture. Hence, AI has an indirect effect on actual human decisions, which are the outcomes of difficult-to-predict individual and organizational learning processes (Schmidt, 2017) in interactions of human, machine and deep learning – this is the triple-loop learning referred to above (Seidel et al., 2018). This interaction can result in incremental single-loop improvements or more radical double-loop learning (Wijnhoven, 2022) innovations. These considerations lead us to the following hypotheses to test the mediating effect of organizational learning on BPP via DMP.

H5a: *Organizational learning mediates the positive impact of AI adoption on decision-making performance.*

H5b: *Organizational learning mediates the positive impact of AI adoption on business process performance.*

Some researchers view knowledge management as integral to organizational learning, emphasizing its role in leveraging technology to create, share, and apply acquired knowledge (Al Mansoori et al., 2020). Modern organizations recognize knowledge management as essential for establishing effective structures and optimizing various tasks and processes, which can lead to discovering new knowledge. These organizations increasingly seek advanced technological capabilities to capture, process, store, and search for information (Al Mansoori et al., 2020).

AI technologies enable organizations to enhance their knowledge management practices (Al Mansoori et al., 2020; Jarrahi, Askay, et al., 2022; Taherdoost & Madanchian, 2023; Tsui, Garner, & Staab, 2000). By integrating AI into business processes, organizations improve knowledge discovery, capture, sharing, dissemination, accessibility, and retention (Jarrahi, Askay, et al., 2022; Taherdoost & Madanchian, 2023). AI enables accelerated and personalized learning experiences, automates knowledge updates, predicts future knowledge needs, and integrates seamlessly with workflows (Taherdoost & Madanchian, 2023; Tsui et al., 2000). These advancements contribute to organizational efficiency, agility, and continuous learning (Jarrahi, Askay, et al., 2022; Taherdoost & Madanchian, 2023).

The adoption of AI, as detailed in Section 3.4.3, underscores its practical application across various domains, as substantiated by current literature on knowledge management practices (Al Mansoori et al., 2020; Jarrahi, Askay, et al., 2022; Taherdoost & Madanchian, 2023; Tsui et al., 2000). These include Cognitive Insights, which fosters predictive analytics through self-learning capabilities; Cognitive Decision Assistance, which analyzes organizational data for knowledge discovery, harvesting, classification, and organization of explicit knowledge; and Cognitive Engagement, which facilitates more accessible and human-centered applications of knowledge.

Organizational learning represents AI’s augmentation potential. We characterize organizational learning as the organization’s dynamic capability to integrate, build, or reconfigure competencies to address a rapidly changing environment (Eisenhardt & Martin, 2000). Developing new knowledge derived from organizational learning reduces the likelihood that an organization’s competencies will become outdated, allowing it to remain dynamic and improve performance (Senge, 1998).

2.8 Ambidextrous Innovation: Interactions Between AI Adoption and Business Process Innovation

AI plays diverse roles in innovation (Makarius et al., 2020). Beyond its application in AI-enabled or AI-driven innovations within business processes, AI is an important source of innovation, significantly influencing an organization's innovation management and capability (Bouschery, Blazevic, & Piller, 2023; Gama & Magistretti, 2023). Recognized as a pivotal technology, AI shapes innovation capabilities by enhancing decision-making processes through augmentation or automation (Pietronudo, Croidieu, & Schiavone, 2022; Raisch & Krakowski, 2021). It also impacts product and service development and fosters abductive reasoning[5] (Brynjolfsson & Mitchell, 2017; Garbuio & Lin, 2021; Kellogg, Valentine, & Christin, 2020).

The innovation process is changing as a result of the increased implementation of digital services and automation coupled with the general transformation to digitized organizations, which has made many and varied data sources available (Big Data; Haefner, Wincent,

[5] Abductive reasoning is a form of synthetic inference through which meaningful underlying patterns of selected phenomena are recognized to comprehend a complex reality and expand scientific knowledge (Garbuio & Lin, 2021).

Parida, & Gassmann, 2021). We can separate the innovation process into three stages: "1) the recognition, discovery, creation, and generation of innovative ideas, opportunities, and solutions; 2) the development or exploitation of various ideas, opportunities, and solutions; and 3) the evaluation and selection of one or several of the most promising ideas, opportunities, and solutions" (Haefner et al., 2021, p. 3).

AI offers possibilities for addressing two specific innovation barriers. First, AI can be used to address information-processing constraints (Williams & Mitchell, 2004) that limit information on new opportunities or possible solutions the organization may pursue. Haefner et al. (2021) present two AI abilities that help overcome this barrier. First, AI systems can extract information from structured and unstructured data, allowing the identification and evaluation of far vast amounts of information and its use to develop ideas (e.g., data storytelling, performance visualization, metasearch, named entity recognition and disambiguation, content discovery, searchable representations, natural language analytics, location discovery, movement patterns, target discovery, legal analysis, ontology creating and management). Compared to human agents, AI systems can recognize more problems, opportunities, and threats that can be used to generate ideas (e.g., predictive modeling and analytics, anomaly and deviant behavior detection, marketing intelligence system, predictive maintenance). One notable instance involves British Petroleum employing AI for predictive maintenance in its oil and gas facilities (Nordal & El-Thalji, 2021). AI predicts potential equipment failures by analyzing data from sensors and equipment logs. This proactive approach allows BP to schedule maintenance preemptively, thereby enhancing operational efficiency and significantly reducing downtime.

The second innovation barrier that AI can help overcome is the problem of ineffective or limited search routines (Katila & Ahuja, 2002). Organizations generally search for solutions in domains related to their existing knowledge base (Posen, Keil, Kim, & Meissner, 2018). Consequently, most solutions will be comparatively incremental in their innovative thrust. Generating more creative and innovative ideas or opportunities requires that organizations be more exploratory and extend their search to new fields and external data sources. AI systems can generate, identify, and evaluate more creative/experimental ideas (e.g., generative AI, including generative design, drug development, product innovation, protein engineering/folding, material discovery, genomics, process mining, context-aware marketing). A well-known example is Autodesk's generative design software, which Airbus has used to optimize aircraft cabin partitions (Shrestha, Timalsina, Bista, Shrestha, & Shakya, 2021). By leveraging AI, the software generated lighter and more efficient designs, surpassing traditional methods in innovation and performance.

According to existing research (Almuslamani, 2022; Calantone, Cavusgil, & Zhao, 2002; García-Morales, Jiménez-Barrionuevo, & Gutiérrez-Gutiérrez, 2012; Liao & Wu, 2010; Mishra & Pani, 2020; Vasylieva, 2013), organizational learning and its output, organizational knowledge, positively impact innovation. Organizational learning prevents stagnation and encourages continuous innovation through the renewal and reinvention of technology and production methods (García-Morales et al., 2012). A higher level of innovation requires greater critical capacity and skills as well as new and relevant knowledge (Senge, 1998). A learning organization increases its innovative capability because this learning stance means it is less likely to miss opportunities emerging in market demand. A learning organization can anticipate and understand customer needs, has more and better state-of-the-art technology, uses that technology to innovate, and has a greater capacity to understand competitors' strengths and weaknesses. The acquisition of relevant knowledge depends upon the organization's internal knowledge base (Salavou & Lioukas, 2003) and on the acquisition of external information and knowledge (Chang & Cho, 2008). According to March (1991), organizations can exploit extant knowledge and explore how technology, such as AI, can be used to generate new knowledge.

Several studies argue that ambidextrous organizations can balance both strategies and avoid overreliance on one (Liu, 2006; O Reilly & Tushman, 2004; Tushman & O'Reilly III, 1996). March (1991) and O'Reilly III and Tushman (2011) emphasize the importance of organizations simultaneously exploring new domains and exploiting existing ones to survive and grow but make it clear that firms frequently have difficulty doing so (Johnson, Laurell, Ots, & Sandström, 2022). Most organizations see AI technology as an opportunity to explore, and others focus on how AI can boost the efficiency of existing operations (Johnson et al., 2022; Zhang, Long, & von Schaewen, 2021). In the BPM context, we expect process improvements to result from AI-driven (embedded technology) or AI-enabled innovation. The exploitation of existing knowledge domains produces incremental innovation, improving business process efficiency, quality, and flexibility; exploration would produce radical improvement through new, transformed, or redesigned processes (Norman & Verganti, 2014). We argue AI adoption facilitates ambidextrous innovation. We propose pairs of hypotheses for incremental and radical innovation as follows:

H6a: *Incremental business process innovation mediates the positive impact of AI adoption on decision-making performance.*

H6b: *Incremental business process innovation mediates the positive impact of AI adoption on business process performance.*

H7a: *Radical business process innovation mediates the positive impact of AI adoption on decision-making performance.*

H7b: *Radical business process innovation mediates the positive impact of AI adoption on business process performance.*

Examining AI's impact on innovation within the proposed AI adoption concept framework reveals significant potential innovation outcomes. Data Acquisition and Preprocessing capabilities are essential to AI-driven innovation management, establishing a solid foundation for developing robust AI models and ensuring meticulously prepared, structured, and optimized data for AI applications. Cognitive Insights strengthens the capacity for targeted innovation and enhances predictive capabilities, enabling timely interventions and continuous improvements in product quality and operational efficiency. Cognitive decision assistance automates processes across the innovation lifecycle, from product design to manufacturing. It also promotes integrating knowledge and technologies across various disciplines, accelerating R&D through generative AI capabilities (Bouschery et al., 2023). Cognitive engagement encourages a human-centric approach and enables real-time interactions. AI has been shown to boost human innovation in team activities by sparking discussion and encouraging divergence in design thinking processes (Bouschery et al., 2023). Harnessing Cognitive Technologies, AI can efficiently utilize existing IT resources, services, and devices. AI's inherent ability to continuously learn and adapt, guided by self-awareness, interaction inputs, and contextual understanding, markedly enhances its effectiveness (Mele, Spena, & Peschiera, 2018).

2.9 Organizational Learning and Business Process Innovation

The influence of organizational learning on BPI is well established and there is general consensus that knowledge is the key component of the relationship (Aragón-Correa, García-Morales, & Cordón-Pozo, 2007; García-Morales et al., 2012; Hung, Lien, Yang, Wu, & Kuo, 2011; Jiménez-Jiménez & Sanz-Valle, 2011; Weerawardena, O'cass, & Julian, 2006). BPI draws from the organization’s knowledge base, and organizational learning builds this base (Cohen & Levinthal, 1990), supports creativity (Sanchez & Mahoney, 1996; Yli-Renko, Autio, & Sapienza, 2001), generates new knowledge and ideas (Damanpour, 1991; Damanpour & Schneider, 2009), facilitates understanding and application of ideas, fosters organizational intelligence and, together with the organization’s culture, creates an environment for organizational innovation.

Innovation requires that individuals acquire and share existing knowledge within the organization (Jiménez-Jiménez & Sanz-Valle, 2011). Knowledge acquisition depends on transforming and exploiting existing knowledge (Salavou & Lioukas, 2003) as well as purchasing knowledge from outside sources. Organizational learning enhances the capacity of the organization to absorb and assimilate new ideas and apply that external knowledge to business operations (Cohen & Levinthal, 1990). The degree of innovation indicates the extent to which new knowledge has been incorporated (Dewar & Dutton, 1986; Ettlie, 1983).

Organizations often underestimate AI's strategic significance, which thrives when machines learn autonomously and collaborate with humans. Achieving effective mutual learning at scale remains challenging (Jarrahi, Kenyon, et al., 2022). IT facilitates knowledge management, while AI redefines how organizations learn and adapt (Ransbotham et al., 2020).

We distinguish two distinct dimensions in the context of AI and the proposed relationship between organizational learning and process innovation. The first is adaptive learning connected to BPII, and the second is generative learning connected to BPIR. These dimensions should be closely and positively connected (Forrester, 2000). The higher the degree of innovation, the greater the learning required.

Adaptive learning aims to improve existing processes and practices using feedback and analysis for incremental improvement. Efficiencies and effectiveness are improved by learning from past experiences and adjusting existing processes. This form of learning is usually reactive, focusing on resolving problems as they arise (Weiner, Helfrich, & Hernandez, 2006).

Generative learning is the process of creating new knowledge and capabilities to adapt to changing conditions and innovate. It involves the organization exploring new ideas and approaches, taking risks, and challenging existing assumptions about its mission, customers, capabilities, or strategy to generate changes in its practices, strategies, and values (Argyris & Schön, 1997; Senge, 1998). Such learning is often proactive, with the organization identifying new opportunities and developing innovative solutions. Aragón-Correa et al. (2007) consider it the most advanced form of organizational learning. Generative learning is a fundamental component of radical product and process innovation (Senge, 1998).

Triple-loop, adaptive, and generative learning are related (Basten & Haamann, 2018; Kamya, 2012). Single-loop learning promotes adaptive learning in which problem-solvers adjust their behavior and work processes in response to changing events or trends (Weiner et al., 2006). The connection between single-loop and adaptive learning lies in their shared focus on modifying and improving existing systems and practices. Single-loop learning involves incremental adjustments to improve efficiency and effectiveness. Adaptive learning involves continuously monitoring and adapting learning strategies in response to changing conditions to improve the efficiency and effectiveness of the current system. Double-loop learning promotes generative learning, in which problem-solvers work to eliminate problems by changing the system's underlying structure (Smith, 2014; Weiner et al., 2006). The connection between these forms of learning lies in their shared focus on questioning and challenging existing premises and beliefs. Double-loop learning involves reflecting on the assumptions and values that guide decision-making and actions. In contrast, generative learning involves exploring ideas and possibilities to create new knowledge and insights.

AI is revolutionizing innovation processes by automating decision-making, potentially leading to partial or complete automation in specific contexts (Brem, Giones, & Werle, 2021b; Makowski & Kajikawa, 2021). This shift promises to streamline problem-solving loops, redirecting human efforts from traditional product and service design to algorithm creation and data provisioning (Verganti, Vendraminelli, & Iansiti, 2020). AI plays a crucial role in the learning phase of innovation (Hutchinson, 2020), reshaping how companies gather and use data to uncover insights and enable new business models. Researchers theorize about the role of AI in reinterpreting existing knowledge and promoting new approaches to engaging with existing services and products, demonstrating its transformative impact on innovation processes (Tekic & Füller, 2023). However, there is a lack of empirical research on whether AI-enabled knowledge acquisition, sharing, and utilization (i.e., organizational learning) influence decision-making and process performance by facilitating innovation. We propose the following pair of hypotheses to test this impact:

H8a: *Organizational learning positively influences incremental business process innovation.*

H8b: *Organizational learning positively influences radical business process innovation.*

2.10 Organizational Context

The organizational context describes the environment in which AI business value is generated. The existing literature on IT business value suggests that organizations might gain significant performance improvements if IT resources are aligned with other organizational factors (Mooney et al., 1996; Wiengarten et al., 2013). Organizational factors are considered complementary non-IT resources (Melville et al., 2004). In this study, these factors encompass the broader organizational context of AI application in keeping with the model's organizational scope (as discussed in Section 2.2). Based on exploratory interviews and the literature review, we identify and include four factors that moderate the relationships studied here (defined moderator variables in parenthesis): digital maturity (*DM*), data-driven culture (*DDC*), BPM maturity (*BPMM*), and organizational culture (*OC*).

2.10.1 Digital Maturity

The literature offers various definitions of digital maturity (Grooss, Presser, & Tambo, 2022; Nwankpa & Roumani, 2016; Schatsky et al., 2014). Based on the definitions by Kane, Palmer, Nguyen-Phillips, Kiron, and Buckley (2017) and aligned with Salviotti, Gaur, and Pennarola (2019), we understand digital maturity as "the extent of the learned ability to adapt to the ongoing digital changes and digital transformation efforts in an appropriate manner." According to previous research, digital maturity correlates with the development of specific digital capabilities (Westerman, Bonnet, & McAfee, 2014). Gurumurthy and Schatsky (2019) propose a set of digital capabilities, including a flexible infrastructure, a digital talent network, business model adaptability, data management, ecosystem engagement, intelligent workflows, and a unified customer experience.

Following, greater digital maturity positively impacts organizational performance (Table 2). Nwankpa and Roumani (2016) present empirical evidence of digital maturity being a significant mediator between IT capability and organizational performance. We consider it necessary to probe the relationships between AI technology and digital maturity, with the latter as a moderator since the two are closely related. AI technology relies on digital data and computing power and is often seen as a core component of digital transformation, which refers to the use of digital technologies to transform business processes, operations, and customer experiences. We expect digital maturity to amplify the impact of AI adoption by providing a digital environment in which the extent of AI adoption would be significant.

Table 2: Selected Empirical Studies on Digital Maturity, Automation, Process and Firm Performance

Author	Scope	Theory	Findings
Eremina, Lace, and Bistrova (2019)	Official secondary data sources for 28 companies: 13 Estonian, 11 Lithuanian, and 4 Latvian companies		(+) Digital Maturity → Process Automation
Nwankpa and Roumani (2016)	Survey, 167 CIOs from the US	RBV	(+) IT capability → Digital Transformation → Innovation and Firm Performance
Guo and Xu (2021)	Official secondary data sources from 2010 to 2020 for the manufacturing companies listed on the A-share market of China		(+) Digital Transformation → Process-based Operating Performance
Çallı and Çallı (2021)	Survey, 119 respondents from SMEs in the Marmara Region of Turkey		(+) Digital Maturity → Firm Performance
Tsou and Chen (2022)	Survey, 227 respondents from Taiwanese financial, and industrial companies		(+) Digital Transformation → Firm Performance

Note. (+) Positive impact; (−) Negative impact; ( ) No impact. RBV = Resource-Based View.

Source: Own work.

2.10.2 Data-Driven Culture

A data-driven culture (*DDC*) is one in which the participants follow a set of behaviors, practices, and beliefs that support analytical decision-making (Holsapple, Lee-Post, & Pakath, 2014). According to Gupta and George (2016, p. 16) a data-oriented culture is “the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data.” We prefer a definition that is more far-reaching and not limited to decision-making. We thus adopt the description by Kiron and Shockley (2011, p. 11) of a data-oriented culture as “a pattern of behaviors and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization.” This aligns with existing empirical studies that position a data-oriented culture as a mediator or moderator variable in the relationship between IT capabilities and innovation or performance (Table 3).

Chatterjee, Chaudhuri, and Vrontis (2021) argue that Big Data and related technologies have radically changed organizations’ cultural landscape and how they arrive at accurate decision-making and improve their innovation and performance. Gupta and George (2016) suggest that having a data-oriented culture is one of the critical intangible resources that can be used to make the best use of data through Big Data capabilities. McAfee, Brynjolfsson, Davenport, Patil, and Barton (2012) explain that a culture of decision-making among senior-level executives being evidence (rather than instinct) based will likely improve business performance. A data-driven culture is one characterized by a decision process that emphasizes testing and experimentation, where data outweigh opinions, and failure is accepted as long as something is learned from it (Berndtsson, Forsberg, Stein, & Svahn, 2018).

Because of the relationship between Big Data and AI (considered in Section 3.1), we expect that having a data-driven culture will impact the relationship between AI, innovation, and the various performance variables (decision-making, process, and organizational performance).

Table 3: Selected Empirical Studies on Data-Driven Culture, IT and Firm Performance

Author	Scope	Theory	Findings
Duan, Cao, and Edwards (2020)	Survey, 218 medium and large enterprises in the UK	Absorptive capacity theory	(+) DDC → Innovation → Competitive Advantage
Chatterjee, Chaudhuri, et al. (2021)	Survey, 456 respondents from 69 firms of India's top 1000 companies	Absorptive capacity theory, RBV, DCV	(+) DDC → Product & Process Innovation → Firm Performance
Chaudhuri, Chatterjee, Vrontis, and Thrassou (2021)	Survey, 532 respondents from 29 firms, randomly selected from the Bombay Stock Exchange	Absorptive capacity theory, RBV, DCV	(+) DDC → Product Innovation & Business Process Performance → Organizational Performance
Yu, Wong, Chavez, and Jacobs (2021)	Survey, 307 manufacturing firms in China	Organizational information processing theory	(+) Big Data Analytics Capability → DDC → Supply Chain Finance integration
Karaboga, Zehir, Tatoglu, Karaboga, and Bouguerra (2022)	Survey, 432 respondents from Turkish firms actively using Big Data	RBV, DCV	(+) Big Data Analytics → DDC → Firm Performance (operational/financial)
Agyei-Owusu, Amedofu, Asamoah, and Kumi (2021)	Survey, 123 respondents from manufacturing and service firms operating in Ghana	Absorptive capacity theory, DCV	(+) DDC → Supply Chain Information Sharing / Quality → Customer Development → Firm Performance

Note. (+) Positive impact; (−) Negative impact; ( ) No impact. RBV = Resource-Based View. DCV = Dynamic Capabilities View. DDC = Data-Driven Culture.

Source: Own work.

2.10.3 Business Process Management Maturity

Given our focus on BPM, we incorporate BPM maturity as a contextual factor that, according to existing studies, should improve process performance (Dijkman, Lammers, & De Jong, 2016; McCormack & Johnson, 2001; Škrinjar, Bosilj-Vukšić, & Indihar-Štemberger, 2008; Škrinjar, Indihar-Štemberger, & Bosilj-Vukšić, 2010; Van Looy, Poels, & Snoeck, 2017).

We propose that the impact of AI is fully mediated by CBPA, organizational learning, and business process innovation. As seen in Table 4, we can expect BPM to have a positive effect in the relationships between these mediators and BPP. However, researchers and practitioners argue that maturity models make organizations rigid and bureaucratic (Adler, McGarry, Irion-Talbot, & Binney, 2005; Antoniol, Gradara, & Venturi, 2004; Dijkman et al., 2016; Nawrocki, Walter, & Wojciechowski, 2002) negatively affecting innovativeness (Herbsleb, Zubrow, Goldenson, Hayes, & Paulk, 1997). The reasoning is that higher BPM maturity implies more strictly defined processes, negatively influencing an organization's potential for finding innovative solutions. In our model, we expect BPM maturity to have either a negative or positive impact (Dijkman et al., 2016) on process innovation and, by extension, organizational learning. Organizational learning, the output of this learning, and organizational knowledge are closely related antecedents of innovation (Jiménez-Jiménez & Sanz-Valle, 2011).

The concept of BPM has evolved. A higher level of maturity presumes business operations supported by a portfolio of digital solutions that include digitalization and automation of processes, data analytics, AI solutions, and virtual workforce solutions (König, Bein, Nikaj, & Weske, 2020; Pinto & dos Santos, 2020; Van Looy, De Backer, & Poels, 2011). Accordingly, we can presume higher levels of BPM will positively impact CBPA.

Table 4: Selected Empirical Studies on BPM Maturity, Innovation, OL and Process Performance

Author	Scope	Theory	Findings
Loggen and Ravesteyn (2022)	Survey, 55 respondents from Dutch housing associations		(+) BPMM → Process Performance
ME de Waal, Maris, and Ravesteyn (2017)	Survey and interviews, 469 respondents from organizations in the Netherlands during the period 2010 to 2015		(+) BPMM → Process Performance
Dijkman et al. (2016)	Survey, 120 German and Dutch organizations		(+) BPMM → Process Performance (+) Innovativeness → BPMM
Pejić Bach, Bosilj Vukšić, Suša Vugec, and Stjepić (2019)	Survey, 107 companies from Croatia and Slovenia		(+) BPM/BI alignment → Process Performance
Janssen and Revesteyn (2015)	Survey, 225 members of the Dutch BPM forum and 58 Portugal commercial organizations		(+) BPM maturity → BPM Performance
Ongena and Ravesteyn (2020)	Survey and structured interviews, 532 respondents from 165 organizations, collected in Dutch companies over three years (2010, 2013 and 2017)	Contingency Theory	(+) IT, Resource, Knowledge → BPM maturity → Process Performance
Pinto and dos Santos (2020)	Case study, a global company that operates in the energy sector and has an operation in Portugal		(+) BPMM → Process Performance

Note. (+) Positive impact; (−) Negative impact; ( ) No impact. BPMM = Business Process Management Maturity.

Source: Own work.

Although digital maturity and BPM maturity are complementary concepts that determine an organization's readiness and state of digital transformation, there are some key differences that necessitate their separate inclusion in the organizational context (Putra & Mahendrawathi, 2024). Compared to digital maturity, which focuses on ongoing digital changes and digital transformation efforts, BPM maturity focuses on process management capabilities and the organization's ability to manage and improve processes (Van Ee, El Attoti, Ravesteyn, & De Waal, 2020). In terms of tools and technologies, digital maturity involves a wide range of digital tools (e.g., cloud services, communication and collaboration tools, project management, and sales pipeline management tools, business intelligence platforms), and BPMM primarily involves BPM tools, and systems for process modeling, execution, automation, and monitoring (e.g., process mining, workflow automation, RPA). The scope of impact for digital maturity is broader across various aspects of the organization, including customer experience, product development, and overall innovation (as seen in the operationalized construct's items, Section 5.5.9). We must also mention the interdependence. There is a strong correlation between digital maturity and BPM maturity. As an organization becomes more digitally mature, it is typically able to better manage and optimize its business processes through digital tools and technologies (Van Ee et al., 2020; Vugec, Stjepić, & Vidović, 2018). High digital maturity can enhance BPM maturity by providing advanced process automation and improvement tools. Likewise, mature BPM practices can support digital initiatives by ensuring that processes are well-managed and optimized for digital transformation (Flechsig, Lohmer, Voß, & Lasch, 2022). By developing digital and process capabilities, an organization can identify its strengths, weaknesses, and potential for optimization, resulting in numerous benefits, including increased productivity, quality, and customer service. Assessing both provides a comprehensive view of the organization's transformation progress and guides targeted improvement efforts, which can influence AI adoption (Silva & Gonçalves, 2022).

2.10.4 Organizational Culture

We understand organizational culture as "the values, beliefs, and hidden assumptions that organizational members have in common." We adopt the definition from Rohit and Webster Frederick (1989), Miron, Erez, and Naveh (2004), and Cameron and Quinn (2011). Organizational culture can be a source of sustained competitive advantage (Barney, 1991), and existing research confirms a positive relationship between organizational culture and performance (Deal & Kennedy, 1982; Ezirim, Nwibere, & Emecheta, 2010; Peters, 2004; Wilkins & Ouchi, 1983). However, organizational culture has distinct dimensions and types. Only competitive forms of culture have an impact on organizational performance. According to existing research, the impact originates from the direct influence on innovation, knowledge management, and organizational learning (Table 5).

Organizational culture may be characterized by highly motivated employees seeking solutions to problems and coordinating through knowledge sharing and cultural values (Shivers-Blackwell, 2006). It can significantly stimulate creativity and innovative behavior among employees. Innovation can emerge from organizational culture when viewed as a core value (Hartmann, 2006). An organization's culture must promote communication among employees and establish links for sharing different viewpoints. Interaction and cooperation are essential for diffusing implicit knowledge, transforming tacit into explicit knowledge, and transforming individual into organizational knowledge (Song-zheng & Xiao-di, 2008). Organizational culture affects innovative behavior in two ways (Martins & Terblanche, 2003). First, through socialization, individuals learn how to act and behave.

Second, fundamental values, beliefs, and assumptions reflect the organization's structure, policy, management concept, and procedures.

Knowledge management, which we understand as "organization, creation, sharing and flow of knowledge within organizations" (Davenport, 1999; Lin, 2014), is often considered in the context of organizational culture. Many researchers and practitioners have concluded that knowledge management must facilitate the creation of new knowledge for sustained competitive advantage; successfully gaining knowledge in management processes affects organizational innovation (Kaklauskas & Kanapeckiene, 2005). Organizational culture may be the most influential factor in determining the effectiveness of knowledge management initiatives, although it is invisible and intangible (Davenport & Prusak, 1998; Lee & Choi, 2003). The researchers posited that organizational culture is intimately related to knowledge management. Its successful implementation depends on the culture that believes that the right organizational culture is essential for knowledge management to generate innovation (Abdi et al., 2018; Taleghani & Talebian, 2013).

Organizational learning has emerged as a capability that allows organizations to face changes in turbulent and dynamic environments (Vieira do Nascimento, 2013). Findings in the literature show that organizational learning is positively associated with technical innovation and that organizational culture can foster organizational learning and technological innovation but can also act as a barrier (Sanz-Valle, Naranjo-Valencia, Jiménez-Jiménez, & Perez-Caballero, 2011). A culture that encourages change is a critical feature in supporting organizational learning. Particularly in competitive environments, an organization needs a strong adaptive culture to promote cooperation and learning among its employees (Liao, Chang, Hu, & Yueh, 2012).

Organizational culture and habit positively impact employees' intention to use AI, whereas job insecurity has a negative effect. Perceived self-image and perceived usefulness fully mediate the relation between job insecurity and intention to use AI (Dabbous, Aoun Barakat, & Merhej Sayegh, 2022), and perceived self-image and usefulness partially mediate the relationship between habit and intention to use.

Organizational learning and process innovation are important concepts in our proposed model. Therefore, we include organizational culture or, more specifically, four types of organizational culture: adhocracy, hierarchy, clan, and market (Quinn & Cameron, 1999).

Table 5: Selected Empirical Studies on Organizational Culture, Innovation, Organizational Learning and Firm Performance

Author	**Scope**	**Theory**	**Findings**
Shahzad, Xiu, and Shahbaz (2017)	Survey, 215 respondents from 29 software companies in Pakistan	KMT	(+) OC → Organizational Innovation Performance
Sanz-Valle et al. (2011)	Survey, 451 Spanish companies with more than 15 employees		(+) OC: Adhocracy → OL (–) OC: Hierarchy → OL

To be continued

Table 5: Selected Empirical Studies on Organizational Culture, Innovation, Organizational Learning and Firm Performance (cont.)

Author	Scope	Theory	Findings
Song-zheng and Xiao-di (2008)	Survey, 490 Chinese companies		(+) OC → Knowledge Integration Capability (+) OC → Social Capital (+) OC → Organizational Learning
Uzkurt, Kumar, Semih Kimzan, and Eminoğlu (2013)	Survey, 154 respondents from the top 15 Turkish banks		(+) OC → Incremental Innovation → Firm Performance (+) OC → Firm Performance
Nold III (2012)	Financial data, "Great Place to Work" list of 100 best companies publicly traded on the US stock exchange during the test period 2004 and 2008		(+) OC (Trust) → KM → Operational Performance
Boardman, Harden, and Martínez (2018)	Survey, 295 respondents from national and global firms (manufacturing, finance and telecommunication) in Turkey		(+) Leadership → OC (Competitive, Bureaucratic, Community Culture) → Organizational Performance
Dabbous et al. (2022)	Survey, 203 organizations from Lebanon	Technology acceptance mode, Theory of reasoned action	(+) OC → The intention to use AI
Sadegh Sharifirad and Ataei (2012)	Survey, 245 respondents from six large auto companies in Iran		(+) OC (Involvement) → Innovation Infrastructure (+) OC (Adaptability → Innovation Propensity and Infrastructure (+) OC (Mission) → Innovation Implementation
Chen, Huang, Liu, Min, and Zhou (2018)	Survey, 183 respondents from 236 Chinese companies	Contingency theory, Configuration theory	(+) OC → Innovation Performance
Abdi et al. (2018)	Survey, 272 respondents, companies from Iranian automotive industries	KMT, Competitive Value Framework	(+) OC → Organizational Innovation (+) OC → Organizational Learning (+) OC → KM
Hosseini, Hajipour, Kaffashpoor, and Darikandeh (2020)	Survey, 329 respondents from Mobarakeh Steel Company	Transformational leadership theory	(+) Leadership style → OC → OL
Pérez López, Manuel Montes Peón, and José Vázquez Ordás (2004)	Survey, 195 respondents from Spanish industrial and service sector companies		(+) Collaboration Culture → OC → Organizational Performance
Liao et al. (2012)	Survey, 449 respondents from the top 100 financial enterprises in Taiwan		(+) OC (Bureaucratic, Innovative, Supportive Culture) → KM (+) OC (Bureaucratic, Innovative, Supportive Culture) → OL → Organizational Innovation
Raj and Srivastava (2013)	Survey, 321 respondents from public and private sector manufacturing and service organizations located in various parts of India		(+) OC (Clan, Adhocracy, Market) → OL → Innovativeness
Hogan and Coote (2014)	Survey, 91 respondents from Law firms within a large geographic area that included the metropolitan hub of Sydney, Australia		(+) Artefacts of innovation → Innovation behaviours → Firm Performance
Prajogo and McDermott (2011)	Survey, 194 respondents from Australian companies		(+) OC (Group) → Process Quality, Process Innovation (+) OC (Developmental) → Product Quality, Product Innovation, Process Innovation (+) OC (Hierarchical) → Process Quality (+) OC (Rational) → Product Quality, Process Quality
Kim and Chang (2018)	Competing values framework and balanced scorecard, panel data with more than 400 Korean companies		(+) OC (Clan, Adhocracy and Market Culture) → Performance (HR, Customer and Process performance)

Note. (+) Positive impact; (−) Negative impact; ( ) No impact. OC = Organizational Culture. KMT = Knowledge Management Theory.

Source: Own work.

Data-driven culture and organizational culture are related but distinct concepts. While complementary, especially regarding AI adoption, they have different focuses and implications for organizations (Leal-Rodríguez, Sanchís-Pedregosa, Moreno-Moreno, & Leal-Millán, 2023; Sadegh Sharifirad & Ataei, 2012). Organizational culture encompasses all aspects of an organization's social and psychological environment (Cameron & Quinn, 2011). Data-driven culture is an aspect of organizational culture that emphasizes the use of data (Gupta & George, 2016). More precisely, organizational culture deals with overall values and norms, while data-driven culture explicitly addresses how data is used in decision-making. Organizations typically exhibit a dominant cultural archetype that defines their identity. However, organizational cultures are not monolithic. Multiple microcultures within them coexist in a delicate balance between dominant and competing values (Leal-Rodríguez et al., 2023). A data-driven culture can be a component of the broader organizational culture, especially in organizations prioritizing evidence-based practices. An organization with a strong data-driven culture might be more adaptable and innovative as it relies on data to drive changes and improvements (Chaudhuri et al., 2021). This results in an organizational context appropriate for technological innovation adoption, such as AI (Ali Taha, Sirkova, & Ferencova, 2016; Chatterjee, Chaudhuri, et al., 2021; Ghafoori, Gupta, Merhi, Gupta, & Shore, 2024). Both culture-related concepts are crucial for the success and sustainability of modern organizations, with a data-driven culture that often enhances and supports the broader organizational culture (Leal-Rodríguez et al., 2023). Their separate inclusion in the organizational context is therefore warranted.

2.11 Brief Overview of Hypotheses

In total, we formulate the following 14 hypotheses.

Table 6: Summary of Formulated Hypotheses

Hypotheses	Definition	Brief explanation
H1	*AI adoption directly positively influences organizational performance.*	The AI-specific ability to create intelligent agents facilitating the automation–augmentation of decision-making and transformation (improvement and redesign) of business processes can unlock considerable OP gains.
H2	*Business process performance positively influences organizational performance.*	Business processes encompass the management of key business operations that lead to business growth and success. Superior business process performance is related to the transformation process as part of the organizational productivity dimension, which includes individual and operational efficiency (i.e., doing things right), customer service efficiency, and product/service development. Therefore, the aggregated outcomes of various processes directly influence an organization's performance.
H3a	*Decision-making performance positively influences business process performance.*	Business processes entail various decisions, ranging from routine operational choices to strategic planning and resource allocation. These decisions affect the process's outcome. Organizations employ various IS tools to improve performance and guide business process decision-making. AI resources can increase the speed, flexibility, and quality (more data sources, better predictions) of the decision-making process and, in turn, business process performance.

To be continued

Table 6: Summary of Formulated Hypotheses (cont.)

Hypotheses	Definition	Brief explanation
H3b	*Decision-making performance positively influences organizational performance.*	Organizational decision-making includes high-level decisions that shape the organization's overall direction and long-term vision. They involve critical choices about market positioning, product development, and other initiatives that impact the organization's future growth and sustainability. AI-enabled processing capabilities can significantly impact strategic decision-making by extracting information from Big Data, providing valuable insights, improving forecasting accuracy, and facilitating data-driven strategies.
H4a and H4b	*Cognitive business process automation mediates the positive impact of AI adoption on decision-making performance and business process performance.*	The ability of an organization to automate complex and knowledge-intensive business processes (KiPs) using Cognitive technologies can significantly enhance the effectiveness and efficiency of both DMP and BPP.
H5a and H5b	*Organizational learning mediates the positive impact of AI adoption on decision-making performance and business process performance.*	AI holds considerable potential to explicate the organizational knowledge base provided that it is represented in Big Data. It can develop new, incremental knowledge or update existing knowledge. Thus, knowledge has the potential to influence decision-making and process performance.
H6a and H6b **H7a and H7b**	*Incremental business process innovation mediates the positive impact of AI adoption on decision-making performance and business process performance.* *Radical business process innovation mediates the positive impact of AI adoption on decision-making performance and business process performance.*	Organizations can significantly enhance decision-making and business process performance by integrating AI technology or an AI-enabled innovation process. The exploration approach involves incremental improvements to existing processes focusing on increasing decision-making and business process efficiency and effectiveness. In contrast the exploration approach pursues more radical or transformative changes enabled or driven by AI.
H8a **H8b**	*Organizational learning positively influences incremental business process innovation.* *Organizational learning positively influences radical business process innovation.*	Knowledge assets are the foundation for all organizational capabilities and core competencies, representing a fundamental strategic tool for fostering ongoing innovation. OL prevents stagnation and promotes continuous innovation through the renewal and reinvention of technology and the transformation of business processes.

Source: Own work

3 COMPONENT-BASED VIEW OF AI ADOPTION[6]

Our empirical research requires a concept that captures the main components of AI adoption on an organizational level in the BPM context. Drawing from Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019), we understand AI adoption *as implementing, deploying, and using AI resources (data, AI infrastructure, skills, capabilities) in business processes.* The AI adoption constructs we identify measure adoption in relation to the antecedents and determinants of readiness for adoption, the process of adoption, and adoption intention (Alsheibani, Cheung, & Messom, 2018; Chen, 2019; Chetty, 2019; Mikalef & Gupta, 2021). Since we could not identify any comprehensive constructs (Bag, Gupta, et al., 2021; Wamba, 2022), we developed a new construct assessing AI adoption level as an exogenous, component-based variable (unlike antecedents or determinants) related to the level of deployment and actual use of particular AI applications and technologies.

[6] Parts of this chapter were previously published in the BPM 2020 International Workshops (Zebec & Indihar Štemberger, 2020).

3.1 Big Data and AI

Digitalization continues to transform services, products, and business processes (Peppard & Ward, 2016). With technologies like the Internet of Things, digital representations mediate the experience of the real world (Lyytinen, 2022) and enormous quantities of data are generated (Big Data). Big Data combines unstructured, semi-structured, or structured data collected by organizations. In data-driven business models, data are the key information assets (i.e., resources; Hartmann, Zaki, Feldmann, & Neely, 2016) with sufficiently high volume, velocity, and variety to require specific technology and analytical methods for its transformation into value (De Mauro, Greco, & Grimaldi, 2016; Mashingaidze & Backhouse, 2017). Organizations that treat data as a key resource can gain a significant advantage over the competition (Kühne & Böhmann, 2019). Organizations thus actively look for opportunities to harness Big Data, and managers have always exploited the opportunities provided by IT.

While developments in AI technology have increased opportunities, the issues encountered in ensuring successful implementation are no easier to resolve (Peppard & Ward, 2016). AI depends on data and domain knowledge, making it challenging to integrate and align with existing business processes and their management (Chui, 2017; Mikalef & Gupta, 2021). Legacy data mining methodologies, optimized for centralized processing architectures, encounter significant challenges when confronted with Big Data’s volume, velocity, and variety (Li, Ye, & Zhang, 2022). AI, by contrast, leverages ML algorithms to extract valuable insights, automate data management tasks, and introduce novel paradigms for data interaction. AI can significantly enhance organizational data literacy by democratizing access to data and fostering a data-driven culture (Dubey, Bryde, Dwivedi, Graham, & Foropon, 2022).

3.2 Cognitive Computing and Technologies

Cognitive computing is a technological approach that allows human–machine collaboration. These systems are able to learn at scale, reason with purpose, and interact with humans and other intelligent systems. Rather than being explicitly programmed, these systems learn and reason based on their interactions with humans and their experiences in the environment (Demirkan, Earley, & Harmon, 2017; Hurwitz et al., 2015). Cognitive computing systems comprise advanced technologies and algorithms to mimic human cognitive abilities, including perception, reasoning, learning, and problem-solving, to understand, interpret, and analyze complex data more effectively. All cognitive computing systems are learning systems (Noor, 2014).

Academics and industry have paid considerable attention to cognitive computing due to the rapid development of computer software and hardware technologies, Big Data, and AI (Chen, Herrera, & Hwang, 2018). Cognitive computing assists humans in decision-making, whereas AI-based systems assume that machines (i.e., automation) can make better decisions on their behalf (Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018). Cognitive computing systems can be regarded as “more human” AI (Coccoli, Maresca, & Stanganelli, 2016). It can be argued that cognitive computing is a subset of AI; anything cognitive is also AI (Gupta et al., 2018). Cognitive computing system emulates human reasoning methodologies, demonstrating special capabilities in dealing with uncertainties and solving problems involving computation. Additionally, it has the ability to make progress and develop by using accumulated experiences to learn from past successes and failures (Coccoli et al., 2016); that is, a computerized model captures the human thought process and improvises on the basis of the mistakes the system makes every time it executes (Modha et al., 2011). This self-learning mechanism can be beneficial for decision-making by controlling how much data is analyzed (Raghavan, Gudivada, Govindaraju, & Rao, 2016). This reduces the shortcomings and concerns faced in business data analysis (Hurwitz et al., 2015).

Despite their similarity, cognitive computing and cognitive technologies are different concepts. Cognitive technologies are a broader category that includes the many technologies and tools that leverage cognitive capabilities. They are a more comprehensive set that includes, for example, AI (natural language processing, machine learning, computer vision, speech recognition, and other AI-based techniques), advanced analytics, high-performance computing, and cyber-physical systems (Elia & Margherita, 2022). We can also understand cognitive technologies as the products of AI that perform tasks that were once the exclusive domain of humans (Schatsky et al., 2014).

To summarize, cognitive computing is a distinct technological approach that falls within the broader category of cognitive technologies. Cognitive computing focuses on building intelligent systems replicating human cognition. In contrast, cognitive technologies encompass a wide range of AI-based tools and techniques that enhance human–machine interactions and enable problem-solving.

We use the term “cognitive” in our construct definitions to emphasize the human–computer interaction and the automation–augmentation perspective on AI adoption. To his end, we adopt the definition proposed by (Roeglinger et al., 2018, p. 421). “Cognitive computing is an umbrella term for new problem-solving models that strive to mimic the cognitive capabilities of the human mind by autonomously reasoning and learning based on incomplete structured and unstructured contextual data and through natural interactions with humans and machines.”

3.3 AI-Related Technologies

In this research we refer to business intelligence, business analytics, Big Data analytics, knowledge discovery, and data mining as AI-related technologies and rely on theory and empirical evidence related to these technologies and concepts. Next, we provide a rationale.

3.3.1 Data Analytics

Although there is no generally accepted unified framework encompassing the fields of BI, business analytics, Big Data analytics, data analytics, knowledge discovery, data mining, and AI, together they constitute “a cluster of concepts concerned with analyzing massive amounts of data” (Dedić & Stanier, 2017). As Holsapple et al. (2014) point out, analytics can be categorized as a movement, a collection of practices and technologies, a transformation process, a set of capabilities, or a decisional paradigm. However, in the field of information systems, analytics are primarily considered in connection to technology and decision-making capabilities (Hassan, 2019). The concepts of business intelligence, business analytics, Big Data analytics, data analytics, knowledge discovery, data mining, and, to some extent, AI all concern data analytics to some degree (it is the lowest common denominator). Data analytics is “the process of supporting effective decision-making through analysis of the existing data sets using computer systems” (Runkler, 2020, p. 2). Data analytics is a multidisciplinary field that encompasses various discourses that affect analytics, including computational intelligence, statistics, machine learning, signal theory, pattern recognition, machine learning, operations research, predictive analytics, Big Data, knowledge discovery, data mining, artificial intelligence, visualization, natural language processing, decision support systems, business intelligence, prescriptive analytics, and descriptive analytics (Dedić & Stanier, 2017; Hassan, 2019).

As data analytics developed, different rules came to apply to it than are applicable to statistics. There is a move from statistics toward data science (Hassan, 2019) in the form of “generalizable knowledge extraction from data.” Dhar (2013) distinguishes between statistics and data science: 1) the variety of data, especially the growing volume of unstructured data, differs from data traditionally handled by statistics; 2) analyzing the data has evolved from traditional statistical inference and causal modeling to integrating, interpreting, and making sense of it using tools from computer science, linguistics, sociology, and other fields; 3) the shift in focus from testing causal hypotheses to generating new hypotheses based on interesting and insightful patterns in the data; and 4) the focus on prediction rather than statistical explanatory power. These differences also pertain to the distinctions between business intelligence, business analytics, Big Data analytics, data analytics, knowledge discovery, data mining, and AI.

In business, accessing and analyzing data enables organizations to gain valuable insights into significant trends and patterns, providing managers with timely and helpful information to enhance decision-making. Over the last few years, data-driven approaches like business intelligence and business analytics have become indispensable to business operations (Vassakis, Petrakis, & Kopanakis, 2018).

3.3.2 *Business Intelligence*

Business intelligence, the application of data analytics to generate information to support business decision-making, has been an important research area for more than two decades (Hassan, 2019; Liang & Liu, 2018). Business intelligence is content-free expression and has been variously interpreted in the literature. The confusion about business intelligence in the literature lies in the flurry of associated acronyms and buzzwords. We understand business intelligence as "an umbrella term that combines the methodologies, systems, and applications for collecting, preparing, and analyzing data to provide information to help decision-makers" (Sharda, Delen, & Turban, 2016, p. 42). As such, "BI systems are data-driven decision-making systems" (Vassakis et al., 2018, p. 8). Business intelligence transforms raw data into information, insight, and meaning for business purposes (Ghavami, 2019).

Several authors emphasize that business analytics, Big Data analytics, knowledge discovery, data mining, and AI must be integrated into business intelligence, presenting them as the advanced potential of artificial intelligence, especially for decision-making (Chen, Li, & Wang, 2022). The integration process occurred over three generations of business intelligence (Alghamdi & Al-Baity, 2022), and clearly delineating these concepts is difficult (Dedić & Stanier, 2017).

The first generation of business intelligence is mainly understood as the analysis of historical and current data, situations, and performance to provide a relevant snapshot using static dashboards and reports and allowing decision-makers valuable insights for more informed and better decisions (Ghavami, 2019; Sharda et al., 2016). First-generation business intelligence works with normalized and complete data, typically arranged in rows and columns. The data are structured and assumed to be accurate and typically stored in a data warehouse or a data mart. Data that are out of range or outliers are removed before processing. Data processing uses simple, descriptive statistics such as mean, mode, and possibly trend lines and simple data projections to extrapolate about the future (Ghavami, 2019).

Second-generation business intelligence has the ability to perform analytics. By analyzing data, organizations can determine the reasons for past events and make predictions based on the information extracted (business analytics) as well as gain insight into what happened and how (business intelligence part; Bulusu & Abellera, 2020). Both causation and correlation must be considered in the analysis. Second-generation business intelligence generates a more complete view of business and allows more insightful decisions.

Third-generation business-intelligence-enabled ecosystems involve the integration of a plethora of AI tools and technologies to boost and enhance business intelligence (Bulusu & Abellera, 2020)—from data preparation (including data quality) to data integration (via

ETL/ELT[7] or data virtualization) to data warehousing (including data lakes that act as sources to the data warehouse) to data presentation (via data marts, data warehouses, and business intelligence dashboards) and data visualization, and from decision support to decision-making.

3.3.3 Business Analytics

Business analytics has largely replaced previously available computerized decision support technologies. Indeed, many practitioners and academics now use the word analytics instead of business intelligence (Sharda et al., 2016). The definitions offered for business analytics are not very different from those for business intelligence. Generally, two key aspects are included: technology and the ability to make informed decisions (Holsapple et al., 2014; Power, Heavin, McDermott, & Daly, 2018).

Davenport and Harris (2017, p. 36) define business analytics as “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions” and consider it a subset of business intelligence (Hassan, 2019). Predictive analytics is one of the most significant business intelligence processes in business analytics. It is intended to support managers in making reasonable decisions by predicting future trends based on historical data. Various analytic tools and technologies are available to aid in expectations forecasting and strategy simulation. These tools involve statistical modeling, mathematical calculations, result simulation, and visualization techniques (Chen, Li, et al., 2022).

Business analytics is essentially the implementation of conventional analytics (Vassakis et al., 2018) and involves 1) descriptive[8], diagnostic[9], or predictive[10] analytics, 2) it is hypothesis-based, 3) the primary objective is internal decision support and performance management, and 4) it is based on structured data.

In the late 2000s, business analytics became the principal analytical element in business intelligence. Thereafter, the terms Big Data and Big Data analytics are used interchangeably to describe analytical techniques for data sets that are so large and complex that they require advanced storage, management, analysis, and visualization technologies (Vassakis et al., 2018).

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[7] ETL/ELT (extract, transform, and load) is extremely important for data integration and warehousing (Sharda et al., 2016).

[8] Descriptive analytics (business intelligence or performance reporting) is the provision of historical and current data access, offering organizations the ability to alert, explore, and report using internal and external data from various sources (Davenport & Harris, 2017).

[9] Diagnostic analytics, also based on historical data, provides insights into the root cause of past outcomes (Vassakis et al., 2018).

[10] Predictive analytics uses quantitative techniques (e.g., propensity, segmentation, network analysis, and econometric forecasting) and technologies (such as models and rule-based systems) that use past data to predict the future (Davenport & Harris, 2017).

3.3.4 Big Data Analytics

Conventional analytics cannot handle vast quantities of data, and Big Data (defined in Section 3.1) is too large and complex to be manipulated or managed using standard tools and methods. Big Data analytics emerged in response and is commonly understood as “large-scale analysis and processing of information, encompassing data sets that go beyond the capacity of conventional databases” (Chong & Shi, 2015; Dedić & Stanier, 2017; Zakir, Seymour, & Berg, 2015). The power of business analytics is that vast amounts of data can be streamlined to enhance their value (Vassakis et al., 2018) and that advanced analytics are employed that can manage Big Data. Big Data analytics uses various advanced methods of data analysis, such as clustering, classification, association rule, and sequential patterns, to discover new knowledge.

Big Data analytics involves the implementation (Vassakis et al., 2018) of 1) predictive and prescriptive[11] analytics, 2) using machine learning, 3) with the primary objective of driving business processes and data-driven products and services, and 4) based on unstructured, semi-structured, and structured data.

3.3.5 Knowledge Discovery and Data Mining

Knowledge discovery, according to Cortez and Santos (2013), is a branch of AI in which the aim is to extract high-level knowledge from complex and voluminous data in a form that is useful and understandable (Dedić & Stanier, 2017). Fayyad, Piatetsky-Shapiro, and Smyth (1996, p. 82) define knowledge discovery as an “overall process of discovering useful knowledge from data.” Knowledge discovery is a high-level concept, which, in addition to other methods, includes advanced data analytics to discover or produce new knowledge (Hassan, 2019).

Advanced analytics are utilized for discovery, knowledge creation, assertion, and communication of patterns, associations, classifications, and learning from data using advanced statistics, AI techniques, machine learning, deep learning, feedback, and natural language processing to mine data (Ghavami, 2019). Data Mining is considered a powerful approach to developing knowledge from data (Dedić & Stanier, 2017). Data analysis and discovery algorithms are utilized to generate models based on existing data.

Knowledge discovery and data mining concern the implementation of 1) advanced data analytics, 2) using natural language programming, classifiers, machine learning, pattern recognition, predictive modeling, optimization, and model-based methods, 3) with the

[11] Prescriptive analytics involves the use of quantitative techniques (such as optimization) and technologies (e.g., models, machine learning, and recommendation engines) to specify optimal behaviors and actions (Davenport & Harris, 2017).

primary objective of discovering knowledge, insight, and patterns, and learning from data, 4) based on unstructured, semi-, and structured data (Ghavami, 2019).

3.3.6 Integration of AI-Based Methods

AI brings a set of sophisticated algorithms to data analytics for descriptive, diagnostic, predictive, and prescriptive analytics (Carlile, Marti, & Delamarter, 2017). AI-based methods can automate the analytics cycle for business and facilitate the preparation of data, generation of insights, and interpretation. These methods can transform how analysts execute and share data insights and how users explore and analyze data in analytics and business intelligence platforms (Alghamdi & Al-Baity, 2022).

AI-based methods refer to techniques and approaches that leverage AI technologies to solve problems or perform analytical tasks. These methods typically involve machine and deep learning, natural language processing, computer vision, and other AI subfields (Alghamdi & Al-Baity, 2022). This degree of analytical capabilities is referred to as intelligent analytics and as an intelligence that integrates AI, human intelligence, analytics, data, information, knowledge, intelligence, and wisdom using advanced computing to provide intelligent services, business, management, and governance (Sun, 2021).

The most relevant areas of analytics impacted by AI-based methods are the following (Surya, 2015): 1) data management (AI makes customized suggestions based on machine learning and real-time data utilization); 2) patterns management (AI identifies anticipated and unanticipated signals, occurrences, and trends quickly and in detail); 3) context management (AI facilitates complex computer processes using data, learning subtle variations and context-specific distinctions); 4) decision management (AI supports the use of information and skills in a dynamic environment, scales key resources, such as Big Data, to address business objectives and customer expectations, enhances user experiences, resolves consumer complaints, recommends decision options, analyzes and forecasts decision outcomes, and tracks output against key metrics); 5) action management (AI analyzes activities and associates these with previous decision steps, selects inventoried actions, modifies rules and parameters, recommends new actions, and incorporates AI in executing tasks); 6) goal management (AI autonomously modifies targets to guide humans, snippets, bots, applications, and scalable infrastructures); and 7) risk management (AI supports organizations in identifying and responding to potential threats by analyzing incidents, trends, system logs, personal input, and cultural behavior, thereby facilitating early detection and implementation of appropriate protection measures).

The growth in AI-based methods is evidenced by the surge in research citations for data mining (citation burst in 2012), digital storage (burst in 2013), predictive analytics (burst in 2014), machine learning (burst in 2015), the distributed computer system (burst in 2016), predictive modeling and visualization (burst in 2016), support vector machines (burst in 2016), regression (burst in 2016), classification algorithms (burst in 2017), neural networks (burst in 2018), random forest (burst in 2018), decision trees (burst in 2018), deep learning (burst in 2018), prediction algorithms based time-series (burst in 2019), sentiment analysis (burst in 2020), and text mining (burst in 2021; Chen, Li, et al., 2022).

The use of AI-based methods in business intelligence, Big Data, and data analytics is also evident in the surge in research citations for decision-making (citation burst in 2013), business process intelligence (burst in 2013), competitive intelligence and competition analysis (burst in 2014), enterprise resource management (burst in 2014), administrative management (burst in 2015), commerce enhancement (burst in 2015), manufacturing development (burst in 2015), sale prediction (burst in 2016), information management (burst in 2017), quality management (burst in 2017), knowledge management (burst in 2017), risk assessment (burst in 2018), customer satisfaction management (burst in 2018), service improvement (burst in 2020), user acceptance development (burst in 2020) and satisfaction improvement (burst in 2021; Chen, Li, et al., 2022).

Intelligent analytics builds on Big Data analytics (Alghamdi & Al-Baity, 2022) and includes 1) predictive, prescriptive, and real-time advanced analytics; 2) using AI and machine learning; 3) with the primary objective of data storytelling, scenario analysis, search-based visual analysis, and conversational analytics driven by natural language programming, smart discovery and automated insights, accelerated data preparation, and Big Data analytics; and 4) is based on unstructured, semi-, and structured data.

Several artifacts of AI implementation overlap with business intelligence, business analytics, Big Data analytics, knowledge discovery, data mining, and Big Data implementation. This is because of the ultimate relationship between AI and digital transformation; for example, implementing AI requires that Big Data be in place (Brock & Von Wangenheim, 2019; Gupta & George, 2016). Therefore, the various technologies can be seen as complementary, and we expect them to eventually evolve into AI technologies (Metcalf, Askay, & Rosenberg, 2019). To summarize, we present data analytics as the factor that links the concepts and technologies assessed as complementary and intricately intertwined (Hassan, 2019).

3.4 Development of the Concept

Our development of concepts follows the guidelines in the literature (MacKenzie et al., 2011; Podsakoff et al., 2016). The "adoption of AI" is defined in three stages:

1. possible attributes of the construct are gathered by examining and assembling a set of definitions from the literature and in-depth semi-structured interviews,
2. key potential attributes are compiled to generate a preliminary definition, and
3. the definition is refined.

3.4.1 Literature Identification

We conduct a thorough review on the literature on information systems from the SCOPUS and Web of Science databases to identify existing definitions of AI adoption and organiztation-level models. The literature review includes studies defining AI adoption and that specify models at the organizational level. Our search yields several empirical studies that utilized well-known theories and frameworks such as resource-based view, dynamic capability view, knowledge management theory, organizational information theory, the diffusion of innovations theory, and the technology-organization-environment framework (as presented in Table 7).

The AI adoption constructs and measurement scales we identify focus on various factors, including the antecedents and determinants of adoption readiness, the process of adoption, and adoption intention. However, we find that no constructs assessed AI adoption as an exogenous, comprehensive, and component-based variable related to the level of deployment, actual use, or utilization of specific applications and technologies. Therefore, we argue that there is a need to develop a new construct.

Table 7 summarizes the descriptions and definitions of AI adoption at the organizational level, as identified in our literature review.

Table 7: Studies on AI Adoption at the Firm-Level

Author	**Scope**	**Theory**	**Findings**
Mikalef and Gupta (2021)	Survey, 143 senior US firm managers	RBV, DCV	Determinants of AI Capability. Tangible resources → Tangible resources are considered those that can be sold or bought in a market. Human resource → AI-specific technical and business skills. Intangible resources → Inter-departmental coordination, organizational change capacity, and risk proclivity.
Wamba (2022)	Survey, 205 US firm managers	RBV, DCV	Indefinite components of AI assimilation → Deployment and use of AI tools.
Wamba-Taguimdje et al. (2020a)	150 AI-related case studies	RBV, DCV	Determinants of AI Capability. AI Management Capability → *Ability of an organization and its staff to administer or to model intelligent behaviour in a computer or technology to create added value for the organization's sustainability.* AI personal Expertise → *The professional skills and knowledge of AI-related technologies, business functions and relational (or interpersonal) domains is required by the organization's staff for modeling and/or using intelligent behaviour in a computer or technology to accomplish the assigned tasks.* AI infrastructure → *The composition of all technological assets (software, hardware and data, etc.), systems and their components, network and telecommunication installations and applications necessary to implement an AI system capable of performing tasks.*

To be continued

Table 7: Studies on AI Adoption at the Firm-Level (cont.)

Author	**Scope**	**Theory**	**Findings**
Chen, Esperança, et al. (2022)	Survey, 394 e-commerce entrepreneurs	RBV, DCV	Determinants of AI Capability. Basic → *Tangible Resources* Skills → *Human Resources* Proclivity → *Intangible Resources*
Bag, Gupta, et al. (2021)	306 senior executives in South Africa	KMT	Determinants of Big data powered AI technology
Mishra et al. (2022)	10-K data from US firms		Determinants of AI adoption → *AI Focus.*
Lyu and Liu (2021)	US Energy Sector Compustat data during the period 2010–2019		Antecedents of AI adoption → *AI related Job Listings.*
Rammer et al. (2022)	Germany Community Innovation Survey (CIS) 2018		Combination of determinants and components. AI development Breadth of AI us Experience in AI use AI methods → *Language or text understanding, image or pattern recognition, machine learning, and knowledge or expert systems.* AI application areas → *Products or services, automation of processes, interaction with clients, data analysis, and other applications (including R&D).*
Kim et al. (2022)	395 US-listed firms using AI between 2000-2018		A limited set of technological components of AI adoption → *Natural Language Processing, pattern recognition, neural network and artificial intelligence.*
Alekseeva et al. (2020)	Compustat Online US job postings during the period 2010–2018		Antecedents of AI adoption → *Demand for AI-related skills in online job postings*
Babina et al. (2021)	Job postings from the US during the period 2010–2018		Antecedents of AI adoption → *AI-related worker resume and job posting datasets.*
Sullivan and Wamba (2022)	Survey, 107 business and IT executives from UK and France	DCV, Organizational Information Theory	Determinants of AI adoption. Coordinating/integration → *Assess the value of existing resources and integrate them to shape new capabilities.* Learning → *Explore and exploit internal and external knowledge.* Strategic competitive response → *Scan the environment, identify new opportunities, and assess the firm's competitive response.*
Alsheibani et al. (2018)		TOE	AI readiness: factors (determinants) for preparing organizations to adopt AI. Technological readiness → *The ability of a firm to adopt new technology.* Organizational readiness → *Availability of the needed organizational resources for adoption.* Environmental readiness → *How the organization perceives external factors to adopt AI.*
Chen (2019)	Survey, 289 telecommunication companies	TOE, DOI	The antecedents of AI adoption. Innovation attribute of AI → *Compatibility; Relative advantage; Complexity* Organizational capability → *Managerial support; Technical capability* External environment → *Government involvement; Market uncertainty; Competitive pressure; Vendo partnership* Managerial capability → *The ability of managers to influence, motivate and enable employees to contribute toward the effectiveness and success of the organization.*

Note. RBV = Resource-Based View. DCV = Dynamic Capabilities View. KMT = Knowledge Management Theory. TOE = The technology-organization-environment framework. DOI = The Diffusion of Innovations Theory.

Source: Own work.

We separately examine the concepts of "adoption" and "AI" to develop the definition of AI adoption operationalized in this study. Following Podsakoff et al. (2016), for our focal construct, we apply multiple techniques to gather potential attributes and produce an illustrative set of definitions. We examine dictionary definitions and antonyms and draw material from our literature review and in-depth semi-structured interviews with subject-matter experts and practitioners.

3.4.1.1 Adoption

It is well known that IT usage is a key dependent variable in management information systems research and that numerous empirical studies examine its determinants (Karahanna, Straub, & Chervany, 1999). We must also consider the temporal dimension of the adoption process, that is, the sequence of events leading to the initial adoption and continued use of an IT innovation. Renaud and Van Biljon (2008) assert that technology adoption is a multi-phase process that begins with the decision to adopt (the selection, purchase, or commitment to use) and ends with "permanent use." Karahanna et al. (1999, p. 183) distinguish between "pre-adoption" and "post-adoption (continued use)." Accordingly, adoption and sustained engagement can be treated as distinctive parts of the adoption process (Nadal, Doherty, & Sas, 2019).

It is essential to first distinguish between the acceptance and adoption of technology. According to Renaud and Van Biljon (2008), technology adoption is becoming aware of, embracing, and utilizing the technology. Rogers (2010) defines adoption as making full use of technology and rejection as not accepting the technology. In contrast, technology acceptance is an attitude toward technology influenced by various factors. Acceptance refers to the willingness to use the technology for the purpose for which it was designed (Wong, 2016). A distinction is also made between individual and organizational acceptance and adoption of technology, that is, between the acceptance and adoption of technology as a personal choice and as an organization's policy (Jeyaraj, Rottman, & Lacity, 2006).

Several theories and models in the literature address the adoption of technology, including the technology acceptance model, the technology acceptance model 2 and the theories of diffusion of innovation, reasoned action, and planned behavior, the technology-organization-environment framework, and the unified theory of acceptance and use of technology (Dube, Van Eck, & Zuva, 2020; Taherdoost, 2018). However, the theories and models concern the antecedents and determinants of adoption, with actual use positioned as a dependent variable. In this study, we position adoption as an independent variable and address post-adoption (continued use). Rather than antecedents and determinants of adoption, we are interested in the component parts of AI adoption, such as the implementation, integration, deployment, use, and exploitation of AI applications, tools, and technologies.

We examine definitions of "adoption" in dictionaries and top journals in the field of management information systems to extract common attributes centered on the use of the technology at an organizational level. The common attributes we identify are the following: implementation, integration, deployment, use, and exploitation. We discard attributes that concern the process of adoption: investment decision, acceptance, selection, planning, and configuration. Exemplary definitions are presented in Table 8.

Table 8: Exemplary Definitions of Adoption from Management Information Systems Journals

Conceptualization of Adoption	**Author(s)**
"use of computer hardware and software applications to support business operations, organizational management, and decision making processes"	Thong and Yap (1995)
"a process that includes decision-making, planning, design, implementation, and integration with other technologies through which a firm becomes capable of using a technology"	Chan and Mills (2002); Iacovou, Benbasat, and Dexter (1995)
"For these kinds of technologies, the very notion of adoption deserves special scrutiny. Should we consider an organization to have "really" adopted when senior managers give the goahead? Or would it perhaps be better to wait until some threshold level of actual use is reached?"	Fichman (2000)
"adoption is the intention to use and the actual use of technology"	Venkatesh, Morris, Davis, and Davis (2003)
"the first use or acceptance of a new technology or new product"	Khasawneh (2008)
"a decision to make full use of a technology as the best course of action available"	Rogers (2010)
"adoption including selection and configuration, deployment and exploitation"	Culnan, McHugh, and Zubillaga (2010)
"the use and deployment of concepts in different kinds of organizations"	Reijers, van Wijk, Mutschler, and Leurs (2010)
"the decision to accept or invest in a technology"	Reijers et al. (2010)
"adoption and its actual penetration; whether the technology is in place and ready for use, and penetration is the degree of actual use"	Gefen, Ben-Assuli, Stehr, Rosen, and Denekamp (2019)

Source: Own work.

3.4.1.2 Definitions of Artificial Intelligence

Next, we examine definitions of AI in dictionaries and the information systems literature (Table 9). Our analysis shows that some definitions are more precise than others. Some emphasize the capacity of computers to mimic human intelligence, while others are more precise and focus on the technologies that enable human characteristics to be emulated.

Table 9: Exemplary Definitions of AI from Management Information Systems Journals

Conceptualization of Artificial Intelligence	**Author(s)**
"…science and engineering of making intelligent machines, especially intelligent computer programs"	McCarthy, Minsky, Rochester, and Shannon (1955)
"acts like a human or acts and interprets the world like a human"	Russell and Norvig (2020)
"the theory and development of computer systems (mostly machines) or technologies capable of performing tasks that normally require human intelligence"	Bawack and Wamba (2019)
"set of technologies, machines or systems capable of emulating human performance typically by learning to understand complex data that normally requires cognition"	Bawack et al. (2019)
"… a set of tools and technologies that has the ability to augment and enhance organizational performance. This is achieved by creating artificial systems to solve complex environmental problems, with "intelligence" being the simulation of human-level intelligence."	Alsheibani, Messom, and Cheung (2019)
"a simulation of human intelligence which is processed by machines, especially by robotics or computer system"	Tyagi and Jain (2019)

Source: Own work.

There is no single accepted definition of AI. The available definitions are very general, focusing on two key attributes: learning and perception. Some definitions emphasize a computer's capacity to mimic human intelligence; others are more precise, defining AI as the technologies that simulate human cognitive functions. Many definitions present the idea of an intelligent agent as the central unifying theme (Russell & Norvig, 2020). The AI Group of Experts at the OECD (OECD, 2019) defined an intelligent agent or AI system as "a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. It does so by using machine and/or human-based inputs to 1) perceive real and/or virtual environments, 2) abstract such perceptions into models through analysis in an automated manner (e.g., with machine learning or manually), and 3) use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy."

The definition is amended to accommodate the emergence of large language models and define the AI system as "a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment." (OECD, 2024, p. 7).

We further investigate AI types, features, technologies, and application domains to identify more specific characteristics and uncover themes in AI adoption. These categories help us develop a concept-centric structure to understand AI adoption, use, and impact. Based on the meanings of the categories, we are able to determine AI characteristics, capabilities, principles, and technologies that can be used to manage and implement AI.

3.4.1.3 AI Types

AI is generally classified into three types, as shown in Table 10. These classifications of AI are based on the similarity between AI capabilities and human cognitive abilities. They do not capture the application of AI in an organizational context.

Table 10: AI Types

AI type	Definition
Artificial Narrow Intelligence (ANI), also referred to as narrow/applied	*"they operate strictly within the confine of the scenarios for which they are programmed"* (Miailhe & Hodes, 2017) *"application of AI techniques to narrower or specific problems" (Bawack et al., 2019)*
AI, Pragmatic AI, or Weak AI	*"AI which is specialized in one task."* (Ganji & Karandikar, 2019)
Artificial General Intelligence (AGI), also referred to as general/generalized AI, Pure AI or Strong AI	*"… is able to mimic all of the capabilities of the human brain, not just the very narrow ones"* (Burgess, 2018) *"…an autonomous machine's ability to perform any intellectual tasks that a human can perform. This implies generalizing and abstracting learning across various cognitive functions. Transferring learning autonomously and nimbly from one domain to another has happened only very embryonically thus far"* (Miailhe & Hodes, 2017) *"AI that can perform any/multiple intellectual tasks in a way that matches or surpasses human intelligence."* (Bawack et al., 2019) *"AI which seems like a human to some extent, simulating the entire human brain is one of the methods of AGI"* (Ganji & Karandikar, 2019)
Artificial Super Intelligence (ASI)	*"AI which is smarter than humans, this is the future Artificial Intelligence where computers start simulating themselves and they will become smarter than humans"* (Ganji & Karandikar, 2019)

Source: Own work.

3.4.1.4 AI Capabilities

AI capabilities represent the potential of AI to perform or develop certain aptitudes. Burgess (2018) presents an AI capabilities framework, a set of discrete AI capabilities focusing on capturing information and understanding data. Bawack and Wamba (2019) more comprehensive framework includes four distinct categories. In Table 11, we present a set of definitions.

Table 11: AI Capabilities

AI capability	Definition	Key technologies
Learn	*"ability to leverage algorithms for the interpretation of input data"* (Bawack & Wamba, 2019)	neural networks, machine learning, deep learning, genetic programming, data analysis/clustering
Sense	*"ability to process information like images, sound, speech, and text"* (Bawack & Wamba, 2019)	computer vision, speech recognition, biometrics, search, image recognition
Act	*"ability to interpret data, make rational decisions and execute them automatically ability to leverage algorithms for the interpretation of input data"* (Bawack & Wamba, 2019)	expert systems, decision support systems, robotic process automation, intelligent agents, recommendation systems, robotics, fuzzy logic systems
Comprehend	*"pattern recognition capabilities"* (Bawack & Wamba, 2019) *"…the ability of a machine to have conscious awareness of what it is doing or thinking (or to act like it does)"* (Burgess, 2018)	natural language processing, text analytics, knowledge engineering, pattern recognition, ontology creation, optimization, prediction, awareness

Source: Own work.

3.4.1.5 AI Application Domains

We expect AI to enable or facilitate the transformation or redesign of business processes (Bawack et al., 2019). In Table 12, AI is categorized based on business capabilities or application domains rather than technology (Davenport & Ronanki, 2018). Several authors (Forbes Insights, 2019; Hull & Motahari-Nezhad, 2016; Roeglinger et al., 2018; Schatsky et al., 2014; Watson, 2017) emphasize AI's vast and versatile potential, which can be applied to a wide range of business problems.

The practical application domains highlight how AI can enhance efficiency, provide deep insights, personalize experiences, and support decision-making. Understanding these domains helps strategize the implementation of AI technologies to maximize benefits and mitigate risks.

Categorizing AI technology use cases using application domains offers insights into how AI can impact various aspects of a business. The domains of AI applications share common themes, providing a basis for distinguishing AI based on its characteristics within organizations.

Table 12: AI Application Domains

AI application domain	**Definition**
Robotics and cognitive automation, Enhanced process automation	*"…the automation of digital and physical tasks…", "…uses cognitive technologies such as natural language processing to automate knowledge-intensive processes…"*
Cognitive insights	*"…algorithms to detect patterns in vast volumes of data and interpret their meaning…", "…employs data science and machine learning to detect critical patterns, make high-quality predictions, and support business performance…"*
Cognitive engagement, Cognitive interaction	*"…engage employees and customers using natural language processing chatbots, intelligent agents, and machine learning…", "…applies machine learning and advanced analytics to make customer interactions dramatically more personalized, relevant, and profitable…"*
Cognitive Decision Support	*"…decisions based on deep experience and with reference to large volumes of unstructured data…", "…leveraging cognitive computing technologies to process information, generate insights, and facilitate decision-making…", "…aim to augment human decision-making by automating certain analytical tasks, surfacing relevant information, and providing decision support tailored to the user's needs…"*

Source: Own work.

3.4.1.6 AI Technologies

We analyze various definitions of specific AI technologies, including biometrics, collaborative systems, computer vision, deep learning, expert systems, generative adversarial networks, image analysis, image recognition, knowledge engineering, knowledge representation, automated reasoning, planning, optimization, verification, logic networks, machine learning, natural language generation, nlp, natural language understanding, neural networks, ontology creation, pattern recognition, robotic process automation (RPA), robotics and smart robotics, speech recognition, text analysis, video analysis, and virtual agents. We then extract various AI-specific attributes and organize these thematically using the lens of business capabilities or application domains rather than technological capabilities (Davenport & Ronanki, 2018): robotics and cognitive automation, enhanced process automation, cognitive insights, cognitive engagement, cognitive interaction, and cognitive decision support.

3.4.2 Exploratory Research

We follow the guidelines established in the literature (MacKenzie et al., 2011; Podsakoff et al., 2016) and supplement the findings from the literature review with expert interviews to extract additional definitions and attributes.

3.4.2.1 Expert selection

We selected organizations and experts based on their involvement with AI technology or AI-related projects. Six were approached at the GoDigital 2019 – Data and Artificial Intelligence Conference, organized by the Association of Informatics and Telecommunications at Slovenia's Chamber of Commerce and Industry (*GoDigital 2019 - Data and Artificial Intelligence conference*, 2019). Three were identified and contacted via LinkedIn. All experts were from Slovenian organizations.

3.4.2.2 Ethical Considerations

During exploratory research interviews, informed consent was obtained via a signed form before each interview (included in Appendix 2). The informed consent forms included full disclosure of the interview process, the benefits of the study, and the confidential nature of the data collection process. Participants were provided with a written explanation of the informed consent material before they gave written consent.

3.4.2.3 Insights

During the nine in-depth semi-structured interviews, we discussed the broader scope of AI adoption and the interviewees' experiences with AI implementation, deployment, and use. We align their views on the technology with the conceptual themes we identify (application domains); these were the classifications with which experts and practitioners were most comfortable. We present the excerpted results in Table 13.

Table 13: Main Findings From Expert Interviews

Findings	**Theme**
Financial Services; 5,900 employees; Chief Data Officer (CDO)	
AI adoption began within the analytics department, driven by a new business strategy emphasizing advanced pattern recognition techniques for customer insights. The objectives were to enhance process performance and leverage AI capabilities to boost revenue. Recognizing data as a pivotal resource, the organization appointed a CDO to oversee data management. As part of the Lean initiative, they prioritize automation to optimize business processes and maximize value with reduced human intervention. Their focus is on non-deterministic decision processes, such as credit scoring. Furthermore, they've integrated AI into their products, including personal finance management and automated revenue and expense classification.	Business insights, Data management, Automated decision-making, Engagement, AI techniques
Insurance company; 5,200 employees; Head of the team responsible for developing DWH/BI/AI solutions	
They are integrating chatbots for customer support and deploying advanced AI functionalities organization-wide for decision support, such as an automated model for detecting insurance policy renewals. Their focus lies on automating and optimizing processes and identifying various opportunities for Robotic Process Automation (RPA). Additionally, they're in the process of developing a centralized data repository to eradicate data silos and are collecting publicly available data from the environment. Following the data's availability in the data warehouse, they explore opportunities using Business Intelligence and AI techniques.	Human-computer interaction, Decision support, AI technology, Data acquisition
Financial services; 1,010 employees; Head of Analytics Department	
They have implemented a next-best-offer solution for sales representatives. Utilizing machine learning and decision trees, the organization employs these techniques primarily in marketing. Their main focus lies on propensity to buy and churn management, with AI-enabled predictive analytics holding the highest value for them. Ensuring high-quality data remains a key priority for them.	Decision support, AI techniques, Business insights, Data management
Multinational tech. company: hardware, middleware, and software; Vendor; 345,900 employees; Technical Consultant/IT architect	
Organizations adopt AI technologies primarily for competitiveness, addressing user expectations for more innovative services and products, and optimizing business operations. Successful AI integration starts with identifying real business problems rather than adopting technology for its own sake. Despite the hype driven by market demands and tech corporations, many companies lack a strategic vision, focusing on short-term gains. Limited AI applications like chatbots are typical, but comprehensive implementations are rare. AI capabilities require leadership support and interdisciplinary knowledge, with platforms like IBM Cloud easing infrastructure concerns but raising GDPR issues. The future of AI in organizations involves balancing data-driven decisions with intuition, viewing machine learning models as valuable intellectual property, and anticipating more successful implementations within five years.	AI techniques, Machine learning, Cognitive technologies, Business insights, Data management, Data acquisition, Data preprocessing, Automated decision-making, Decision support, Reasoning, Process Automation, Cognitive agents, Personalization, Context awareness, Human-computer interaction, Learning, Analytics
Service provider; Software; 15 employees; Digital Solution Designer	
Specializing in AI project implementation, the organization integrates cloud computing for scalable infrastructure, machine learning for predictive modeling, natural language processing for customer service enhancement, and computer vision for visual data analysis, particularly in manufacturing and logistics. These technologies drive efficiency, improve accuracy, and support strategic decision-making, ensuring AI initiatives align with broader business goals for competitive advantage. Emphasizing data-driven value extraction and leadership support for comprehensive integration across organizations, they address varying AI development levels between Europe (strong in research) and the US (leading in practical application and startup innovation). They advocate robust cloud computing to facilitate scalable AI solutions across sectors, tackling data quality and bias through rigorous validation and mitigation strategies to ensure reliable, fair AI outcomes. Their approach fosters continuous innovation, effectively empowering clients to optimize productivity and competitiveness.	Machine Learning, Natural Language Processing, Computer Vision, Cloud Computing, Data Validation, Predictive Modeling, AI Algorithms, Data Cleansing
Public security; Government; 279 employees; End-user; Head of Analytics Department	
The organization has been gradually adopting AI technologies amidst significant challenges. These include a substantial gap between theoretical knowledge and practical application, particularly in the public sector. While efforts to implement advanced analytics and AI have been made, progress remains slow due to legislative constraints limiting data accessibility, insufficient support and understanding of AI among leadership, and a resistant organizational culture. The organization aims to develop a comprehensive digital strategy integrating AI, improve data management practices, enhance leadership support and understanding, foster an innovative culture, invest in training, address legislative hurdles, secure adequate resources, and promote transparency. These steps are crucial for overcoming current barriers and leveraging AI to improve operational efficiency and service delivery.	Data Analytics, Business Intelligence, Predictive Modeling, Facial Recognition, Natural Language Processing, Automation, Process Optimization, Data Management

To be continued

Table 13: Main Findings From Expert Interviews (cont.)

Findings	**Theme**
Computer and Information Science; Educational Services; 182 employees; Vendor; Head of Visual Cognitive Systems Laboratory	
The organization focuses on AI projects, primarily using machine learning and deep learning techniques. They emphasize quality data, recognizing that better data leads to better results, and continually refine their models with new data. They address data issues by obtaining well-labeled data, refining models with feedback, and collaborating with domain experts to minimize bias. Key AI applications include defect detection, cognitive task automation, organizational learning, and predictive maintenance. Domain experts provide essential insights and aid in development. Challenges include maintaining data quality, iterative model development, addressing biases, seamless production integration, and resource allocation. Continuous improvement is achieved through iterative refinement, data enhancement, feedback loops, and expert collaboration. AI integration enhances business processes, leading to consistent, efficient results and better decision-making.	Data Quality, Machine Learning, Deep Learning, Model Refinement, Defect Detection, Cognitive Task Automation, AI Integration
AI Software Vendor; Manufacturing; 10 employees; Vendor; Managing Director	
The organization has been deeply engaged in AI development for over a decade, focusing primarily on creating solutions for manufacturing companies to tackle operational challenges both locally and globally. They have actively pursued digitalization and the integration of AI to boost operational efficiency and scalability. Despite facing challenges like the conservative nature of Slovenian businesses and a strong emphasis on cost-efficiency over technological investment, the organization remains optimistic about AI's potential to enhance processes and catalyze revolutionary changes incrementally. They stress the importance of fostering AI literacy within companies to leverage data effectively and drive competitive advantage through continuous learning and adaptation. Transparency in AI models is also highlighted as crucial for building trust and facilitating organizational growth. The organization sees AI as pivotal in transforming business processes, improving decision-making, and nurturing a culture of innovation and efficiency.	Data management, Decision support, Process automation, AI Trust and Transparency, Continuous learning, Optimization
Energy company; Energy Services; 4508 employees; Director Business Intelligence	
The adoption of AI has been a gradual and evolving process. Initially, the focus was on predictive analytics and the use of neural networks, which began during the academic studies of key employees. Early projects included forecasting sales trends and organizing sales data to identify customer purchasing patterns. Significant efforts were made as the organization progressed to organize databases and predict customer churn using AI. This involved creating scoring models to predict which customers might leave and automating targeted campaigns to retain them. The organization also faced technical challenges, such as ensuring call quality. Collaboration with the Jožef Stefan Institute was crucial in advancing AI projects. The interviewee emphasized that successful AI adoption requires a mature company culture ready to implement data-driven changes and continuously improve models and practices.	Business insights, Data management, AI techniques, Decision support, Process automation, Predictive Analytics

Source: Own work.

3.4.3 Five-Dimensional Conceptualization

Based on the guidelines proposed in the literature on the development of conceptual definitions (MacKenzie et al., 2011; Podsakoff et al., 2016) and using Mrad (2018) as an example, we organize the extracted attributes into a smaller set of themes and then aggregated these into dimensions. As indicated in Table 14, we organize the attributes (i.e., first-Order Attributes) into 17 related themes (i.e., second-order themes) and five dimensions (i.e., aggregate dimensions): data acquisition and preprocessing, cognitive insights, cognitive engagement, cognitive decision assistance, and cognitive technologies.

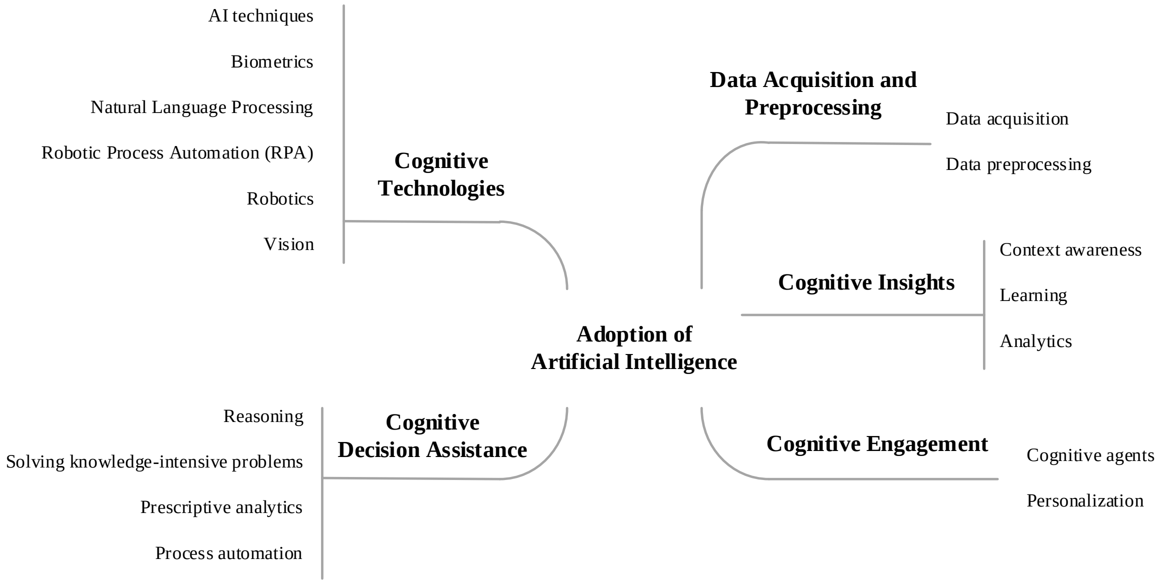
Table 14: Organizing Attributes Into Common Themes and Dimensions

First-Order Attributes	Second-Order Themes	Aggregate Dimensions
big data, gathering data from the environment, storing information, data warehouse/data lake, creating knowledge-base	Data acquisition	Data Acquisition and Preprocessing
ensuring data quality, producing new data, searching (information extraction), representing information	Data preprocessing	
act, predictive and adaptive decision support, decision trees, using optimization (problem solving and planning)	Reasoning	Cognitive Decision Assistance
automation of intelligent behaviour, automation and optimization of processes, automated decisions, automation of activities, enhanced process performance	Solving knowledge-intensive problems	
reason, abstracting, acting rationally, algorithms that reason, computational approach to uncertain inference, constructing ontologies from textual domain descriptions, generalizing	Prescriptive Analytics	
performing tasks that require human intelligence, using inference engines, using knowledge, using reasoning methodologies, using rules, solving complex problems, using AI techniques aimed at specific problems	Process automation	
intelligent agents, chatbots, simulate conversations, simulate nonverbal behaviors	Cognitive agents	Cognitive Engagement
personalized digital characters, recommendation systems	Personalization	
awareness, to perceive and interpret events from data, interpret meaning from data	Context awareness	Cognitive Insights
learn from experience, detect patterns, understand complex data, produce general hypotheses, machine learning	Learning	
descriptive analytics, diagnostic analytics, predictive analytics	Analytics	
simulation of human intelligence, use of computational models, deep learning, fuzzy logic systems, generative deep learning models, genetic programming, intelligent behavior, logic-based techniques, neural networks	AI techniques	Cognitive technologies
statistical analysis of biological data, automated recognition of individuals based on their behavioral and biological characteristics	Biometrics	
speech recognition, natural language understanding, natural language generation	Natural Language Processing	
software robots, AI workers	RPA	
physical task automation,	Robotics	
AI-enhanced robots	Computer Vision	

Source: Own work.

As depicted in Figure 4, the construct is a multidimensional, second-order construct, reflective-reflective type I (Jarvis, MacKenzie, & Podsakoff, 2003).

Figure 4: Conceptual and Dimension Attributes



Source: Own work.

In the last stage of the conceptual analysis, we refine each construct definition through discussion with subject-matter experts and peers. We then modify the scope of the definition and present the refined definition.

The focal construct is defined as follows: "The implementation, deployment, and use of AI resources (data, AI infrastructure, skills, capabilities) in business processes." We use the term "AI resources" for AI-related elements that must be brought together to ensure the successful deployment and use of AI technology. Key AI-related elements are scalable infrastructure, AI assets (data and trained models), AI skills, domain knowledge, expertise, capabilities, partnerships, AI talent, processes, and privacy policies.

The definition of a construct must incorporate the "property" characterized by the construct and the "entity" to which that property relates (MacKenzie et al., 2011). We define the property "adoption of AI" as *the organization's ability to develop a set of distinct AI-enabled capabilities (the ability to mobilize AI resources to exploit strategic assets and achieve innovative changes) through the implementation, deployment, and use of AI applications, tools, or technology.* The general property type is intrinsic characteristics and applies to the entity of an organization (Table 15).

Table 15: Factors in Conceptualizing Constructs[12]

Nature of construct's conceptual domain	Entity = organization; General property = *The organization's ability to develop a set of distinct AI-enabled capabilities (the ability to mobilize AI resources to exploit strategic assets and achieve innovative changes) through the implementation, deployment, and use of AI applications, tools, or technology.*
Common attributes	Data-driven: the ability to learn and make decisions from large amounts of data.
	Data processing: the ability to collect and manipulate digital data to produce meaningful information.
	Connectivity: the ability to connect with other systems and devices through the internet.
	Intelligent decision making: the ability to make intelligent decisions based on data.
	Human-computer interaction: the ability to interact with humans more naturally and intuitively.
Unique attributes/characteristics	Reasoning: the ability to understand and respond to the context in which it is being used.
	Solving knowledge-intensive problems: the ability to make decisions independently without human supervision, based on the data they have been trained on.
	Prescriptive Analytics: the process of using data to determine an optimal course of action.
	Process automation: the ability to provide advanced capabilities like decision-making, pattern recognition, and natural language processing to automate processes requiring significant knowledge, expertise, and decision-making.
	Cognitive agents: are designed to simulate the cognitive abilities of a human.
	Personalization: the ability to customize products, services, or experiences to meet an individual's specific needs and preferences.
	Context awareness: the ability to understand and respond to the context in which it is being used.
	Learning: the ability to learn from large amounts of data and make predictions or decisions based on complex patterns in the data or learn through trial and error and improve their performance by being rewarded or penalized.
	Generative models: the ability to generate new content, such as text, images, and music, based on the data they have been trained on.
	AI techniques: machine, deep, supervised, unsupervised, Reinforcement learning.
	Biometrics: biometrics provide unique identifiers for individuals, such as fingerprints, facial features, and iris patterns, and AI can analyze and interpret this biometric data to make decisions or predictions.
	Natural Language Processing: the ability to understand and respond to human language.
	RPA) software robots automate repetitive, rule-based tasks typically performed by humans.
	Robotics
	Computer Vision: the ability to interpret and understand visual information, such as images and videos.
Breadth/inclusiveness	It encompasses the various stages (implementation, deployment, and use), capabilities, technologies, applications, and tools at the organizational level and supports all business operations.
Dimensionality	Multidimensional
Stability	Stable across cases
Indicators	Reflective-reflective
Model	Reflective-reflective type I (Jarvis et al., 2003); second-order construct

Source: Own work.

Data are exploited, examined, renewed, or reconfigured through AI-enabled capabilities. We argue that, by itself, AI does not constitute a capability. AI becomes part of a capability when applied to a problem, and a goal is assigned. Without a goal, there is no evaluative frame of reference and, thus, no way to improve performance. In conceptualizing the "adoption of artificial intelligence," we describe the level of adoption through five distinct and progressive AI-enabled capabilities (components of AI adoption) conceptualized around

[12] The conceptual domain refers to the fundamental essence or scope of the construct. We specify the general type of property to which the focal construct refers, e.g., thought, feeling, perception, action, outcome, or intrinsic characteristics. The object to which the property applies, e.g., a person, a task, a process, a relationship, a dyad, a group/team, a network, an organization, or a culture. The general property of the construct refers to the overarching characteristics that define the construct. Common Attributes are the features or characteristics that are shared across different instances of the construct. Unique Attributes/Characteristics are the specific features that set the construct apart from other constructs. Breadth/Inclusiveness refers to the range or extent of the construct's domain. Breadth or inclusiveness indicates the construct is comprehensive, covering various aspects, dimensions, or instances. Dimensionality involves the number of underlying dimensions or facets that comprise the construct. Stability refers to the consistency or reliability of the construct over time and across different situations.

specific application domains that encompass business problems that technology aims to solve and the goals it strives to reach within that context. These capabilities support business processes and become integral to an organization's ability to generate value from data. Next, we present the dimensions that we conceptualize.

3.4.3.1 Data Acquisition and Preprocessing

Data acquisition and preprocessing is *the organization's ability to extract data from structured and unstructured sources, new and legacy systems, and internal and external sources and to prepare it for analysis.* The three basic routines are data extraction, preprocessing, and continuous assurance of data quality. These routines are established to deal with Big Data (ever-increasing volume, variety, and velocity of data) from internal and external sources. Preprocessing includes consolidation, organization, validation, cleaning, transformation, reduction, summarization, labeling, and loading into a data warehouse, data lake, NoSQL database, relational database, or other application. High-quality data has become a vital business resource and can have a considerable impact on organizational performance (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017). We propose measuring this dimension by assessing the successful deployment and use of data management applications and tools (e.g., information propagation, data warehousing/data lakes, data capturing system, Internet of Things/SCADA, content creation, discovery, creation, and computational creativity).

3.4.3.2 Cognitive Insight

Cognitive insight is *the organization's ability to use AI to detect patterns in data and interpret their meaning.* This dimension relates to context awareness, learning, and analytics themes. AI recognizes patterns or clusters of data otherwise invisible to humans (Burgess, 2018). It can interpret events and contextualize recognized patterns to derive their true meaning. The learning aspect of AI allows for predictions based on past experience (Bawack & Wamba, 2019) and, through continuous learning, enables improved insight (Davenport & Ronanki, 2018). Cognitive analytics (knowledge representation, inference, reasoning, learning and adaptation, hypothesis generation and validation, domain cognitive models, and machine or deep learning) offer better results in terms of speed, scale, accuracy, and granularity. We propose measuring this dimension by assessing the successful deployment and use of AI analytics applications and tools (e.g., predictive sales, churn management, fraud detection, and risk management).

3.4.3.3 Cognitive Engagement

Cognitive engagement is *the organization's ability to support AI-enhanced human–computer interaction and collaboration.* Engagement consists of several key elements, including understanding, perception of intention, and domain knowledge (Roeglinger et al., 2018). Understanding encompasses, natural language processing and understanding, automated speech recognition, and text-to-speech conversion. Leveraging contextual information about humans to develop human-like empathy and communication skills in human–computer interactions or collaborative applications involves the perception of intention, tone, sentiment, emotional state, environmental conditions, and the strength and nature of a person's relationships (Davenport & Ronanki, 2018).

All the elements are used to reason through all structured and unstructured data and determine the optimal approach for engagement (Kelly, 2015). This allows automated interactions to reliably support customers' activities and prompt their engagement (Klumpp, 2017; Mele et al., 2018) in customer-facing business processes. Organizations are also increasingly using cognitive engagement to interact with employees (to support routine activities), augment information, improve knowledge acquisition, exploration, and understanding, and support the collaborative formulation of goals and decisions (Davenport & Ronanki, 2018). We propose measuring the dimension by assessing the successful deployment and use of AI-enabled applications and tools related to user engagement (e.g., virtual assistants, chatbots, avatars, and recommendation systems).

3.4.3.4 Cognitive Decision Assistance

Cognitive decision assistance is *the organization's ability to use AI in decision-making processes.* AI technologies and techniques enable AI-assisted decision-making and render decision support more intelligent. Some standard abilities descriptive of AI's capability are the acceleration of information flows, predictive and adaptive decision support, automated reasoning to solve knowledge-intensive problems, making sense of ambiguous or contradictory messages in large data sets, recognizing the relative importance of situational elements, responding quickly and successfully to a new situation, and applying knowledge to manipulate the environment (Phillips-Wren, 2012). We propose measuring the dimension by assessing the successful deployment and use of AI-assisted decision-making applications and tools (e.g., AI-enabled decision support systems, expert systems, fuzzy logic systems, optimization, and knowledge engineering).

3.4.3.5 Cognitive Technologies

Cognitive technologies are *the organization's ability to integrate AI technologies with other IT resources, services, and devices.* This dimension is isolated for cases where organizations do not deploy and use AI in a specific domain as a particular application or tool. The AI-enabled capability of cognitive technologies is the highest level of AI adoption; AI is not merely used but utilized (implying innovation or creative use beyond the intended use). AI technologies can radically transform data utilization and processing within existing processes of value creation. The ability of AI technology to learn and adapt continuously due to self-awareness, input from those with whom it interacts, and the context in which it is embedded amplifies its usefulness (Mele et al., 2018). The cumulative effects can be seen in the interactions between the knowledge of the AI-enabled device or service and the knowledge and action of humans. We propose measuring this dimension by assessing the successful integration of AI technologies in other IT resources, services, and devices. The AI technologies most suitable for integration include machine and deep learning, neural networks, natural language processing, genetic programming, sensor networks, augmented reality, computer vision, speech recognition, and robotic process automation (Zasada, 2019).

We posit that the dimensions presented impact all forms of business value generation (automation, innovation, organizational learning, decision-making), although to a different extent.

3.4.4 AI-Enabled Dynamic Capabilities

The ability of an organization to adapt to changes in its business environment is rooted in its dynamic capabilities (Teece et al., 2016). Compared to regular operational decisions, this proactive approach promotes differentiation and establishes the organization's decision-making as a dynamic capability (Hossain, Agnihotri, Rushan, Rahman, & Sumi, 2022; Steininger, Mikalef, Pateli, & Ortiz-de-Guinea, 2022; Wang & Ahmed, 2007). These capabilities are the key to sustainable competitive advantage, implying that dynamic capabilities affect performance. However, they do so indirectly by reconfiguring operational capabilities to better fit the environment, as argued in proposing our research model (Section 2.2).

Organizations increasingly use data and analytics to make better and more informed decisions (Hossain et al., 2022). Adopting a data-driven approach allows them to make accurate decisions based on data and analytics, with AI at the core, improving their control over business operations, marketing planning and implementation, and internal and external resource allocation (Martínez-López & Casillas, 2013). In the BPM context, Wamba-Taguimdje et al. (2020a) argue that the main objective of AI adoption is to solve a problem at the level of process or concerning dynamic process-oriented capabilities. The authors emphasize four capabilities: 1) modifying organizational processes to enhance integration, reducing costs, increasing BI, and avoiding ecosystem and business-line risks; 2) improving and optimizing business processes; 3) enhancing the acquisition and assimilation of internal and external knowledge; and 4) aligning resources, strategies, and processes with the organization's goals.

Dynamic capabilities can be broken down into three distinct processes that are focused on driving strategic change to sustain competitive advantage (Mikalef et al., 2021). Sensing capabilities concern the ability to identify opportunities and threats and seizing capabilities refer to the ability to capitalize on new business model designs and strategic investments, and transform capabilities to change operational processes or reconfigure existing business models and strategies. Existing studies argue that AI is closely related to dynamic capabilities (Drydakis, 2022; Gallego-Gomez & De-Pablos-Heredero, 2020; Gupta, Modgil, Choi, Kumar, & Antony, 2023; Hossain et al., 2022; Mikalef et al., 2021; Wamba-Taguimdje et al., 2020a; Wang, Lin, & Shao, 2022). To illustrate the relationship between dynamic capabilities and the developed concept of a component-based view of AI adoption, we compare the capabilities enabled by AI technology with the three distinct dynamic capabilities processes.

3.4.4.1 Sensing

Sensing describes the assessment of opportunities and needs in and outside the organization. Organizations can use the insights allowed by AI to identify opportunities and engage with the right customers to understand their needs better. Organizations can use this capability to identify profitable market segments to increase market share and profit margins, gain an advantage over competitors, and monitor the quality of their products and services, and by doing so, improve customer satisfaction, retention, experience, purchases, and risk reduction (Drydakis, 2022; Mikalef et al., 2021).

Data acquisition and preprocessing make it possible to leverage diverse information sources. Cognitive insights optimize the identification of themes in unlabeled data, real-time sensing of core needs, anomaly and threat detection, forecasting of trends, aggregation of customer sentiment, and isolation of faulty features. Cognitive engagement can offer personalized services and communication (e.g., chatbots). Cognitive decision assistance enables learning to find new solutions (i.e., innovation) and create new knowledge.

3.4.4.2 Seizing

Seizing involves an organization's agile response to market needs, optimizing production and marketing processes, resource allocation, cost reduction, fault prevention, and resource efficiency, aiming to boost profitability, financial performance, turnover, and market share (Teece et al., 2016).

By leveraging cognitive insights, organizations can utilize aggregated evidence to initiate routines and dynamically adjust pricing, resource allocation, investment forecasts, cash flow predictions, and competitor behavior analysis in real time through cognitive decision assisted knowledge visualization (Basri, 2020; Drydakis, 2022; Hansen & Bøgh, 2021). This fosters more effective decision-making, enhancing processes and business models for competitive advantage (Mendonça & Andrade, 2018).

3.4.4.3 Transforming (Reconfiguration)

Transforming refers to proactively working to streamline, adapt, and improve operational processes based on empirically grounded best practices and maintaining their relevance (Teece, 2018).

Cognitive decision assistance can facilitate organizational transformation through the adoption and development of innovative technologies and operational systems and the development of new business models and revenue-generating strategies. Based on data acquisition and preprocessing, New services based on insight generated using data acquisition and preprocessing. Insights can be employed and commercialized, for example, in consulting and collaborative activities. Cognitive engagement and technologies increase the level of integration in existing organizational processes, producing incremental and more extensive innovation. The application of these is expected to bring possibilities for market disruption, increased market share, profitability, and sustainabilit (Drydakis, 2022; Mikalef et al., 2021).

3.5 Development of the Measure

The next step in the process was to generate items that fully represent the conceptual domain.

3.5.1 Generated Items

We generated items from the literature review, the theoretical definition of the construct, previous academic research, and interviews with experts (MacKenzie et al., 2011).

Next, we validated the items by analyzing 1,860 AI-related projects (i.e., use cases) from businesses and classifying them according to the proposed items. For each use case, all utilized AI applications or AI technologies were extracted and then classified according to the proposed scale items. The extracted AI applications were later used to describe specific scale items in the implemented online questionnaire (see Table 16). Thus, we have ensured that the proposed items will address real-world business AI applications. The sources for use cases were: 1) a public directory of AI startups from Israel (571 use cases; The AI Hub of Israel, 2019); 2) a list of best AI startups in the EU (9 use cases; Thorsen, 2018); 3) a curated list of business, industry-specific, and personal AI projects (1,171 use cases; Hänel, 2017); 4) CB Insights list of top 100 AI projects (100 use cases; CB Insights, 2021); and 5) specific AI projects from the tech news (9 use cases; TechCrunch, 2021).

Some items were modified or merged during the process to capture better a specific set of AI applications, tools, or technologies represented by the items. As a result, 28 items were generated (see Table 16), delineating the key components of AI adoption. We combined them based on similarity and separated them into five distinct groups representing the five conceptualized dimensions of the focal construct.

Table 16: Items Generated to Measure AI Adoption

Dimension/Items	**Source(s)**
Data Acquisition and Preprocessing The organization can extract data from structured and unstructured sources, new and legacy systems, and internal and external sources and prepare it for analysis.	
1. Data warehousing A Data Warehouse consists of data extracted from transactional systems or data that consists of quantitative metrics with their attributes. The data is cleaned and transformed. It captures structured information and organizes it in schemas defined for data warehouse purposes. Data warehouse uses a conventional ETL (Extract Transform Load) process (Khine & Wang, 2018).	Aydiner, Tatoglu, Bayraktar, and Zaim (2019); Prieto (2019)
2. Data Lake A Data Lake is a massive data repository based on low-cost technologies that improve an organization's capture, refinement, archival, and exploration of raw data. It contains raw unstructured or multi-structured data that, for the most part, has unrecognized value for the organizations. Data Lakes use the ELT (Extract Load Transform) process (Khine & Wang, 2018; Stein & Morrison, 2014).	From interviews
3. Data Capturing System (I)IoT; SCADA; Synthetic Data: simulation, data not obtained by measurement; High-quality 3D scanning; Data as a Service Platform; Biometric device; Sensor networks; (Industrial) Control Systems; Video Analysis.	Aydiner, Tatoglu, Bayraktar, and Zaim (2019); Prieto (2019)
4. Document Management System Converting Paperwork into Digital Data; collecting, searching and extracting data from documents; Document processing; Document Intelligence; Document Life-Cycle Management.	Aydiner, Tatoglu, Bayraktar, and Zaim (2019)
Cognitive Insight The organization's ability to use AI to detect patterns in data and interpret their meaning.	
1. Predictive Modeling and Analytics Predictive modeling uses a regression model and statistics to predict the probability of an outcome and can be applied to any unknown event. Predictive Analytics is extracting information from data to predict trends and behavior patterns. It uses present or past (historical) data to predict future outcomes and drive better decisions. *Use cases: Credit Scoring Models; Churn Management; Risk Assessment (Compliance and governance, Geopolitical, Vendor, Merchant, Nonlinear-dynamic models of credit risk); Forecasting (Sales, Traffic, Intensive care unit, Staffing, Resource, Power and Weather, Time to Market, Production, Counterterrorism, Operational Efficiencies, Financial, Simulate inventory risk, Photovoltaic generation, Stock-Market); Predictive models (Claim Development Modeling, Commodities performance, Crypto Environments and Market behaviors, Cash Management, Human and Group Behavior, Patient No-Shows, Patient or member length of stay, Pedestrian behavior, Project Timelines, Revenues and investment outcomes, Predictive Marketing, Sales leads and opportunities, Clinical trial outcomes, Hospital-acquired infections, Hospital readmissions, ICU Transfers, Analysis for IT Network Management, Customer Lifetime Value, Disaster recovery, Fleet management, Fruit Yield Estimation, Manufacturing design, Microbiome Data, Timing intervals, Use cases, Propensity to lease, Protein structure, Bad payments, Disease Modeling, Parking availability, Predictive Agriculture, Prediction to Recovery, Fraudulent Payment Activity, Touchpoint Inventory, Diagnostics and predictive medicine, Capitalizing on Subrogation, Drug Development and Repurposing, Maturity in horticulture, Actuarial science, Cooling, heating and humidity stabilization, Deal Discovery, Intelligent content management, Location Discovery, Movement Patterns, Predictive models in End-to-end solutions, Target Discovery, Predictive lead scoring, Biomarkers, Insurance Pricing,, Exploratory Drilling, Customer Engagement Timing); Predictive analytics (End-to-end supply chain visibility and transparency, Invoice Funding, Legal analysis, Education planning, Disease Propensity, Network Management, Log Analysis, Clinical, Medical, Energy, Drilling, Real Estate lucrative opportunities, Sports analysis, Player Projection, Manufacturing).*	Kuhn and Johnson (2013); Tavana, Szabat, and Puranam (2016)

To be continued

Table 16: Items Generated to Measure AI Adoption (cont.)

Dimension/Items	**Source(s)**
2. Anomaly and Deviant Behavior Detection Anomaly detection is a method used to identify unusual patterns that do not conform to expected behavior, called outliers. As anomalies in information systems often suggest security breaches or violations, anomaly detection has been applied in various industries to advance IT safety and detect potential abuse or attacks. *Use cases: Anti-Cheating; Anti-Fraud Detection; Anti-Misinformation/Disinformation/Misinformation; Quality Control: defect, proactive incident detection; Event, Risk, and Compliance Issues Detection; Behavioral Anomaly Detection: employee misbehavior, misconduct, malicious chats; Provider-Consumer Anomaly Detection for Healthcare Systems; Security: surveillance, vehicle security, security screening, threat detection; Safety: traffic, maritime, industrial, personal safety; Accounting: auditing, fund valuation errors detection; Structural Health Monitoring; Business Monitoring: incidents impacting revenue, supply chain visibility, logistics, price anomalies; DevOps Monitoring; Smart City: traffic, air quality, water distribution, energy consumption; Smart Home Monitoring; Concealed mineral deposits detection; (I)IoT; Medical profiling and testing.*	Roeglinger et al. (2018)
3. Marketing Automation Marketing automation uses software to automate marketing processes such as customer segmentation, customer data integration, and campaign management. *Uses cases: Account opening and Client Onboarding; Audience Segmentation; Advanced Targeting; Retargeting; Affiliate services; Content Performance Analytics; Cross-Sells/Up-Sells; Digital advertising; Data-driven marketing; Lead Generation and Scoring; Marketing Strategy Reverse Engineering; Self-optimizing campaign design and management; Direct Marketing; Multichannel Marketing Attribution; Context-Aware Marketing.*	Heimbach et al. (2015); Todor (2016); Tussyadiah (2020)
4. Marketing Intelligence System A Market Intelligence system focuses on collecting and processing information from all the relevant sources to ascertain the changing trends in the marketing environment. *Use cases: Competitive Intelligence; Demand forecasting; Predictive Market Intelligence; Revenue Intelligence; Trends identification; Pricing; Market Segmentation; Market simulations; Brand voice; Product Analytics, Predictive Product Assortment; E-Commerce; Behavioral analytics; Behavioral Segmentation, Conversion Modeling; Marketing Research; Spatial data analytic; Corporate Sponsorship; Technology Scouting; Crowd Sourced Market Research.*	Aydiner, Tatoglu, Bayraktar, and Zaim (2019)
5. CRM and CX System A Customer Relationship Management (CRM) System focuses on the management of information about customers. It collects necessary information regarding the customers from various channels. It offers insights regarding the sales cycle, performance of marketing campaigns, strategies for acquiring customers, and other customer metrics. Customer Experience Management (CX) drills deeper into customers' experiences to overview their unique perspectives. The CX system aims to collect and manage all those data regarding expertise, improve the customer experience further and strengthen loyalty to your company. *Use cases: Customer Acquisition; Customer Loyalty (Retention); Customer Support; Know your customer (KYC); Account-Based Engagement; Customer Data Enrichment; Identifying potential customers; Identify customer preferences; Lifetime Value; Predictive Customer Analytics; Real-time segmentation; Sentiment and Emotional Analytics; Audience Monetization Optimization; Pipeline Management; Customer Journey Optimization; Customer Intelligence; Customer Experience Analysis; Customer Feedback Management; Customer Conversation Analytics; Customer Data Visualization as Personas; Customer Behavior Modeling, Discovery, and Predictions; Sales Force Automation.*	Prieto (2019)
6. Predictive Maintenance Predictive maintenance systems provide insights from regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating state. They can forecast the trend of performance degradation and estimate when maintenance should be performed. *Use cases: Digital Twin; Failure prediction; Processing and Refining Maintenance; Machine monitored workflows; Preventing dangerous failures in machinery; Acoustics Predictive Maintenance; Predictive disaster recovery; Smart Buildings; Infrastructure Maintenance; Facilities management.*	Prieto (2019)

To be continued

Table 16: Items Generated to Measure AI Adoption (cont.)

Dimension/Items	**Source(s)**
7. Cyber and Network Security, Data Privacy Cyber Security, Network Security, and Data Privacy systems help detect and protect systems, networks, personal data, and programs from digital attacks. *Use cases: Anti-virus; Anti-phishing; Threat Detection; Automated risk profiling; Cyber Intelligence; Application Security Testing; Data Leakage Prevention; Data Privacy Compliance; Endpoint and Device Protection; Attack Surface Reduction; Identity Management, Authentication, and Access Control.*	Prieto (2019)
8. Business Process Intelligence System Business Process Intelligence systems are used for managing process execution by offering several features such as analysis, prediction, monitoring, control, and optimization. They include process mining, discovery, conformance checking, predictive analytics, and other techniques. *Use cases: Predictive Business Process Analytics; Process Model and Requirement Discovery for Automation; Process Mining; Process Monitoring; Sensor-enabled Process Intelligence.*	Zasada (2019)
9. Talent Management System A talent management system covers the full scope of talent management: recruitment and employee onboarding, performance management, learning and development, compensation management, and succession planning. *Use cases: Onboarding; Recruit vs Develop; Candidate screening; Stack Ranking; Employee Experience Analytics; Employee Attrition; Employee retention; Employee Stress Heatmaps; Employee Training; Measuring Employee Emotional Intelligence; Skill mapper; Recruitment Analysis; Talent acquisitions and assessment; Personality traits identification.*	Prieto (2019)
Cognitive Engagement The organization’s ability to support AI-enhanced human-computer interaction and collaboration.	
1. Conversational AI Conversational AI is software agents that can engage in natural conversational interactions with humans. Use cases: Chatbots; Virtual Agent; Personal or Virtual Assistant (Healthcare, Scheduling, Traveling, Financial, Medical, Real Estate, Recruitment, Security, Senior Care, Shopping; Self-diagnosis); Conversational Voice Interfaces (Voice control, Transcription, Voice Routing).	Davenport and Ronanki (2018); Roeglinger et al. (2018)
2. Personalization and Recommendation System Personalization and Recommendation systems solve the problem of information overload by searching through a large volume of dynamically generated information to provide users with personalized content and services. *Use cases: Content, Product, Service Recommendations (Spending, Stock, Loyalty Program Usage, Coding, Shopping, Virtual try-on, Interior home designer, Employee Benefit Plans, Travel); Content, Product, Service Personalization (Diagnosis and treatment, Investing, Marketing, Nutrition, Video Content, Rate Management, Banking, Financial optimization, Health, Content Curation, Content Discovery, Content Censoring, Content Targeting); Customer Engagement (Gamification, Driver engagement, Account Engagement Platform, Employee Engagement Platform); Learning Management System; Website personalization.*	Davenport and Ronanki (2018)
3. Visualization System: Virtual reality (VR), Augmented reality (AR), Mixed Reality (MR) Using visual elements like charts, graphs, maps, visual (graphical) objects, their attributes, relationships, possible dynamics, and interaction methods, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data and interact in a virtual environment. *Use case: Location Intelligence; Contextual Graph; Data storytelling; Performance Visualization (Dashboard, Scorecard); Virtual try-on; Interior home designer; 3D Analytical Geometry; 3D Object Recognition; 3D Printing; 3D Modeling; 3D Imaging; AR in Surgery; Enhanced Vision Engine; Indoor spatial mapping.*	Dunston and Wang (2005); Farshid, Paschen, Eriksson, and Kietzmann (2018)

To be continued

Table 16: Items Generated to Measure AI Adoption (cont.)

Dimension/Items	**Source(s)**
4. Content Generation Automatically Generated Content using artificial intelligence. *Use case: 3D Asset Generation; Design Concepts Generation; AI-Generated Art; Automated Web Design; Automated Video Generation; Automated Poll Generation; Automated Text Creation: by topic, keywords, social media content, and articles; Content rewriting; Clinical, Medical, Financial Document Generator; Text to Video; Self-optimizing emails and subject lines; Programmatic Influencer campaigns; Contract Generation; Marketing Content Generation; Converting the data into engaging narratives.*	Liu et al. (2020); Suvetha, Swathi, Rani, Vinoth, and Suriya (2018)
5. Search and Discovery AI-enabled search technology is about finding specific things known or assumed to exist. The discovery involves using the search/browse interface to discover the available content. *Use case: Knowledge sharing; Conversational Search; Product, Patent, Contract, Accommodations, Site, Social Media, Business, Location-Based, E-commerce, Medical Citations, Research Papers, Project Data, Real Estate, Voice conversations, Chemical Structure Search Engine; Visual Search; Metasearch engine; NLP & Neuroscience based Search; Named Entity Recognition and Disambiguation; Content Discovery; Searchable representations; Natural Language Analytics.*	Kelly (2015)
Cognitive Decision Assistance The organization’s ability to use AI in decision-making processes.	
1. Decision Automation System Decision Automation Systems (also known as Decision Management Systems), unlike Decision Support Systems, are focused on decision automation, taking or recommending an action. *Use case: Next Best Action; Next Best Offer; Optimization (Customer Service, Drug Delivery Optimization, Ad optimization, Floor price, Logistics, Energy, Yield, Assortment, Manufacturing, Marketing, Media content and audience analytics, Networks and services, Carrier, Inventory, Job Ads, Pricing, Price sensitivity incentive, Promotions, Time, Supply Chain, Sales, Spending, Route, Restaurant delivery, Job description, Indoor farming, Process Optimization); Programmatic Media; Automated Scheduling; Automated Routing (Call, Document, Task, Case, Email); Automated Call Center Staffing, Claims Processing, Investment, Procurement, Accounts payable, Mailroom, Payments, Patient/doctor matching, Claim Payment, Project staffing, Usage-Based Insurance, Retail stocking, Customs clearance process, Crop Management, Travel Management, Contract Approval Process, Regulatory reporting, Project report generation, Billing and accounts receivable, Customer Service, Warehouse Management, Security, Tax filing and processing; Algorithmic Merchandising, Repricing, Trading and Bidding; Dynamic Pricing Precision; Video Content Analytics.*	Taylor (2011)
2. Knowledge Engineering and Expert Systems An expert system is designed to help a person make decisions using explicit expert knowledge. Such a system is usually semi-detached from an organization’s operational environment and not part of a process or transactional environment. *Use case: Knowledge Representation, Reasoning, Ontology Creation and Management; Root-cause analysis; Optimization (Manufacturing, Marketing Planning, Patient Treatment and Therapy, Patient flow, Maintenance schedules, Photovoltaic Energy, Hydroponic Food and Plant Growth, Pricing and Repricing, Warehouse Logistics, Route, Bond Investing); Planning (Supply Chain, Gathering and Transportation, Logistics, Flight-ground trajectories, Mobility Management); Design (Generative design; Drug Development, Product Innovation, Protein engineering, Material Discovery, Genomics); Design compliance; Asset, Application Resource, Drone Fleet, Inventory Shipments, Invoice, Recruitment, Traffic Congestion, Regulatory and Compliance, Threat Management; Autonomous Software Testing.*	Phillips-Wren (2012)

To be continued

Table 16: Items Generated to Measure AI Adoption (cont.)

Dimension/Items	Source(s)
3. Decision Support System Decision Support Systems are focused on helping (supporting) someone make the decision, not necessarily on the actions to be taken. *Use case: Actionable analytics and recommendations (Financial, Location-based, Underwriting, Coding, Performance, IT Operations, Threat and Risk Mitigation, Operating project); Clinical Decision Support (Precision Diagnostics, Therapy and Treatment Recommendations, Injury Analysis, Phenotypic Analysis); Decision Intelligence and Modeling; Medical Imaging; Geospatial insights; Hyperspectral, Multi-spectral, Acoustic, Fluorescent Microscopy Imaging Systems; Management Decision Support Systems (Supply Chain, Stakeholder, Medication, Loan, Freight, (Digital) Wealth, Customer Efficiency, Contract, Claims, Plant and Crop, Pest and disease, Traffic, Vendor, Supplier, Portfolio, End-to-End Productivity, Capital); Marketing Strategy Engineering; Smart Products and Manufacturing; Decision Support Systems in Construction (Estimating, Measuring site progress, Construction site inspection, Contractor Analysis), Litigation, Investment, Finance, Bioengineering.*	Phillips-Wren (2012); Taylor (2011)
Cognitive Technologies The organization's ability to integrate AI technologies with other IT resources, services, and devices.	
1. Machine learning *Use case: Deep Neural Networks; Neural Networks Neural Networks; Multi-Agent Frameworks; Federated, Sequential learning; Optimization and Regularization Methods; Logistic Regression Methods; Linear and Non-Linear Methods; Cloud Machine Learning Services.*	Bawack et al. (2019); Schatsky et al. (2014); Zasada (2019)
2. Natural Language Processing (NLP) *Use case: Natural Language Understanding (NLU); Natural Language Generation (NLG); Text Analytics; Text Mining; Intent Classification; Sentiment Analysis; Summarization of textual information; Translation.*	Bawack et al. (2019); Schatsky et al. (2014); Zasada (2019)
3. Audio and Speech Processing *Use case: Speech to text; Text to speech; Language transcription and recognition; Embedded voice recognition; Synthetic voice; Voice Analysis.*	Interviews; Bawack et al. (2019); Schatsky et al. (2014); Zasada (2019)
4. Planning, scheduling & optimization *Use case: Partial-Order Planning; Requirement Engineering; Stream processing; Controlling Multiple UAVs; Software System Integration; Automated Web Services Composition; Business Workflow Management; Project Planning.*	Bawack and Wamba (2019); Schatsky et al. (2014)
5. Autonomous Systems & Robotics *Use case: Advanced Driver or Rider Assistance Systems; Autonomous Vehicles and Mobile Robots; Autonomous Drone Systems; Autonomous Robotics; Collaborative Industrial Robots; Vehicle automation for heavy equipment; Warehouse Logistics Automation; Automated Fulfillment Processes; Medical robotics and computer-assisted surgery; Autonomous Harvesting, Irrigation, and Pest Detection; Automated Pot-Hole Repair System; Automated Photovoltaic Module Cleaning; Automated Waste Recycling; Autonomous Navigation.*	Interviews; Bawack and Wamba (2019); Schatsky et al. (2014)
6. Computer Vision *Use case: Image Classification; Image Processing for Control and Measurement Systems; Object Recognition; Facial Recognition; Facial Expressions; Scene Understanding; Optical character recognition; Motion Analysis; Gesture Control Recognition; Visual Perception.*	Interviews; Bawack et al. (2019); Schatsky et al. (2014); Zasada (2019)
7. Rules-based systems *Use case: RPA, Back Office Automation.*	Schatsky et al. (2014); Zasada (2019)

Source: Own work.

3.5.2 Content Validity Assessment of the Items

Next, we assessed the content adequacy of items, the degree to which created items represent the target, and the aspect of the construct (Beck & Gable, 2001). Content validity is based on the judgment of experts regarding the content relevancy of the test domains and the representation of items to their domains (MacKenzie et al., 2011). This study evaluated the items based on their relevance and representativeness.

3.5.2.1 Expert Participation

Invitations were sent to seven experts. Four experts accepted the invitation and participated. Two were from academia, and two were from business.

Participants were given three weeks to complete the review. The instructions explained the main objective, the purpose of the study, the target population, and the aim of collecting the content rating. The review form consisted of 5 columns. The first column placed the items to be evaluated. The second column showed the rating scale of 0 to 4, where the experts were expected to rate the item. The third column allows the experts to place their suggestions, ideas, opinions, and revisions. The fourth column represented “Is the item well explained?” – Yes / No, and the fifth column denoted “Is the item essential to the domain?” – Yes / No. The experts were supposed to mark yes or no on both columns.

3.5.2.2 Expert Rating

Hellsten (2008) proposed classifying expert ratings using three different approaches: descriptive, quantitative, and qualitative. This study focused on two methods: descriptive and quantitative.

3.5.2.3 Descriptive Approach

- **Median:** A higher median value of an item relevance rating indicated a more relevant item. This study used a rating scale of 0 to 4, and an item with a median value of 2.75 and above accounted for acceptance (Hellsten, 2008).
- **Item Ambiguity:** Each item's ambiguity score has been calculated. Items with lower ambiguity scores are desired to indicate a consensus among experts. A range of 3 or more between scores (or Rk of 4 or higher) is considered ambiguous. Hence, low ambiguity values such as 1, 2, or 3 are acceptable for this study.
- **Agreement Percentage:** 80% of experts' agreement is considered acceptable.

3.5.2.4 Quantitative Approach

- **Content Validity Index (CVI):** CVI for each item is the percentage of experts who rated the item as 3 or 4 (Lynn, 1986). Polit, Beck, and Owen (2007) observed that the CVI value of 1.00 is acceptable for panels of three or four experts, whereas 0.80 was considered acceptable for a panel of five experts.

- **Content Validity Ratio:** The CVR range should be -1 to +1. The number was equal to zero when half of the experts rated the item as essential (Lawshe, 1975). The minimum CVR for each item to be acceptable was 0.99 for a one-tailed test at the 95% confidence level, as four experts were used for the study (Lawshe, 1975).
- **Content Validity Coefficient (VIk):** An item is highly accepted if the coefficient is closer to 1. The coefficient value is compared with a table of right-tail probabilities (p) to determine the significant value (Aiken, 1985). For four experts, the significant value is V = 0.88 and p = 0.24.

Table 17: Definition of Descriptive and Quantitative methods

Descriptive Approach	**Formula**	**Description**
Median	If n is odd, then median (M) = ((n+1) / 2)) If n is even, then median (M) =[(n/2) + ((n/2) +1)] / 2. Arrange ratings in ascending order and find the rating in the calculated median position.	n = no. of experts
Item ambiguity (IA)	$R_k = (X_{kjh} – X_{kjl}) + 1$	X_{kjh} is the item's highest rating; X_{kjl} is the lowest rating.
Percentage Agreement (PA)	(No. of experts rated "YES" / Tot. no. of experts) * 100	
Quantitative Approach	**Formula**	**Description**
Content Validity Index (CVI)	(No. of experts who rated 3 or 4 / Tot. no. of experts)	CVI is expressed in percentage
Content Validity Ratio (CVR)	$(n_e – N/2) / (N/2)$	n_e is the no. of experts indicating that the item is essential; N is the no. of experts on the panel; CVR ranges from -1 to +1
Content Validity Coefficient (VI_k)	S / [j (c-1)]	S is the sum of sj ($s_j = r_j – l_o$); r_j is the j's rating; l_o is the lowest category value (0); j is the tot. no of experts; c is the no. of rating categories (5); s_j & r_j (j represents 1,2,3…n experts)

Source: Own work.

Table 18: Acceptable Measure Values for Content Validity

Median	**Item Ambiguity**	**Agreement Percentage**	**Content Validity Index**	**Content Validity Ratio**	**Content Validity Coefficient**
2.75+	1, 2 and 3	80%	75%	0.99	0.88

Source: Own work.

We applied descriptive and quantitative approaches to determine the content validity of the items. Out of six, any item that satisfies less than four methods was deleted, and any item that meets more than three methods was retained. Table 17 includes formulas for calculating three methods of descriptive approach and three methods of quantitative approach. Table 18 presents the acceptable values for six methods in this study. The results of the analysis are shown in Table 19. Items 16, 23, and 24 were removed due to low IA, CVR, and VI_k values. Eventually, the final list comprised 25 items and was used for data collection and performing Exploratory Factor Analysis.

Table 19: Results of the Content Validity Analysis

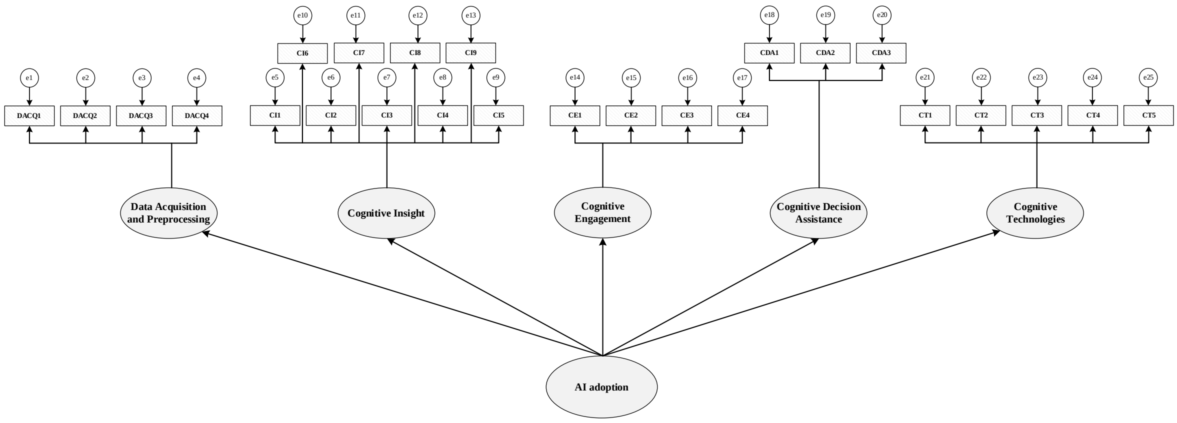
#	Dimension/Items	Median	IA	AP (%)	CVI (%)	CVR	VI_k	Action
	Data Acquisition and Preprocessing							
1	Data warehousing	4.00	1.00	100.00	100.00	1.00	1.00	
2	Data Lake	4.00	1.00	100.00	100.00	1.00	1.00	
3	Data Capturing System	4.00	1.00	100.00	100.00	1.00	1.00	
4	Document Management System	4.00	1.00	100.00	100.00	1.00	1.00	
	Cognitive Insight							
5	Predictive Modeling and Analytics	4.00	1.00	100.00	100.00	1.00	1.00	
6	Anomaly and Deviant Behavior Detection	4.00	1.00	100.00	100.00	1.00	1.00	
7	Marketing Automation	4.00	2.00	100.00	100.00	0.50	0.94	
8	Marketing Intelligence System	4.00	1.00	100.00	100.00	0.50	1.00	
9	CRM and CX System	3.00	1.00	100.00	100.00	1.00	0.75	
10	Predictive Maintenance	4.00	2.00	100.00	100.00	0.50	0.94	
11	Cyber and Network Security, Data Privacy	4.00	2.00	100.00	100.00	1.00	0.94	
12	Business Process Intelligence System	4.00	1.00	100.00	100.00	1.00	1.00	
13	Talent Management System	4.00	2.00	100.00	100.00	1.00	0.94	
	Cognitive Engagement							
14	Conversational AI	4.00	3.00	100.00	75.00	1.00	0.88	
15	Personalization and Recommendation System	4.00	2.00	100.00	100.00	1.00	0.94	
16	Visualization System: Virtual reality, Augmented reality, Mixed Reality	4.00	4.00	100.00	75.00	0.50	0.81	Exclude
17	Automatically Generated Content using AI	4.00	1.00	100.00	100.00	1.00	1.00	
18	AI-enabled Search and Discovery	4.00	5.00	100.00	75.00	1.00	0.75	
	Cognitive Decision Assistance							
19	Decision Automation System	4.00	3.00	100.00	75.00	1.00	0.88	
20	Knowledge Engineering and Expert Systems	3.50	3.00	100.00	75.00	1.00	0.81	
21	Decision Support System	4.00	3.00	100.00	75.00	1.00	0.88	
	Cognitive Technologies							
22	Machine learning	4.00	3.00	100.00	75.00	1.00	0.88	
23	Natural Language Processing	4.00	4.00	100.00	75.00	0.50	0.81	Exclude
24	Audio and Speech Processing	4.00	4.00	100.00	75.00	0.50	0.81	Exclude
25	Planning, scheduling & optimization	4.00	3.00	100.00	75.00	1.00	0.88	
26	Autonomous Systems & Robotics	4.00	1.00	100.00	100.00	1.00	1.00	
27	Computer Vision	4.00	2.00	100.00	100.00	1.00	0.94	
28	Rules-based systems	4.00	2.00	100.00	100.00	1.00	0.94	

Source: Own work.

3.6 Formal Measurement Model Specification

The second-order reflective indicator measurement model (Figure 5) captures the expected relationships between the generated indicators (Table 16) and the focal construct they are intended to represent.

Figure 5: AI Adoption – Latent Construct Measurement Model



Source: Own work.

3.7 Scale Purification and Refinement

Data was analyzed in three steps. In step 1, we performed a preliminary analysis of the scale by Exploratory Factor Analysis (EFA) using the Maximum likelihood and Varimax rotation with IBM SPSS Statistics version 26. Step 2 further validated the factor structure using Confirmatory Factor Analysis (CFA). For CFA, we used IBM SPSS AMOS version 28.

3.7.1 Pilot study

We used a single-source, self-report, cross-sectional design to gather the data for the pilot study. The data was collected through a questionnaire survey and distributed electronically. The questionnaire was anonymous and in the English language. We sourced the participants from LinkedIn. We targeted Chief Experience Officers, senior business managers, IT directors and managers, Business Process Architects, BPM Consultants, Business Analysts, Chief Process Officers, Chief Digital and Data Officers, and other senior business decision-makers or people directly involved in executing the organization's AI strategy. We connected with 300 individuals and sent direct message invitations. The invites were sent at the start of February 2022.

3.7.1.1 Sample

The sample of usable questionnaires for the pilot study consisted of 80 EU organizations from 23 countries. 42.5% were from Information and communication and Professional, scientific, and technical activities. 87.5% had fewer than 50 employees. 81.25% had been in business for less than 30 years. 58.75% of revenues are less than 1 million EUR in revenues. Most respondents (88.75%) were senior and executive managers and had been at the company for, on average, about ten years. According to the information in Table 20, we conclude the sample is somewhat representative of the sample frame and the population.

Table 20: Characteristics of the Pilot Study Sample

Characteristics		**Number**	**%**
Respondent's position	Senior/executive manager	59	73.75
	Middle/first line manager	12	15.00
	Other: Data Analyst, AI Engineer, Data Engineer, Software Developer, IT Specialist, Scientist, Consultant, Statistician	9	11.25
Respondent's time at the organization	0 - 2 years	14	17.50
	3 - 5 years	18	22.50
	6 - 9 years	15	18.75
	10 - 14 years	8	10.00
	More than 14 years	25	31.25
Organization size	Micro: with less than 10 persons employed	30	37.50
	Small: with 10-49 persons employed	34	42.50
	Medium-sized: with 50-499 persons employed	10	12.50
	Large: with 500 or more persons employed	6	7.50
Organization age (years of operation)	< 5 years	16	20.00
	5 - 10	14	17.50
	11 - 30	35	43.75
	31 - 50	5	6.25
	> 50	10	12.50
Annual revenue (€)	< €10.000	3	3.75
	€10.000 - €24.999	5	6.25
	€25.000 - €49.999	2	2.50
	€50.000 - €99.999	2	2.50
	€100.000 - €199.999	9	11.25
	€200.000 - €499.999	12	15.00
	€500.000 - €599.999	4	5.00
	€600.000 - €999.999	10	12.50
	€1 million - €2.5 million	3	3.75
	€2.5 million - €5 million	9	11.25
	€5 million - €10 million	5	6.25
	€10 million - €20 million	1	1.25
	€20 million - €30 million	2	2.50
	> €50 million	5	6.25
	Not sure	8	10.00
Industry sector	Agriculture, forestry, and fishing	6	7.50
	Manufacturing	5	6.25
	Electricity, gas, steam, and air conditioning supply	1	1.25
	Construction	3	3.75
	Wholesale and retail trade; repair of motor vehicles and motorcycle	5	6.25
	Transportation and storage	2	2.50
	Accommodation and food service activities	1	1.25
	Information and communication	22	27.50
	Financial and insurance activities	5	6.25
	Real estate activities	1	1.25
	Professional, scientific, and technical activities	12	15.00
	Administrative and support service activities	1	1.25
	Education	1	1.25
	Human health and social work activities	2	2.50
	Arts, entertainment, and recreation	6	7.50
	Other service activities	7	8.75
Country/GEO	Austria	4	5.00
	Belgium	1	1.25
	Bulgaria	2	2.50
	Croatia	1	1.25
	Czech Republic	2	2.50
	Denmark	2	2.50
	Finland	1	1.25
	France	7	8.75
	Germany	16	20.00
	Greece	3	3.75
	Hungary	2	2.50
	Ireland	6	7.50
	Italy	9	11.25
	Lithuania	1	1.25
	Netherlands	4	5.00
	Poland	2	2.50
	Portugal	2	2.50

To be continued

Table 20: Characteristics of the Pilot Study Sample (cont.)

Characteristics		**Number**	**%**
	Romania	1	1.25
	Slovakia	1	1.25
	Slovenia	1	1.25
	Spain	3	3.75
	Sweden	1	1.25
	Norway	1	1.25
	Switzerland	2	2.50
	United Kingdom	1	1.25
	Other	4	5.00

Source: Own work.

3.7.1.2 Non-Response Bias

The response and non-response biases were tested in this study using Levene's Homogeneity of Variance Tests (Table 21). We compared the responses from early and late respondents to our pilot survey and found no statistically significant differences ($p > 0.05$). Hence, no evidence was found for non-response bias.

Table 21: Assessment of Non-Response Bias Using Independent Samples t-Test

					Levene's Test for Equality of Variances		**t-test for Equality of Means**			**Effect Size**
Latent Variables	**Response Type**	**N**	**Mean**	**SD**	**F**	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Eta squared**
AI	Early Response	30	2.380	0.881	0.272	0.604	1.815	78.000	0.073	0.0405
	Late Response	50	2.017	0.856			1.802	59.837	0.077	
CBPA	Early Response	30	2.686	0.866	1.212	0.274	2.348	78.000	0.021	0.0660
	Late Response	50	2.189	0.944			2.400	65.412	0.019	

Source: Own work.

3.7.2 Exploratory Factor Analysis

We performed EFA using the Maximum Likelihood method with orthogonal rotation type Varimax to analyze the factor structure and correlation between items included in the scale. The Maximum Likelihood method maximizes differences between factors and provides a Model Fit estimate. The same method is used in IBM SPSS AMOS SEM. Therefore, it is recommended to use it for EFA (Gaskin, 2021b). Varimax rotation minimizes the number of variables with extreme loadings (high or low) on a factor and makes identifying a variable with a factor possible. It is a commonly used Orthogonal rotation type.

3.7.2.1 Scale Purification

Items "Visualization System: Virtual reality, Augmented reality, Mixed Reality," "Natural Language Processing," and "Audio and Speech Processing" were removed by assessing content validity (Section 3.5.2). "Cyber and Network Security & Data Privacy" were removed due to low communalities (< 0.400), and "Document Management System" due to a low value of 0.532 for Corrected Item-Total Correlation as indicated by Reliability Analysis. Removing the item increased Cronbach's Alpha (Cronbach, 1951) to a value of 0.816. Next, cross-loadings with an absolute difference of less than 0.200 were removed (Gaskin, 2021b): "Automatically Generated Content using AI," "Planning, scheduling & optimization," "Rules-based systems," "Business Process Intelligence System," "Talent Management System". In line with convergent validity, items with factor loadings below 0.60 (Gaskin, 2021b) were removed: "Predictive Maintenance" and "AI-enabled Search and Discovery."

3.7.2.2 Indicators

Table 22: Indicators, the Results of Scale Purification

Factor	Indicators		Scale
Data Acquisition and Preprocessing	***Please identify the relative use of AI applications in your organization.***		
	DACQ1	Data warehousing	5 points Likert scale; Scored as 1 - Never, 2 - Rarely, 3 - Sometimes, 4 - Very Often, 5 - Always
	DACQ2	Data Lake	
	DACQ3	Data Capturing System	
Cognitive Insight	***Please identify the relative use of AI applications in your organization.***		
	CI1	Marketing Automation	5 points Likert scale; Scored as 1 - Never, 2 - Rarely, 3 - Sometimes, 4 - Very Often, 5 - Always
	CI2	Marketing Intelligence System	
	CI3	CRM and CX System	
Cognitive Engagement	***Please identify the relative use of AI applications in your organization.***		
	CE1	Conversational AI	5 points Likert scale; Scored as 1 - Never, 2 - Rarely, 3 - Sometimes, 4 - Very Often, 5 - Always
	CE2	Personalization and Recommendation System	
	CE3	Autonomous Systems & Robotics	
	CE4	Computer Vision	
Cognitive Decision Assistance	***Please identify the relative use of AI applications in your organization.***		
	CDA1	Decision Automation System	5 points Likert scale; Scored as 1 - Never, 2 - Rarely, 3 - Sometimes, 4 - Very Often, 5 - Always
	CDA2	Knowledge Engineering and Expert Systems	
	CDA3	Decision Support System	
Cognitive Technologies	***Please identify the relative use of AI applications in your organization.***		
	CT1	Predictive Modeling and Analytics	5 points Likert scale; Scored as 1 - Never, 2 - Rarely, 3 - Sometimes, 4 - Very Often, 5 - Always
	CT2	Anomaly and Deviant Behavior Detection	
	CT3	Machine learning	

Source: Own work.

3.7.2.3 Scale Refinement

The results of the abridged 5-factor matrix are provided in the following tables.

Table 23: KMO and Bartlett's Test

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy		0.848
Bartlett's Test of Sphericity	Approx. Chi-Square	834.412
	df	120
	Sig.	< 0.001

Source: Own work.

According to Table 23, the KMO value is above 0.50, indicating that the sampling adequacy criteria are met. The Bartlett test of sphericity is statistically significant ($p < 0.05$), meaning that our correlation matrix is statistically different from an identity matrix as desired (Table 23). Extracted communalities[13] are presented in Table 24 and are above 0.40.

Table 24: Extracted Communalities

	Communalities	
	Initial	**Extraction**
DACQ1	0.646	0.767
DACQ2	0.497	0.517
DACQ3	0.599	0.593
CI1	0.738	0.884
CI2	0.639	0.645
CI3	0.545	0.515
CE1	0.504	0.466
CE2	0.651	0.675
CE3	0.542	0.677
CE4	0.649	0.777
CDA1	0.726	0.764
CDA2	0.675	0.678
CDA3	0.807	0.894
CT1	0.802	0.791
CT2	0.737	0.706
CT3	0.722	0.885

Source: Own work.

The diagonals of the anti-image correlation matrix were all over 0.50 (Table 25).

[13] Extracted communalities are estimates of the variance in each variable accounted for by the factors in the factor solution. Small values indicate variables that do not fit well with the factor solution and should possibly be dropped from the analysis.

Table 25: Anti-Image Correlation

	DACQ1	DACQ2	DACQ3	CI1	CI2	CI3	CDA1	CDA2	CDA3	CE1	CE2	CE3	CE4	CT1	CT2	CT3
DACQ1	**0.864**	-0.400	-0.410	-0.046	-0.080	-0.108	-0.047	-0.080	-0.005	0.146	0.013	-0.087	-0.001	0.146	-0.259	0.162
DACQ2	-0.400	**0.921**	0.030	-0.084	0.033	-6.841E-05	0.053	0.001	-0.132	-0.094	0.067	-0.012	0.025	-0.053	0.035	-0.147
DACQ3	-0.410	0.030	**0.838**	-0.113	0.058	0.169	0.061	-0.119	-0.124	-0.240	-0.093	-0.283	0.304	-0.141	0.151	-0.169
CI1	-0.046	-0.084	-0.113	**0.730**	-0.565	-0.409	-0.094	0.051	0.351	0.124	-0.293	0.197	0.034	-0.086	0.023	-0.180
CI2	-0.080	0.033	0.058	-0.565	**0.769**	0.049	0.156	-0.098	-0.255	-0.158	-0.060	-0.065	-0.040	0.295	-0.130	0.136
CI3	-0.108	-7E-05	0.169	-0.409	0.049	**0.841**	-0.036	-0.082	-0.027	-0.263	-0.104	-0.058	0.153	-0.231	0.098	0.067
CDA1	-0.047	0.053	0.061	-0.094	0.156	-0.036	**0.878**	-0.192	-0.575	-0.018	-0.093	0.048	-0.045	-0.010	0.134	-0.136
CDA2	-0.080	0.001	-0.119	0.051	-0.098	-0.082	-0.192	**0.941**	-0.199	0.146	-0.057	0.096	-0.176	-0.116	0.088	-0.187
CDA3	-0.005	-0.132	-0.124	0.351	-0.255	-0.027	-0.575	-0.199	**0.849**	0.071	-0.067	0.135	-0.007	-0.016	-0.213	-0.083
CE1	0.146	-0.094	-0.240	0.124	-0.158	-0.263	-0.018	0.146	0.071	**0.839**	-0.204	-0.126	-0.243	0.062	-0.099	0.032
CE2	0.013	0.067	-0.093	-0.293	-0.060	-0.104	-0.093	-0.057	-0.067	-0.204	**0.914**	0.051	-0.299	0.130	-0.153	0.087
CE3	-0.087	-0.012	-0.283	0.197	-0.065	-0.058	0.048	0.096	0.135	-0.126	0.051	**0.695**	-0.533	-0.071	0.080	-0.083
CE4	-0.001	0.025	0.304	0.034	-0.040	0.153	-0.045	-0.176	-0.007	-0.243	-0.299	-0.533	**0.764**	-0.118	0.127	-0.194
CT1	0.146	-0.053	-0.141	-0.086	0.295	-0.231	-0.010	-0.116	-0.016	0.062	0.130	-0.071	-0.118	**0.829**	-0.619	0.025
CT2	-0.259	0.035	0.151	0.023	-0.130	0.098	0.134	0.088	-0.213	-0.099	-0.153	0.080	0.127	-0.619	**0.833**	-0.404
CT3	0.162	-0.147	-0.169	-0.180	0.136	0.067	-0.136	-0.187	-0.083	0.032	0.087	-0.083	-0.194	0.025	-0.404	**0.909**

Source: Own work.

The results of the exploratory factor analysis presented in Table 27 show that the solution is based on 5 factors, as expected. Initial eigenvalues indicated that the five factors explained 19.613%, 16.732%, 11.818%, 12.127%, and 9.930% of the variance, respectively. The five-factor solution explains 70.220% of the total variance with reliability Cronbach's Alpha between 0.786 and 0.904 (Table 26).

Table 26: Reliability Analysis of Factors

Factor	Cronbach's Alpha
Data Acquisition and Preprocessing (Factor 1)	0.816
Cognitive Insight (Factor 2)	0.814
Cognitive Engagement (Factor 3)	0.786
Cognitive Decision Assistance (Factor 4)	0.904
Cognitive Technologies (Factor 5)	0.895

Source: Own work.

The results of the rotated factor matrix are provided in Table 27. Using the Varimax orthogonal rotation type, we assume no correlation between factors. Nevertheless, we identified several cross-loadings between "Cognitive Engagement" and "Cognitive Technologies," where the difference between loadings was around 0.200. Often, when there is a second-order factor in an EFA, the subdimensions of that factor load together instead of in separate factors (Gaskin, 2021b). We arranged the items of "CT3 - Anomaly and Deviant Behavior Detection" and "CE2 - Personalization and Recommendation System" according to Face Validity into factors with lower loading. This is further addressed in CFA analysis. All other loadings are higher than 0.50, and the average loading for all factors is over or near 0.70. Goodness-of-fit Test indicated reasonable model fit ($\chi 2$ = 51.030, df = 50, p = 0.433).

Table 27: 5-Factor Rotated Matrix

	Factor				
	1	**2**	**3**	**4**	**5**
DACQ1	**0.756**				
DACQ2	**0.563**				
DACQ3	**0.626**				
CI1		**0.916**			
CI2		**0.743**			
CI3		**0.644**			
CDA1			**0.823**		
CDA2			**0.691**		
CDA3			**0.870**		
CE1				**0.548**	
CE2		*0.623*		**0.366**	
CE3				**0.790**	
CE4				**0.800**	
CT1					**0.819**
CT2					**0.622**
CT3			*0.577*		**0.436**

Source: Own work.

The results of the EFA show that our factors have a good level of validity. For further validation, we used the CFA discussed next.

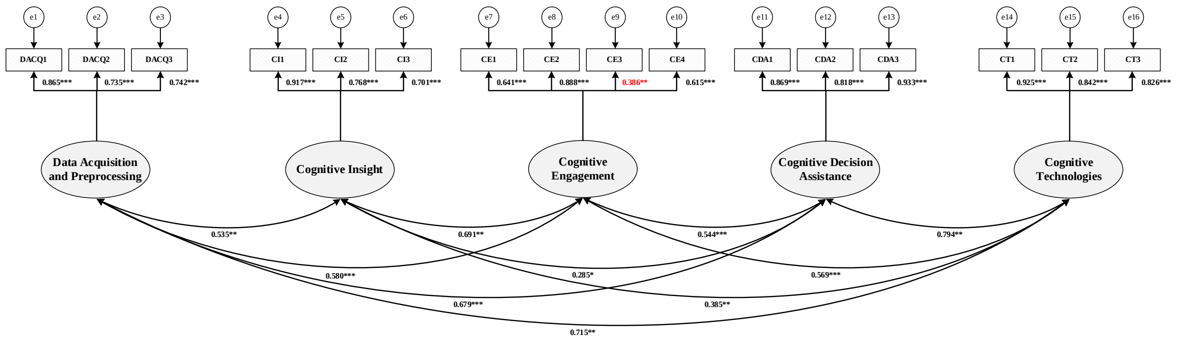
3.7.3 Confirmatory Factor Analysis

We assessed the model for reliability and convergent validity. The graphical representation of the CFA initial model and the final calculated model is followed by results in Table 28.

3.7.3.1 First-Order Unidimensionality: initial CFA

The initial CFA model (Figure 6) had a relatively poor model fit: $\chi 2/df = 1.760$, GFI = 0.805, AGFI = 0.718, TLI = 0.884, CFI = 0.909, RMSEA = 0.098 (p-close = 0.002), and SRMR = 0.0795 (for the description of Fit Indices, refer to Table 74 or Table 83).

Figure 6: First-Order Unidimensionality – Initial CFA



Source: Own work.

3.7.3.2 Eliminate Problematic Indicators

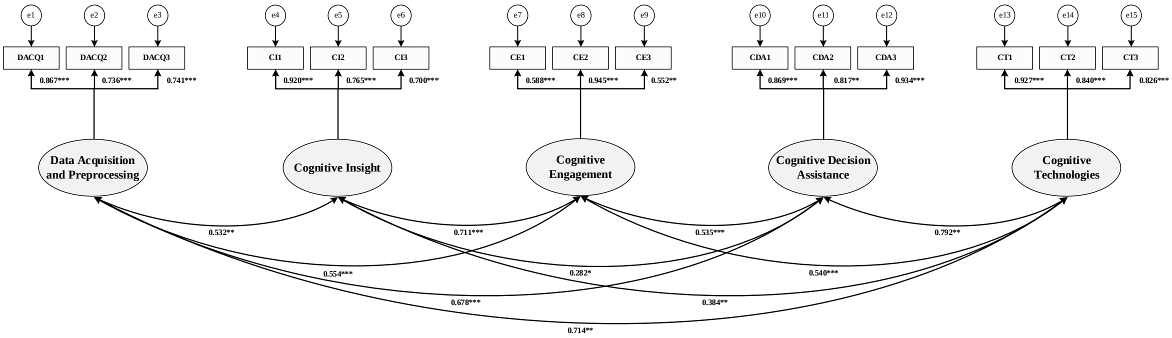
As suggested by MacKenzie et al. (2011), we consider eliminating indicators that have 1) nonsignificant loadings on the hypothesized construct; 2) squared completely standardized loadings that are less than 0.50; 3) high and significant measurement error covariances with other measures.

All loadings are significant. Item CE3 has a loading lower than 0.50. Based on Modification indices indicating the change in the Chi-square of model fit, we identified significant error covariances on items CE3 and CE4. We removed the item CE3 as it has a low loading of 0.386.

3.7.3.3 First-Order Unidimensionality: Abridged CFA

The final CFA model (Figure 7) has a good model fit: $\chi 2/df = 1.410$, GFI = 0.861, AGFI = 0.791, TLI = 0.942, CFI = 0.965, RMSEA = 0.072 (p-close = 0.130), and SRMR = 0.0679. Based on Hu and Bentler (1999) recommendations, we used the suggested model fit measures cutoff values RMSEA < 0.08, SRMR < 0.08, CFI > 0.90. Consequently, we prefer the abridged model to the initially proposed measurement model.

Figure 7: First-Order Unidimensionality – Abridged CFA



Source: Own work.

3.7.3.4 Assessing the Reliability of the Set of Indicators at the Construct Level

All items' standardized factor loading was above 0.55, and the Average Variance Extracted (AVE) was above 0.50. These indicate good convergent validity (Hair Jr, Sarstedt, Ringle, & Gudergan, 2017). Internal consistency reliability (Cronbach, 1951) is higher than 0.70, and the index of construct reliability is higher than 0.70 (MacKenzie et al., 2011). Results are presented in Table 28.

Table 28: Factor Loadings, Cronbach's Alpha, Composite Reliability, AVE

Construct/ Indicators	**Standardized Factor Loadings**	**Cronbach Alpha**	**Composite Reliability (CR)**	**AVE**	**Maximum shared squared variance (MSV)**	**Maximum reliability MaxR(H)**
DACQ		**0.816**	**0.826**	**0.614**	**0.510**	**0.844**
DACQ1	0.867					
DACQ2	0.736					
DACQ3	0.741					
CI		**0.814**	**0.841**	**0.641**	**0.506**	**0.887**
CI1	0.920					
CI2	0.765					
CI3	0.700					
CE		**0.757**	**0.749**	**0.514**	**0.506**	**0.903**
CE1	0.588					
CE2	0.945					
CE3 (former CE4)	0.552					
CDA		**0.904**	**0.907**	**0.765**	**0.627**	**0.923**
CDA1	0.869					
CDA2	0.817					
CDA3	0.934					

To be continued

Table 28: Factor Loadings, Cronbach's Alpha, Composite Reliability, AVE (cont.)

Construct/ Indicators	Standardized Factor Loadings	Cronbach Alpha	Composite Reliability (CR)	AVE	Maximum shared squared variance (MSV)	Maximum reliability MaxR(H)
CT		**0.895**	**0.899**	**0.749**	**0.627**	**0.914**
CT1	0.927					
CT2	0.840					
CT3	0.826					
Model Fit: χ2/df = 1.410, GFI = 0.861, AGFI = 0.791, TLI = 0.942, CFI = 0.956, RMSEA = 0.072 (p-close = 0.130), and SRMR = 0.0679						

Source: Own work.

Next, we present the Factor Correlation Matrix with the Square Root of the AVE on the diagonal (Table 29).

Table 29: Factor Correlation Matrix

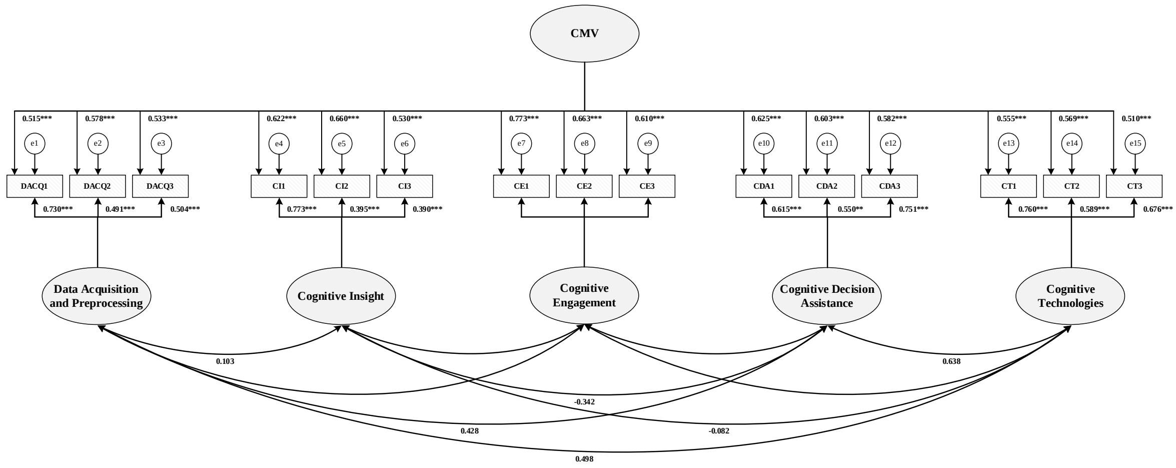
	DACQ	CI	CE	CDA	CT
DACQ	**0.784**				
CI	0.532	**0.800**			
CE	0.554	0.711	**0.717**		
CDA	0.678	0.282	0.535	**0.875**	
CT	0.714	0.384	0.540	0.792	**0.865**

Source: Own work.

3.7.3.5 Common Method Variance

We used a Common Latent Factor (CLF) method to capture the common variance among all observed variables in the model (Eichhorn, 2014). As expected for the second-order latent construct, 51.552% of the variance is shared between first-order factors. Next, we conducted Harman's single-factor test using CFA. Our single-factor model showed a poor data fit (χ2/df = 1.194, GFI = 0.877, AGFI = 0.812, TLI = 0.972, CFI = 0.979, RMSEA = 0.050 (p-close = 0.486), SRMR = 0.0663). The results suggest the existence of a second-order latent variable.

Figure 8: Common Method Variance

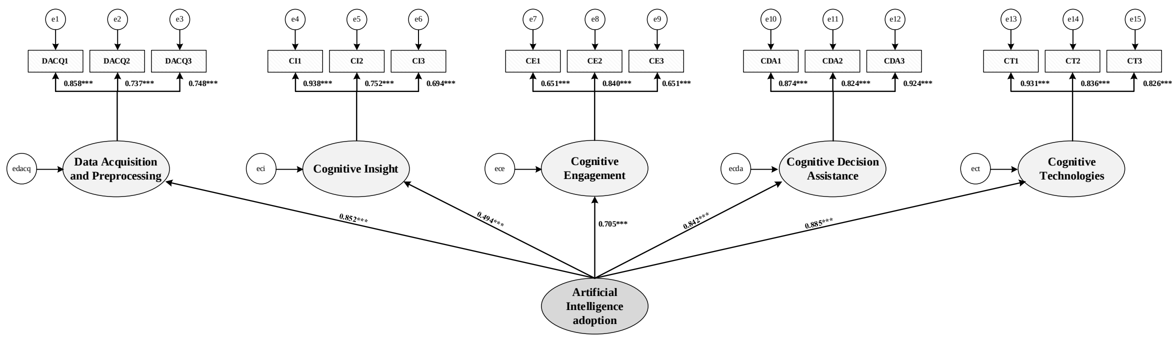


Source: Own work.

3.7.3.6 Second-Order Unidimensionality: CFA

The second-order CFA model (Figure 9) has a good model fit: χ2/df = 1.677, GFI = 0.826, AGFI = 0.755, TLI = 0.904, CFI = 0.922, RMSEA = 0.093 (p-close = 0.008), SRMR = 0.0914. The elevated value of the RMSEA measure is due to the small sample size (Kenny, Kaniskan, & McCoach, 2015).

Figure 9: Second-Order Multidimensionality – CFA



Source: Own work.

All items' standardized factor loading was above 0.60, and AVE for first and second order was above 0.50 (MacKenzie et al., 2011). These indicate good convergent validity (Hair Jr et al., 2017). Internal consistency reliability (Cronbach, 1951) is higher than 0.70, and the index of construct reliability is higher than 0.70 (MacKenzie et al., 2011) at the first-order and second-order levels (Table 30).

Table 30: Factor Loadings, Cronbach's Alpha, CR, AVE

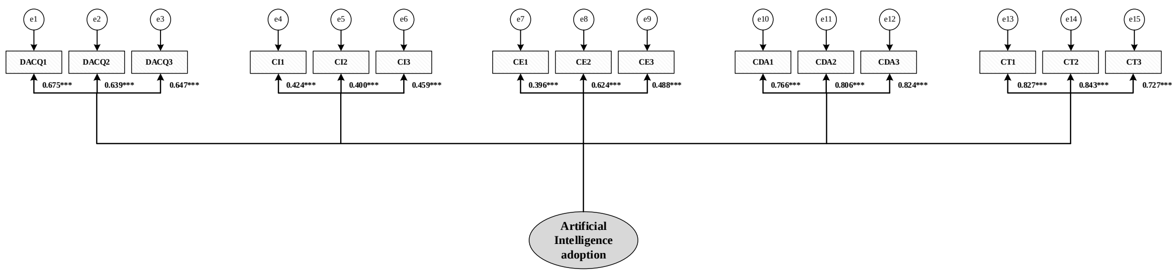
Construct/ Indicators	Standardized Factor Loadings	Cronbach Alpha	CR	AVE
AI			**0.871**	**0.583**
DACQ	0.825	**0.816**	**0.825**	**0.613**
DACQ1	0.858			
DACQ2	0.737			
DACQ3	0.748			
CI	0.494	**0.814**	**0.841**	**0.642**
CI1	0.938			
CI2	0.752			
CI3	0.694			
CE	0.705	**0.757**	**0.760**	**0.518**
CE1	0.651			
CE2	0.840			
CE3	0.651			
CDA	0.842	**0.904**	**0.907**	**0.766**
CDA1	0.874			
CDA2	0.824			
CDA3	0.924			
CT	0.885	**0.895**	**0.899**	**0.749**
CT1	0.931			
CT2	0.836			
CT3	0.826			
Model Fit: χ2/df = 1.677, GFI = 0.826, AGFI = 0.755, TLI = 0.904, CFI = 0.922, RMSEA = 0.093 (p-close = 0.008), SRMR = 0.0914				

Source: Own work.

3.7.3.7 First-Order One Factor Alternative Model

One factor alternative CFA model (Figure 10) has poor model fit: χ2/df = 3.534, GFI = 0.626, AGFI = 0.502, TLI = 0.640, CFI = 0.691, RMSEA = 0.179 (p-close < 0.001), SRMR = 0.1239. Consequently, we prefer the abridged second-order five-factor model to the alternative first-order one-factor model.

Figure 10: First-Order One Factor Alternative Model – CFA



Source: Own work.

Some items' standardized factor loading was below 0.50, and AVE was below 0.50. These indicate poor convergent validity (Hair Jr et al., 2017). Reliability is adequate, internal consistency reliability (Cronbach, 1951) is higher than 0.70, and the index of construct reliability is higher than 0.70 (MacKenzie et al., 2011).

Table 31: Factor Loadings, Cronbach's Alpha, CR, AVE

Construct/ Indicators	Standardized Factor Loadings	Cronbach Alpha	CR	AVE
AI		**0.917**	**0.914**	**0.430**
DACQ1	0.675			
DACQ2	0.639			
DACQ3	0.647			
CI1	0.424			
CI2	0.400			
CI3	0.459			
CE1	0.396			
CE2	0.624			
CE3	0.488			
CDA1	0.766			
CDA2	0.806			
CDA3	0.824			
CT1	0.827			
CT2	0.843			
CT3	0.727			
Model Fit: $\chi2/df = 3.534$, GFI = 0.626, AGFI = 0.502, TLI = 0.640, CFI = 0.691, RMSEA = 0.179 (p-close < 0.001), SRMR = 0.1239				

Source: Own work.

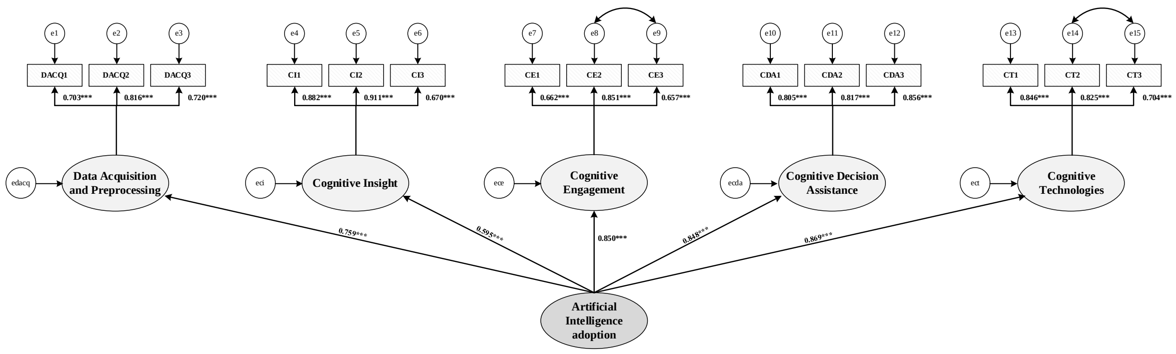
3.8 Validation

Validation was performed on the data collected in the main study. The collected and processed sample consists of 448 EU organizations. A summary of the characteristics of the sample is presented in Table 60.

3.8.1 Confirmatory Factor Analysis

The results show that the final CFA model (Figure 11) has a good model fit: $\chi2/df = 2.753$, GFI = 0.937, AGFI = 0.909, TLI = 0.948, CFI = 0.959, RMSEA = 0.063 (p-close = 0.016), and SRMR = 0.0465. We identified additional significant measurement error covariances between items CE2-3 and CT2-3. According to Bollen and Lennox (1991), correlated errors are possible among items using similar wordings or appearing near each other on the questionnaire. Therefore, we correlated the error terms.

Figure 11: Final Second-Order CFA



Source: Own work.

All items' standardized factor loading was above 0.60, and AVE was above 0.530 (Table 32). These indicate good convergent validity (Hair Jr et al., 2017). Internal consistency reliability (Cronbach, 1951) is higher than 0.70, and the index of construct reliability is higher than 0.7 (MacKenzie et al., 2011).

Table 32: Final Second-Order Model Factor Loadings, Cronbach's Alpha, CR, AVE

Construct/ Indicators	**Standardized Factor Loadings**	**Cronbach Alpha**	**CR**	**AVE**
AI			**0.891**	**0.625**
DACQ	0.759	**0.783**	**0.791**	**0.559**
DACQ1	0.703			
DACQ2	0.816			
DACQ3	0.720			
CI	0.595	**0.854**	**0.865**	**0.686**
CI1	0.882			
CI2	0.911			
CI3	0.670			
CE	0.850	**0.704**	**0.770**	**0.531**
CE1	0.662			
CE2	0.851			
CE3	0.657			
CDA	0.848	**0.864**	**0.866**	**0.683**
CDA1	0.805			
CDA2	0.817			
CDA3	0.856			
CT	0.869	**0.806**	**0.836**	**0.631**
CT1	0.846			
CT2	0.825			
CT3	0.704			
Model Fit: $\chi 2$/df = 2.753, GFI = 0.937, AGFI = 0.909, TLI = 0.948, CFI = 0.959, RMSEA = 0.063 (p-close = 0.016), and SRMR = 0.0465				

Source: Own work.

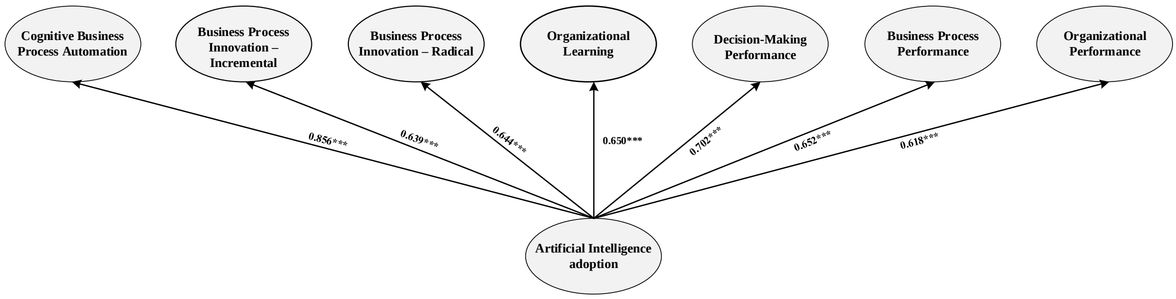
3.8.2 Validity, Reliability and Measurement Model Fit

We assessed the discriminant validity of the construct by testing whether the focal construct is less than perfectly correlated with conceptually similar constructs. Results are presented in Section 6.4.2.

3.8.3 Nomological Validity

Nomological validity was analyzed through SEM between AI and other constructs hypothesized to be in its nomological network (Figure 12).

Figure 12: The Results of the Test of Nomological Validity



Source: Own work.

The 90% CI values were scrutinized to assess significance (Hair Jr et al., 2017). The results provide support for nomological validity. AI is significantly and positively related to *CBPA*, *OL*, *BPII*, *BPIR*, *DMP*, *BPP*, and *OP* (Table 33).

Table 33: Nomological Validity Analysis

Path	β	[90% CI]
AI → CBPA	0.856	[0.798, 0.901]
AI → BPIR	0.644	[0.552, 0.725]
AI → BPII	0.639	[0.563, 0.712]
AI → OL	0.650	[0.568, 0.733]
AI → DMP	0.702	[0.618, 0.782]
AI → BPP	0.652	[0.563, 0.745]
AI → OP	0.618	[0.522, 0.712]

Source: Own work.

4 COGNITIVE BUSINESS PROCESS AUTOMATION

Process automation is recognized as a cornerstone of AI adoption and can produce business value (Davenport & Ronanki, 2018; Hull & Motahari-Nezhad, 2016; van der Aalst, Becker, et al., 2018; Wamba-Taguimdje et al., 2020b; Zasada, 2019). While automation is often used to speed up information flow and provide decision support (Frohm, 2008), automation systems lack many human cognitive skills that are now made possible by AI technologies. We argue that taking advantage of the cognitive capabilities of AI (to sense, comprehend, act, and learn), as presented by Bawack and Wamba (2019), can enable a higher level of cognitive automation and broader deployment.

We conduct a literature review to investigate whether there is a suitable existing model or measurement instrument and thus define a new measurement instrument to measure CBPA.

4.1 Theoretical Foundations

CBPA is a promising approach to integrating BPM into cognitive computing technologies. The theoretical foundations of CBPA from AI and management science provide the basis for a comprehensive understanding of the concept.

4.1.1 Automation

The automation concept was defined by D.S. Harder in 1936 while working for the General Motors Corporation and is understood as "the transfer of work parts between the machines in production efficiency, are now part of the process, without human operation." (Hitomi, 1994, p. 122). Three studies are key to understanding the concept.

1. Diebold (1955) defines automation as "automatic operation or a process of automatically making tangible goods," arguing automation has two meanings: 1) automatic regulation by feedback and 2) integration of several machines.
2. Bright (1958) presents the stages in the development of mechanization and automation.
3. Drucker (2011) recognizes automation as a conceptual system that extends beyond technology.

"Automation" can be considered the abbreviation of "automatization" or "automatic operation." The word is a combination of the Greek "automotos" (self-moving) and Latin the Latin "ion" (a state). "Mechanization" is the replacement of human physical labor with machines; however, the machine's operations are controlled by human operators. "Automation" replaces the control actions of machines; that is, it is the replacement of human physical and mental activities by machines (Hitomi, 1994). We thus rephrase and define automation as *the optimization of a process with reduced human involvement.* Hitomi (1994) suggests three types of automation that follow this understanding:

1. mechanical manufacturing – automatic flow-type production in manufacturing industries;
2. process automation for process and chemical industries – automatic control of continuous production in process industries; and
3. business automation – increase in business efficiency by computers.

Mechanical and process automation are concerned with immediate production processes that convert raw materials into products (the flow of materials) and business automation is concerned with managing and controlling productive activities (the flow of information). The integration of both flows produces enterprise automation (Hitomi, 1994; Parasuraman et al., 2000; Zero, 2020).

4.1.2 Business Process Automation

This research is concerned with the automation of information flow and control, specifically the automation of business processes in the context of BPM. BPM involves any combination of modeling, automation, execution, control, measurement, and optimization of business activity flows in support of enterprise goals. It covers systems, employees, customers, and partners within and beyond the enterprise boundaries (Romao, Costa, Costa, & Ieee, 2019). It is not a domain or method-specific field but continuously enables novel applications through technological innovation. New technologies provide automation and carry both informational and transformational qualities (van der Aalst, Becker, et al., 2018). This construct is concerned with the effects of automation.

An aspect of BPM that involves automating a business process is business process automation, also known as business automation, which is the automation of complex business processes, usually through advanced technologies. It is employed to support knowledge workers (Romao et al., 2019) and often concerns event-driven, mission-critical, core processes. Business automation is pursued to improve the efficiency of business processes (in terms of their cost, required resources, and investment) by automating the management of relevant information and data, the time spent by team members, and the process execution logic (Chakraborti et al., 2020). Tasks in a business process are often either manual and performed by human participants or are system-supported and executed by software systems (Sindhgatta et al., 2020a).

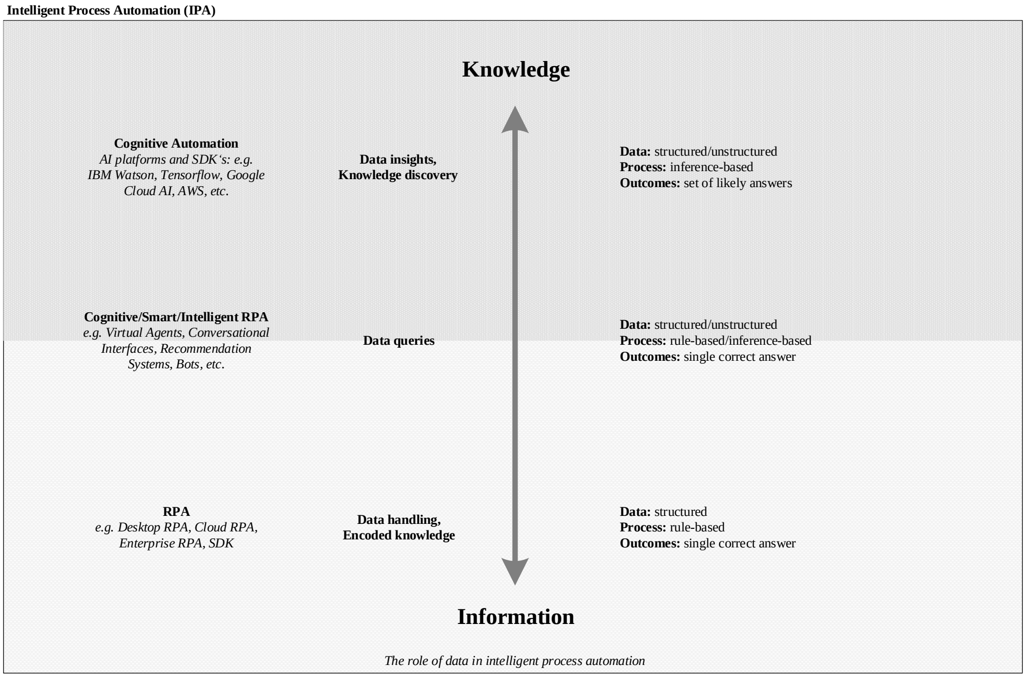
4.1.3 Knowledge Intensive Processes

Sometimes referred to as decision-intensive processes, knowledge-intensive processes or "KiPs" help users perform decision-intensive tasks and provide users with guidance relevant to the process execution context (Vaculín et al., 2011). Various authors defined characteristics: unpredictable, non-repeatable, highly flexible, unstructured, complex, data, and knowledge-intensive (Di Ciccio et al., 2015; Gronau & Weber, 2004; Harmon & Trends, 2010; Marjanovic & Freeze, 2011; Santoro & Baião, 2017). Vaculín et al. (2011, p. 151) provide a precise and comprehensive definition that captures the key characteristics from a process management perspective: "KiPs are processes whose conduct and execution are heavily dependent on knowledge workers performing various interconnected knowledge-intensive decision-making tasks. KiPs are genuinely knowledge, information, and data-centric and require substantial flexibility in design and run-time".

4.1.4 Augmenting Automation With Decision-Making Capabilities

Business process automation is a set of business process improvements and tools that help the knowledge worker eliminate repetitive, replicable, and routine tasks (Suri et al., 2019) through the creation and execution of a process model during runtime. These process models do not necessarily provide the flexibility required to cope with changing operational conditions; process designs may only be optimal under certain operating conditions (Kress & Seese, 2010). Therefore, conventional levers of rule-based automation are augmented (made greater by adding to or increasing) with decision-making capabilities enabled by machine learning and other AI technologies.

Figure 13: The Automation Continuum



Source: Adapted from Lacity and Willcocks (2016); Richardson (2020); Willcocks, Hindle, and Lacity (2018)

We distinguish two approaches to the automation of decision-making in business processes (see Section 2.7.1). IPA is a broad concept encompassing rule- and inference-based decision-making; cognitive automation is at the higher end of the automation spectrum or continuum (Figure 13). Gartner calls this hyper-automation (Burke et al., 2019, p. 12) "a process in which businesses automate as many business and IT processes as possible using tools like AI, machine learning, event-driven software, robotic process automation, and other types of the decision process and task automation tools." The greatest benefits of the process automation these technologies allow are the optimization of internal business operations, the freeing of employees for value-adding tasks, expansion (market/product), and the reduction of workforce size (Naga Lakshmi et al., 2019; Richardson, 2020).

4.1.5 Automation Continuum

The IPA automation continuum (Figure 13) includes technologies that differ in the role played by data, processing, and outcomes, from robotic processes to cognitive automation.

Both ends of the continuum use AI to take intelligent actions (Richardson, 2020), which involves choosing between two or more actions and having the ability to decide what to do instead of performing an automatic and fixed stimulus-response reflex. RPA uses rules-based logic to determine what action should be taken, and, in cognitive automation, rules-based logic is replaced with probabilities developed through reinforcement learning.

4.1.5.1 Robotics Process Automation

RPA is based on software and algorithms that automate rules-based business processes involving routine tasks, structured data, and deterministic, single-correct-answer outcomes.. (Aguirre & Rodriguez, 2017; Ivančić, Suša Vugec, & Bosilj Vukšić, 2019; Zhang, 2019). It is used to support processes in the middle of the frequency spectrum (between repetitive and ad hoc transactional processes) with a high transaction volume and does so by having agents (software robots) interact with the different information systems as if they were humans (van der Aalst, Becker, et al., 2018).

4.1.5.2 Cognitive/Smart/Intelligent Robotics Process Automation

Cognitive/smart/intelligent RPA is expected to produce (and execute) more refined process models (Siderska, 2020) by combining robotics process automation with constructed AI, including machine learning, Big Data, and data mining. An extension of RPA, it can automate rule- and inference-based tasks and process structured and unstructured data with deterministic results. Less complex and context-based repetitive work can be automated using RPA (Angermann & Hänisch, 2020). Various studies argue that RPA is just one step toward more intelligent and cognitive automation (Hofmann, Brunner, & Holschbach, 2020; Hull & Motahari-Nezhad, 2016; van der Aalst, Bichler, & Heinzl, 2018).

4.1.5.3 Cognitive Business Process Automation

Cognitive automation is the identification, assessment, and application of available ML algorithms to leverage domain knowledge and reasoning and further automate ML in a manner considered “cognitive.” With cognitive automation, the system performs corrective actions driven by knowledge of the underlying analytics tool, iterating its automation approaches and algorithms for more extensive analysis and thereby fulfilling its purpose. The automation of the cognitive process refines itself. It dynamically generates novel hypotheses to assess its existing corpus and other information resources ("IEEE Guide for Terms and Concepts in Intelligent Process Automation," 2017). It automates inference-based tasks, integrates knowledge from various structured and unstructured data sources, interacts with users by natural language or visualization, and generates nondeterministic results (a set of likely answers).

The literature fails to explore the concept more deeply and concisely. There is thus a need to develop and operationalize CBPA and measure the impact of cognitive technologies on business process optimization through automation. A detailed conceptual analysis of CBPA is presented in the next section; the concept, its attributes, dimensions, and properties are identified based on an exploration of the theories of BPM, business process automation, and AI.

4.2 Development of the Concept

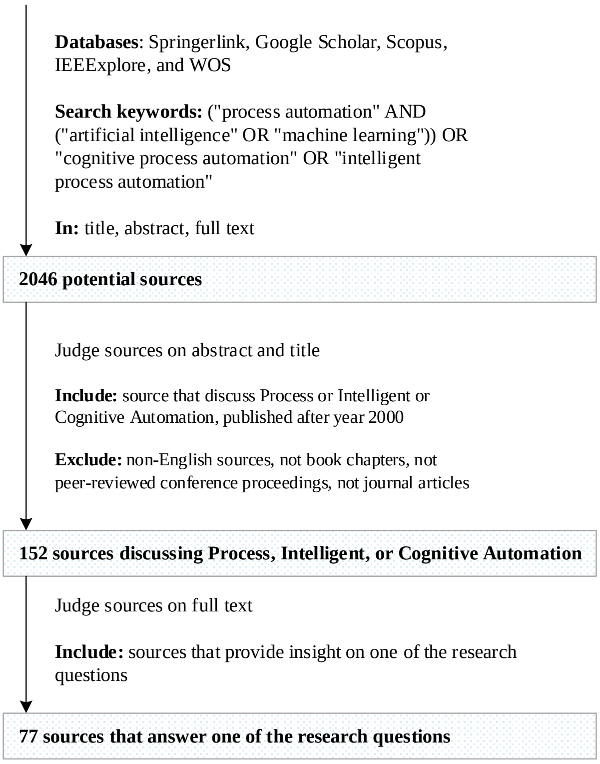
Similar to AI adoption, described in Chapter 3, the definition was developed following the relevant guidelines in the literature (MacKenzie et al., 2011; Podsakoff et al., 2016). The CBPA definition is developed in three stages:

1. collection of possible attributes of CBPA by examining and assembling a set of definitions from the literature and semi-structured interviews;
2. compilation of key attributes and generating a preliminary definition; and
3. refinement of the definition.

4.2.1 Literature Identification

Following Okoli (2015), we conduct a literature review to identify existing definitions and answer several questions: what defines cognitive process automation, how does cognitive automation affect business processes, and how should CBPA be measured? Figure 14 depicts the literature review procedure and parameters. We identify 77 sources that define the concept of cognitive process automation, its dimensions, and attributes.

Figure 14: Systematic Literature Review Procedure



Source: Own work.

We find no constructs measuring CBPA as a dependent variable related to changes in organizational automation using AI or cognitive technologies. We define a new, more focused concept of CBPA and identify its potential attributes following the recommendations in Podsakoff et al. (2016) and using several techniques. We generate an illustrative set of definitions of CBPA from dictionaries, a literature review, and in-depth semi-structured interviews with subject-matter experts and practitioners. First, we extract common attributes from the definitions of business process automation in dictionaries and existing studies. We present our summary of these definitions in Table 34.

Table 34: Main Findings From Dictionaries and Prior Studies on CBPA

Source	Conceptualization of Cognitive Business Process Automation	Key attributes
Hull and Motahari Nezhad (2016)	"Advances in Cognitive Computing will enable new ways of learning and enacting processes at both design- and run-time. It will open opportunities for new levels of automation and business process support for all types of processes including KiPs."	Learns and enacts knowledge-intensive processes with Cognitive Computing
"IEEE Guide for Terms and Concepts in Intelligent Process Automation" 2017)	"The identification, assessment, and application of available machine learning algorithms for the purpose of leveraging domain knowledge and reasoning to further automate the machine learning already present in a manner that may be thought of as cognitive. With cognitive automation, the system performs corrective actions driven by knowledge of the underlying analytics tool itself, iterates its own automation approaches and algorithms for more expansive or more thorough analysis, and is thereby able to fulfill its purpose. The automation of the cognitive process refines itself and dynamically generates novel hypotheses that it can likewise assess against its existing corpus and other information resources."	Leverages domain knowledge and reasoning to automate; Performs corrective actions driven by knowledge of the underlying analytics tool; Refines itself; Dynamically generates novel hypotheses

To be continued

Table 34: Main Findings From Dictionaries and Prior Studies on CBPA (cont.)

Source	Conceptualization of Cognitive Business Process Automation	Key attributes
Williams et al. (2018)	"AI can be combined with RPA to enable new and compelling use cases and unlock new levels of value in two primary new ways: (1) Extending RPA to areas that were previously unfit for automation; (2) Increasing the yield of robotics within a currently enabled process."	Extends to areas that were previously unfit for automation; Increases the yield of robotics within a currently enabled process
Kokina and Blanchette (2019)	"More sophisticated RPA evolves into cognitive or intelligent automation (IA) that is capable of performing non-routine tasks involving judgment based on unstructured data."	Performs non-routine tasks involving judgment based on unstructured data
Naidu and Vedavathi (2019)	"A deterministic task is an activity or a process which will have a sequence of well-defined steps between interaction entities. In such cases, one can develop software to automate the manual process by using any of one of the technology streams like Custom Development or BPM or RPA, etc. The critical component missing in these cases is cognitive nature. Cognitive nature means a process involves psychological thinking, sensing and understating of the knowledge, attitudes, natural behaviors, linguistics, etc.,in order to produce an output or a decision while solving a problem."	Automating using psychological thinking, sensing, and understating of the knowledge, attitudes, natural behaviors, linguistics
Zhang (2019)	"Cognitive computing is a branch of AI that refers to systems that learn at scale, reason with purpose and interact with humans naturally. Cognitive computing combines computer science with cognitive science to simulate human thought processes in a computerized model and aims to augment human capabilities by providing relevant information or recommendations to help humans make better decisions."	Simulation of human thought processes to help humans make better decisions
Suri et al. (2019)	"Cognitive Automation is defined in the context of a Machine Learning automation framework. While the proposed properties are found to be critical to such a system, one could arguably relax some of these or expand the notion to include additional desirables. An algorithmic framework will be called cognitive if it has the following properties: (1) It integrates knowledge from (a) various structured or unstructured sources, (b) past experience, and (c) current state, in order to reason with this knowledge as well as to adapt over time; (2) It interacts with the user (e.g., by natural language or visualization) and reasons based on such interactions; and (3) It can generate novel hypotheses and capabilities, and test their effectiveness."	Automation with Machine Learning; Integrates knowledge from various structured or unstructured sources; Uses past experience and current state to reason with this knowledge as well as to adapt over time; Interacts with the user (e.g., by natural language or visualization) and reasons based on such interactions; Generates novel hypotheses and capabilities, and tests their effectiveness
Etscheid (2019)	"Due to the digitization of the public sector processes, the use of modern technologies and automation mechanisms is indispensable. Thus, the possibilities of using disruptive technologies and their possible effects must be investigated. The big data collected by sensors can be automatically processed and analyzed using the AI and ML technologies to provide real-time decisions. Such system may offer significant advantages over "manual" regulation and improve the quality of life in cities, yet it poses a number of challenges concerning transparency and accountability."	Using Big Data, AI and Machine Learning technologies for automated decision-making
Chakraborti et al. (2020)	"The convergence of AI, automation and customer data has now seen the emergence of a new class of tools, known as intelligent process automation. Beyond automating simple repetitive tasks, IPA achieves more complex automation by using AI to minimize human-dependent training and automating more complex tasks that entail decision making."	Ability to automate complex tasks that entail decision making
Rizk et al. (2020)	"Business process automation takes a step beyond RPAs to automate decision making in business processes. Marella et al. identified the field of automated planning as an enabler to more sophisticated business process automation. Machine learning is another enabler; deep learning models, long short-term memory recurrent neural networks specifically, have also been trained to model business processes, a crucial component for more advanced automation. Machine learning algorithms like support vector machines, shallow neural networks and random forests have been adopt in process mining applications."	Automates decision-making using automated planning, and Machine Learning
Kerpedzhiev et al. (2020)	"Systematic exploitation of automation technologies (e.g., robotic process automation, cognitive automation, social robotics, and smart devices) to assist human process participants in unstructured tasks and complex decisions or to fully automate such tasks and decisions."	Assists human process participants in unstructured tasks and complex decisions; Fully automates tasks and decisions

To be continued

Table 34: Main Findings From Dictionaries and Prior Studies on CBPA (cont.)

Source	Conceptualization of Cognitive Business Process Automation	Key attributes
Siderska (2020)	"The concept of cognitive automation, combining AI with the automation of business processes. Therefore, the combination of RPA with artificial intelligence (mainly including machine learning techniques), big data, and the data mining concept are foreseen to generate and execute refined process models. This is referred to as smart process automation, which is a possible extension of RPA."	Uses AI for automation of business processes; Ability to generate and execute refined process models
Marciniak et al. (2020)	"The most recent advancement of automation solutions uses cognitive systems or artificial intelligence (AI) technologies. They refer to the use of technologies like machine learning (ML) or deep learning (DL), natural language processing (NLP), text analytics and sentiment analytics, or/and computer vision to perform tasks requiring human intelligence. Cognitive systems exceed digitisation, digitalisation and automation in their ability to learn from past decisions and outcomes as well as in continuous self-improvement ability. They can make human-like intelligent decisions. The level of automation that deploys cognitive systems is called cognitive or intelligent automation. It is able to automate non-standard processes using unstructured databases based on artificial intelligence. Cognitive automation uses continuous learning and development with the help of scenarios and data to handle increasingly complex processes and make decisions."	Use of cognitive systems or artificial intelligence (AI) technologies; Ability to learn from past decisions and outcomes; Ability of continuous self-improvement; Can make human-like intelligent decisions; Automates non-standard processes using unstructured databases based on artificial intelligence; Handles increasingly complex processes and decisions
Richardson (2020)	"Cognitive process automation is capable of performing a variety of tasks that were previously considered the sole domain of human knowledge workers, processes that require some amount of judgement and decision-making with uncertainty that can produce highly variable outcomes. As an AI increasingly moves towards knowledge-activities, the potential for errors and the need to handle exceptions grows."	Automates knowledge-intensive tasks; Automates judgment and decision-making with an uncertainty that can produce highly variable outcomes
Keding (2021)	"In the context of strategic management, two main literature streams capture the concept of AI and provide different scopes. While early publications (1979–2005) understood AI as the underlying technology of rule-based expert systems to support and improve strategic decision-making in a top-down approach, more recent articles about AI in strategic management (2015–2019) find their technological foundation in ML algorithms that recognize patterns in datasets with the help of statistical inferences and possess the potential capability to act autonomously in the area of cognitive tasks and process automation."	Possesses the potential capability to act autonomously in the area of cognitive tasks and process automation
Ng et al. (2021b)	"The integration of RPA and AI, namely intelligent automation (IA), can further expand technological capabilities, technological readiness and process automation potential in different engineering and business applications. The cognitive decision-making power of IA can overcome the challenges of RPA implementation in handling unstructured data, computer vision, natural language processing, fuzzy rule-based decision, decision analytics, real-time decision and content-aware computing and supervise the performance of rules-based RPA. Augmented intelligent process automation. In contrast to IPA, AIPA achieves the next level of cognitive decision quality to enable a holistic approach to automating business workflow and digital processes. The AIPA system must be equipped with decision engines with deductive analytics with quick judgement, and the cognitive level of AIPA is close to human intelligence. Learning from human decisions is also one key feature of AIPA engines."	Using the cognitive decision-making power of IA in handling unstructured data and decision-making. A holistic approach to automating business workflow and digital processes and learning from human decisions.

Source: Own work.

Table 34 sets out the sources, definitions, and the key attributes inferred from those. We include all definitions of automation using AI technology, including intelligent automation and cognitive/smart/intelligent RPA. As reported in Table 34, the academic literature does not accurately define the concept of CBPA. The existing definitions are not based on a detailed conceptualization or a set of attributes.

As CBPA brings AI or cognitive technologies to process automation (Marciniak et al., 2020; Siderska, 2020; Williams et al., 2018), we also examine the underlying definitions of process automation. We present the summary of definitions in Table 35.

Table 35: Main Findings From Dictionaries and Prior Studies on Process Automation

Source	Conceptualization of Process Automation	Key attributes
"IEEE Guide for Terms and Concepts in Intelligent Process Automation" 2017)	“Independent machine-managed choreography of the operation of one or more digital systems.”	Machine-managed choreography of operations.
Etscheid (2019)	“The term automation originates from the industrial context. Automated systems are systems that have the technical ability to work independently. On a simple level, these can be everyday things such as vending machines for drinks or tickets. According to the definition, automation is the transfer of functions from humans to artificial systems.”	Technical ability to work independently; The transfer of functions from humans to artificial systems.
Romao et al. (2019)	“Business process automation (BPA) is defined as the automation of complex business processes and functions beyond conventional data manipulation and record-keeping activities, usually through the use of advanced technologies. It focuses on “run the business” as opposed to “count the business” types of automation efforts and often deals with event-driven, missioncritical, core processes. BPA usually supports an enterprise’s knowledge workers in satisfying the needs of its many constituencies.”	Automates complex business processes; Supports knowledge workers.
Chakraborti et al. (2020)	“Business Process Automation seeks to improve the efficiency of business processes in terms of cost, resources and investment through automating the management of relevant information and data, the time spent by team members, and the execution logic.”	Improves the efficiency of business processes; Manages relevant information and data; Manages execution logic; Manages team members' time.
Sindhgatta et al. (2020a)	“Business process automation provides the ability to coordinate tasks and distribute them to resources (humans or software systems) according to certain logical or temporal dependencies.”	Ability to coordinate tasks and distribute them to resources; Enforces logical dependencies; Enforces temporal dependencies.
Marciniak et al. (2020)	“Automation (or automatization) refers to the use of machines and computers to do work that was previously done by people. In many cases, automation results in a complete replacement of human presence; in other cases, it is only a reduction in human involvement. However, automation always requires human labour (as physical and software robots are designed, built, set up, maintained, repaired, etc. by individuals). Although automation existed before digitisation (it could be entirely mechanical as well), in general, the digitisation of activity is not a prerequisite for automation, but today a new wave of automation is realized primarily with the help of physical and software robots where digitisation is also required in all cases. Automation can affect an activity, but it can be extended to an entire process, so it can even replace organizational units or organizations as well. Automation aims to optimise the operation and reduce costs.”	The use of machines and computers for a reduction in human involvement; Aims to optimize the operation and reduce costs.
Richardson (2020)	“The automation of data processing across multiple systems may sound similar to the more established concept of business process automation. However, the key difference is that BPA involves software development to integrate back-end systems.”	Data processing across multiple systems; Involves software development
Siderska (2020)	“The main objectives for business process automation are increasing the efficiency and revenue as well as reducing the overhead.”	Increases efficiency; Reduces overhead.

Source: Own work.

The definitions of process automation set out in Table 35 – the technical ability to work independently, machine-managed choreography of operations, reducing human involvement, supporting knowledge workers, and optimizing tasks – are similar to the definitions for general process and cognitive process automation. The results suggest that these features are attributes of CBPA.

We supplement these findings by extracting additional definitions and attributes from interviews with experts, conducted according to established guidelines (MacKenzie et al., 2011; Podsakoff et al., 2016). The organizations and experts were selected because they work with AI or on AI-related projects and are divided into three categories:

a.) service providers that implement automation and AI solutions,

b.) vendors that develop automation solutions that include AI capabilities,
c.) end-users of automation solutions enabled by AI or Cognitive Services.

Regarding criterion sampling, the interviewees all had extensive experience with analytics, AI, and automation and had been involved in the deployment of automation. During the in-depth semi-structured interviews, we discussed the broader scope of AI as enabling automation and their implementation and deployment experiences. Table 36 summarizes the key results.

Table 36: Main Findings From Expert Interviews

#	Organization	Expert	Findings
1	Bank; Financial Services; 5,900 employees; End-user	Chief Data Officer	They are dealing with automation in the scope of the Lean initiative and improving business processes by creating more value with fewer resources. They are automating processes where decisions are not deterministic, i.e., Credit Scoring.
2	Insurance company; Financial Services; 5,200 employees; End-user	Head of the team responsible for developing Data Warehousing, Business Intelligence, and AI solutions.	They consider AI a key enabler for process automation and optimization. They don't have specific automation strategies or formalized initiatives in the BPM domain for Business Process Automation. They consider automation a part of optimization efforts. Automation as a core orientation when developing new processes is not likely in the short term. It is hard to change processes because of the many involved stakeholders. They identified several opportunities for using rules-based RPA and are integrating Chatbots for customer support.
3	Bank; Financial services; 1,010 employees; End-user	Head of Analytics Department	Potential areas for AI automation are the prevention of money laundering, risk management, and credit scoring. They don't notice any problems with automation or AI replacing manual tasks. Change management is usual in the organization. They want to do more real-time (data stream) analysis. Most of the automation was done in CRM, with decision trees automatically preparing the next-best offers for a specific customer. The system gets feedback from the sales department and recalculates the models, so the models are self-adopting. They also use a scoring model for website behavior to generate leads.
4	Multinational technology company: hardware, middleware, and software; Software; 345,900 employees; Vendor	Technical Consultant/IT architect	A common aspect of AI adoption is automation. The goal is to reduce costs; the highest cost is usually people. Currently, automation projects target mostly routine tasks. Resistance to implementation is primarily due to concerns about job loss. This makes it challenging to automate knowledge-intensive processes. Many deployments are aimed at partial automation: decision support; a human makes the decision. The usual concerns are full-automation traceability, explainability of automated decisions, bias handling, and regular model validations to ensure compliance.
5	Service provider; Software; 15 employees; Service provider	Digital Solution Designer	They mainly observe automation in the context of process bottleneck optimization. Most projects are based on RPA or RPA technology in conjunction with Cognitive Services. Automating internal processes requires much work, high costs, and a willingness to redesign processes. They mainly focus on implementing pre-built software solutions, especially in marketing, specifically CRM, e.g., conversational interfaces. He sees the current state of automation at the decision support level, where decision-making is still in the human domain.
6	Public security; Government; 279 employees; End-user	Head of Analytics Department	Automated data collection to improve prediction and anomaly detection in the formation and movement of criminal organizations. Similarly, automate allocating and placing limited human resources to efficiently cover a larger geographical area for better road safety coverage. However, the amount and quality of data and legal restrictions related to personal data protection remain significant barriers to automation projects.
7	Computer and Information Science; Educational Services; 182 employees; Vendor	Head of Visual Cognitive Systems Laboratory	Previously, we were able to automate routine, rule-based work. Now, we can automate data-intensive tasks, mostly involving pattern recognition. Tasks where people make data-based decisions can now be fully or partially automated. The expert emphasizes the importance of human intuition and a cognitive approach to understanding the problem. AI can be a great tool, but complex solutions still require a human decision. There are significantly more automation opportunities in the industry.

To be continued

Table 36: Main Findings From Expert Interviews (cont.)

#	Organization	Expert	Findings
8	AI Software Vendor; Manufacturing; 10 employees; Vendor	Managing Director	They approach automation with the intention of achieving full automation or decision support. Manufacturing companies can collect large amounts of processing data using sensors and sensor arrays, allowing automation based on machine learning, especially for anomaly detection. Above all, these technologies enable better resource allocation and process optimization. The optimization result is usually a reduction in the required human resources and a significant simplification of the process. Changes are also observed in robotics. Previously, the robot had to be programmed and usually had one job; now, with machine learning, the robot can learn independently. The robot can thus move between jobs and adapt its work to the needs, which has a significant impact from an economic point of view; e.g., the robot works at one job in the morning and another in the afternoon. In terms of automation, manufacturing companies have a more significant advantage because they have been involved in automation for a long time. Processes are actively managed, and automation is an integral part of them. They understand and accept automation solutions. A significant factor is also industry benchmarking and market pressure to stay competitive. The key to cognitive automation implementation is the vast amounts of collected data on the process's operation.
9	Energy company; Energy Services; 4508 employees	Director Business Intelligence	Automation is carried out mainly in marketing and CRM, where the results are quickly visible, especially personalized offers. They see great potential in optimizing energy consumption and other resources, where consumption optimization can be carried out fully automated, e.g., water consumption and heating. They are introducing trading automation, but at the stage of partial automation, as there is not enough trust in machine learning technology. Given the value of the transaction, they estimate that full automation poses too much risk. They point out that this barrier makes it possible to achieve a higher degree of automation in engineering as trust in technology is elevated. In the business world, it is not. Here, they see automation primarily as decision support or automated decision-making with human confirmation.

Source: Own work.

All experts describe automation as the result of efforts to optimize processes. All agree that AI facilitates the automation of non-deterministic decisions and data-intensive tasks. Expert 7 emphasizes computer vision for object recognition. Experts 3, 8, and 9 emphasize personalization at scale, anomaly detection in manufacturing, and automated trading and energy consumption regulation, respectively. In financial services, full automation efforts include marketing, specifically customer relationship management, credit scoring, and customer support with conversational interfaces. Most other automation projects are at the level of decision support or selection. For Expert 4, a lack of codified knowledge or process design to develop and train models is the reason for automating knowledge-intensive processes.

Expert 6 sees potential for automation, prediction, anomaly detection, and resource planning but emphasizes the importance of data quality and legal restrictions concerning personal data protection and data exchange between government agencies. Expert 8 describes the higher levels of automation in manufacturing, noting that sensors can gather large amounts of data in process execution and automate more complex processes with higher accuracy. Expert 8 emphasizes robotics opportunities when AI-enhanced robots can learn a task by themselves and can be easily repurposed and, more often, increase efficiency. Expert 9 compares engineering and business tasks, stating that as trust in technology increases, engineering has higher automation potential. Automation of critical business tasks can be at the level of decision support, selection, or supervision and is lower where there is greater risk or higher value transactions. Experts 7 and 9 emphasize the importance of intuition in decision-making and its lack of cognitive automation in decision-making.

4.2.2 Compilation of the Key Attributes and Preliminary Definition

Following Sonenshein, DeCelles, and Dutton (2014), we organize the extracted attributes into five related themes and then aggregate these into three dimensions, as indicated in Table 37: automation, cognitive technologies, and automation scope.

Table 37: Organizing Attributes Into Common Themes

Attributes	First-Order Categories	Second-Order Themes
Independent machine-managed choreography of operations; Reducing human involvement;	Autonomy	Automation
Increases the yield of robotics; Improves efficiency; Reduces the cost	Optimization	
Automating using simulation of human thought processes; Can make human-like intelligent decisions; Continuous self-improvement; Learn from past decisions and outcomes; Leverages domain knowledge and reasoning to automate; Natural interaction with the user	Cognitive capabilities	Cognitive technologies
Extends to areas that were previously unfit for automation; Handles increasingly complex processes and decisions	Complexity	Automation scope
Integrates knowledge from various structured or unstructured sources; Learns and enacts knowledge-intensive processes; Supports knowledge workers	Knowledge-intensity	

Source: Own work.

4.2.3 Refinement of the Definition

Given that CBPA falls within the domain of process automation, we analyze the construct in terms of family resemblance, distinguishing it from other constructs in related areas. The purpose is to generate underlying conceptual attributes, identify the key attributes for each construct, and then identify the shared attributes. We can thus generate a list of attributes unique to CBPA and those shared with other constructs in the related area.

Table 38: Main Findings From Prior Studies on Robotic Process Automation

Source	Conceptualization of Process Automation	Key attributes
"IEEE Guide for Terms and Concepts in Intelligent Process Automation" 2017), Suri et al. (2019), Eikebrokk and Olsen (2020)	A preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management. See also: activity, choreography, business rule, process, service, task, transaction.	Uses business rules and predefined activity choreography to automate; Includes human exception management.
Hull and Motahari-Nezhad (2016)	Basic Process Automation which focuses on the automation of manual tasks through "screen scraping" and application of rules engines on structured data.	Automation of manual tasks; Uses screen scraping and application of rules engines on structured data.

To be continued

Table 38: Main Findings From Prior Studies on Robotic Process Automation (cont.)

Source	Conceptualization of Process Automation	Key attributes
Aguirre and Rodriguez (2017)	RPA emerges as software-based solution to automate rules-based business processes that involve routine tasks, structured data and deterministic outcomes.	Automates rules-based business processes; Routine tasks, structured data and deterministic outcomes.
van der Aalst, Becker, et al. (2018)	RPA aims to support the middle part of the frequency spectrum (between repetitive and ad hoc) by having agents that interact with the different information systems as if they were humans.	Support the middle part of the frequency spectrum (between repetitive and ad hoc)
Chalmers (2018)	RPA is a fascinating concept, in which a computer program is "taught" by a human worker to perform a repetitive software-based task. Conventional RPA systems might use screenshots, optical character recognition, and input device monitoring to record and reproduce a simple sequence of actions as they are performed by a human worker during their normal workflow.	Automation of repetitive software-based tasks.
Ivančić et al. (2019)	According to the findings of the preliminary literature overview, RPA is defined as the application of specific technology and methodologies which is based on software and algorithms aiming to automate repetitive human tasks.	Automation of repetitive human tasks.
Kirchmer and Franz (2019)	RPA is the best fit for repetitive transactional processes with a high transaction volume.	Automation of repetitive transactional processes with a high transaction volume.
Kokina and Blanchette (2019)	Tasks that are labour-intensive, repetitive, high volume, rules-based, and in digital form using multiple systems and structured data are strong candidates for automation with RPA. Furthermore, tasks that require little human interaction to make decisions or tasks that do not require judgment throughout the process tend to be easier to automate.	Automation of labour-intensive, repetitive, high volume, rules-based, digital form using multiple systems and structured data tasks.
Maalla (2019)	RPA adopts human-computer interaction layer automation technology without affecting the existing IT structure of enterprises or organizations.	Human-computer interaction layer automation technology.
Herm et al. (2020)	RPA is a disruptive technology to automate already digital yet manual tasks and subprocesses as well as whole business processes. In contrast to other process automation technologies, RPA only accesses the presentation layer of IT systems and imitates human behaviour.	Accesses the presentation layer of IT systems and imitates human behaviour.
Marciniak et al. (2020)	RPA, automation is performed by a bot that mimics human workers using software such as ERP systems and can already work with semi-structured databases as well. Its operation is not limited to a specific IT application but is able to bridge several different software environments and databases, thereby integrating many fragmented steps of a whole business process. The process becomes robotic as the software bot performs the task through the user interfaces of IT systems like a human by mimicking the human activity step-by-step, but much faster and more accurately.	Uses bots that mimic human workers; Integrates fragmented steps of a whole business process.
Martínez-Rojas, Barba, and Enríquez (2020)	The term RPA refers to a software paradigm where robots are programs which mimic the behavior of human workers interacting with information systems (ISs), i.e. sets of components that perform actions that solve a particular RPA task.	Uses bots that mimic human workers; Interacts with information systems.
Geyer-Klingeberg, Nakladal, Baldauf, and Veit (2018)	RPA is a fast-emerging process automation approach that uses software robots to replicate human tasks.	Uses software robots to replicate human tasks.
Aguirre and Rodriguez (2017)	RPA is an automation technology based on software tools that could imitate human behavior for repetitive and non-value added tasks such as tipping, coping, pasting, extracting, merging and moving data from one system to another.	Software tools that imitate human behaviour; Automates repetitive and non-value added tasks; Merging and moving data from one system to another.
Slaby (2012)	RPA is the technological imitation of a human worker with the goal of automating structured tasks in a fast and cost efficient manner.	Imitation of a human worker; Automating structured tasks; Fast and cost-efficient automation.
Santos, Pereira, and Vasconcelos (2019)	RPA is only suited for processes that are rule-based, because it is executed by a robot that lacks cognitive skills, needing rules in order to successfully execute its tasks. If the process contains a lot of exceptions, it must be handed to workers, increasing process complexity, as robot and human must be synchronized in order execute the tasks sequentially without any mistakes.	Automates rule-based processes; Lacks cognitive skills; Exceptions are handed to workers.
Quinn and Strauss (2017)	Software robots mimic human actions and automate those repetitive tasks via existing user interfaces	It uses software robots that mimic human actions; Automates repetitive tasks via existing user interfaces.

To be continued

Table 38: Main Findings From Prior Studies on Robotic Process Automation (cont.)

Source	Conceptualization of Process Automation	Key attributes
Lacity and Willcocks (2016)	The tools and platforms that deal with structured data, rules-based processes, and deterministic outcome	Automates structured data and rules-based processes with a deterministic outcome.
Wellmann, Stierle, Dunzer, and Matzner (2020)	RPA incorporates different tools and methodologies aiming to automate repetitive and structured service tasks that were previously performed by humans.	Automates repetitive and structured service tasks.
Richardson (2020)	RPA focuses on information work and utilises classical AI. Key characteristics of an RPA include being highly rule-based, standardised and transactional.	Automates rule-based, standardized, and transactional tasks.
Wanner et al. (2020)	RPA builds upon a set of tools that operate virtual robots on the user interface of PAIS in a human manner.	Operates virtual robots on the user interface.
Willcocks (2020)	RPA uses software to automate tasks previously performed by humans that use rules to process structured data to produce deterministic outcomes. It automates the repetitive, largely physical, clerical tasks typical of much office work.	Automates tasks that use rules to process structured data to produce deterministic outcomes; Automates the repetitive, primarily physical, clerical tasks typical of much office work.

Note. Definitions for evolved RPA types like Cognitive/Smart/Intelligent RPA are omitted because they are included in the definitions of CBPA.

Source: Own work.

The literature on business process automation classifies general process and RPA as a form of IPA. We can thus compare CBPA and differentiate it from these concepts. We examine the literature on BPA, process automation, and RPA to combine the key attributes of these. We collect definitions and key attributes of each listed concept from the literature. The results are presented in Table 39.

Following the guidelines of Podsakoff et al. (2016), we describe and then compare the attributes of CBPA (Table 34) and the attributes of process, business process (Table 35), and robotic process (Table 38) automation in an attribute matrix. The results are presented in Table 39.

Table 39: Concepts Shared and Unique Attributes

Attributes	CBPA/CA	Process Automation/ BPA	Cognitive/ Smart/ Intelligent RPA	RPA
Automates human-computer interaction layer			✓	✓
Automates repetitive transactional processes with a high transaction volume			✓	✓
Automates rules-based tasks			✓	✓
Automating using simulation of human thought processes	✓			
Can make human-like intelligent decisions	✓			
Continuous self-improvement	✓			
Deterministic outcomes			✓	✓
Extends to areas that were previously unfit for automation	✓		✓	
Handles increasingly complex processes and decisions	✓			
Human exception management			✓	✓
Improving efficiency	✓	✓	✓	✓
Increases the yield of robotics	✓			
Independent machine-managed choreography of operations	✓	✓	✓	✓
Integrates different information systems		✓	✓	✓
Integrates knowledge from structured sources	✓	✓	✓	✓
Integrates knowledge from various structured or unstructured sources	✓		✓	

To be continued

Table 39: Concepts Shared and Unique Attributes (cont.)

Attributes	**CBPA/CA**	**Process Automation/ BPA**	**Cognitive/ Smart/ Intelligent RPA**	**RPA**
Involves software development	✓	✓		
Learn from past decisions and outcomes	✓			
Learns and enacts knowledge-intensive processes	✓			
Leverages domain knowledge and reasoning to automate	✓			
Natural interaction with the user	✓		✓	
Reducing cost	✓	✓	✓	✓
Reducing human involvement	✓	✓	✓	✓
Supports knowledge workers	✓	✓		
It uses bots that mimic human workers			✓	✓

Source: Own work.

Table 39 illustrates that variants of RPA share attributes related to the ability to process rule-based tasks using structured data sources. They use software robots to automate the human–computer interaction and the results are deterministic.

Cognitive automation and advanced RPA variants also integrate knowledge from unstructured data sources, use natural interaction with the user (e.g., conversational interfaces), and extend the scope of automation to tasks previously unfit for automation. Cognitive and process automation support knowledge workers and involve software development. The concepts all have automation properties and are concerned with implementing independent machine-managed choreography of operations, reducing human involvement to improve efficiency and cost. These are central attributes and are incorporated in the definition of CBPA.

Table 40 summarizes these findings (based on Table 39).

Table 40: Summary of Shared Attributes Between Concepts

Concepts	**Shared attributes**
Cognitive/Smart/Intelligent RPA, RPA	Automates human-computer interaction layer; Automates repetitive transactional processes with a high transaction volume; Automates rules-based tasks; Deterministic outcomes; Human exception management; Uses bots that mimic human workers.
CBPA/CA, Cognitive/Smart/Intelligent RPA	Extends to areas previously unfit for automation; Integrates knowledge from various structured or unstructured sources; Natural interaction with the user.
CBPA/CA, Process Automation/BPA, Cognitive/Smart/Intelligent, RPA	Independent machine-managed choreography of operations; Improving efficiency; Integrates knowledge from structured sources; Reducing cost; Reducing human involvement.
Process Automation/BPA, Cognitive/Smart/Intelligent, RPA	Integrates different information systems.
CBPA/CA, Process Automation/BPA	Involves software development; Supports knowledge workers.

Source: Own work.

During the final stage of the conceptual analysis, we consult subject-matter experts and peers to test the definition and solicit feedback. Next, we present the resulting definition.

4.2.4 Developed definition of the CBPA concept

We develop a definition of CBPA following the suggestions on conceptual development in the literature (MacKenzie et al., 2011; Podsakoff et al., 2016). According to MacKenzie et al. (2011), the definition of a construct must incorporate the "property" characterizing the concept and the "entity" to which that property relates. We define the property "Cognitive Business Process Automation" as *the organization's ability to develop to automate knowledge-intensive (unpredictable, non-repeatable, highly flexible, and complex) business processes using cognitive technologies*. The general property type is intrinsic characteristics and applies to the entity of an organization (Table 41).

Conceptual definition of focal construct: "The automation of knowledge-intensive business processes using cognitive technologies."

Table 41: Factors of Construct Conceptualization

Nature of construct's conceptual domain	Entity = organization; General property = *The organization's ability to automate knowledge-intensive (unpredictable, non-repeatable, highly flexible, and complex) business processes using cognitive technologies.*
Common attributes	Independent machine-managed choreography of operations (Chakraborti et al., 2020; Etscheid, 2019; "IEEE Guide for Terms and Concepts in Intelligent Process Automation," 2017; Kerpedzhiev et al., 2020; Ng et al., 2021b; Sindhgatta et al., 2020a)
	Reducing human involvement (Etscheid, 2019; Marciniak et al., 2020)
	Increases the yield of robotics (Williams et al., 2018)
	Improving efficiency (Chakraborti et al., 2020; Siderska, 2020)
	Reducing cost (Hofmann et al., 2020)
	Can make human-like intelligent decisions (Etscheid, 2019; "IEEE Guide for Terms and Concepts in Intelligent Process Automation," 2017; Keding, 2021; Marciniak et al., 2020; Naidu & Vedavathi, 2019; Richardson, 2020; Rizk et al., 2020; Siderska, 2020; Suri et al., 2019; Zhang, 2019)
Unique attributes/characteristics	Learn from past decisions and outcomes ("IEEE Guide for Terms and Concepts in Intelligent Process Automation," 2017; Marciniak et al., 2020; Ng et al., 2021b; Suri et al., 2019)
	Natural interaction with the user (Suri et al., 2019)
	Extends to areas that were previously unfit for automation (Williams et al., 2018)
	Handles increasingly complex processes and decisions (Marciniak et al., 2020; Richardson, 2020; Romao et al., 2019; Siderska, 2020)
	Integrates knowledge from various structured or unstructured sources (Marciniak et al., 2020; Suri et al., 2019)
	Learns and enacts knowledge-intensive processes (Chakraborti et al., 2020; Hull & Motahari-Nezhad, 2016; Kokina & Blanchette, 2019)
	Supports knowledge workers (Kerpedzhiev et al., 2020; Romao et al., 2019)
Breadth/inclusiveness	Includes all business processes in an organization (Di Ciccio et al., 2015)
Dimensionality	Unidimensional
Stability	Stable across cases
Indicators	Reflective
Model	Principal factor (reflective model; Jarvis et al., 2003); first-order construct

Source: Own work.

As shown through the conceptualization process, CBPA is an extension of the conventional automation concept using AI technology, specifically with the subset of cognitive technologies. These enable the automation of unpredictable, non-repeatable, highly flexible, complex, knowledge and data-intensive tasks and processes. Cognitive automation systems replace human decision-making and learn from past decisions and outcomes to adapt to changing business contexts. They become context-aware and can refine themselves. There is an increase in the level by which human involvement in tasks decreases, limited mainly by trust, bias, and risk issues with the technology itself. Next, we propose a set of items to measure the level and scope of cognitive automation.

4.3 Development of the Measure

The next step was to generate items that fully represent the conceptual domain. We developed items from literature reviews, the theoretical definition of the construct, previous academic research, interviews with experts, and examination of other measures of the construct that already exist (MacKenzie et al., 2011).

4.3.1 Generated Items

The interviews and literature review yielded 25 question items concerning Cognitive Business Process Automation. We combined them based on similarities and statements made in the interviews to produce 14 distinct items (Table 42).

Table 42: Items Generated to Measure CBPA

Items	**Source(s)**
My company incorporates AI or Cognitive technologies and methods to automate business processes.	van der Aalst, Becker, et al. (2018)
It is difficult to automate processes in my company.	Interviews
Our organization continuously implements business process automation using AI or Cognitive technologies.	Interviews
Our organization has automated many business processes using AI or Cognitive technologies over the past three years.	Interviews
What is the relative level of process automation enabled by cognitive technologies in your firm?	
Manual: the automation agent offers no assistance.	Sindhgatta et al. (2020a); Vagia et al. (2016)
Decision Support: the automation agent cannot perform the action but can provide support to the human.	
Decision Selection: the automation agent selects and executes one decision with human approval.	
Supervisory Control: The automation agent carries out the action; the human may intervene if required.	
Full automation: The automation agent carries out the action autonomously.	
What is the extent of automation enabled by cognitive technologies in your firm?	
Structured (static) business processes are automated. *Highly predictable routine work with low flexibility, process logic is known in advance and definable.*	Di Ciccio et al. (2015); Szelagowski and Lupeikiene (2020)
Structured with ad hoc exceptions, business processes are automated. *The occurrence of external events and exceptions can make the structure of the process less rigid.*	
Unstructured with predefined fragment business processes are automated. *Flow can be strictly determined only for fragments that refer to explicit, prescriptive procedures.*	
Loosely structured business processes are automated. *A set of possible activities may be known and predefined, but their execution ordering is not entirely foreseeable.*	
Unstructured business processes are automated. *It is not possible to define the flow before execution.*	

Source: Own work.

4.3.2 Content Validity Assessment of the Items

Next, we assessed the content adequacy of items, the degree to which created items represent the target, and the aspect of the construct (Beck & Gable, 2001). Content validity is based on the judgment of experts regarding the content relevancy of the test domains and the representation of items to their domains (MacKenzie et al., 2011). This study evaluated the items based on their relevance and representativeness. The same procedure as in Section 3.5.2 was used.

Table 43: Acceptable Measure Values for Content Validity

Median	Item Ambiguity	Agreement Percentage	Content Validity Index	Content Validity Ratio	Content Validity Coefficient
2.75+	1, 2 and 3	80%	75%	0,99	0.88

Source: Own work.

We applied descriptive and quantitative approaches to determine the content validity of the items. Out of six, any item that satisfies less than four methods was deleted, and any item that meets more than three methods was retained. Table 43 presents the acceptable values for six methods in this study. The results of the analysis are shown in Table 44. Items 1 and 2 were removed due to having low values for Median, CVI, and VI_k. Item 1 had a value that was too high for Item Ambiguity. Eventually, the final list comprised 12 items and was used for data collection and performing EFA.

Table 44: Results of the Content Validity Analysis

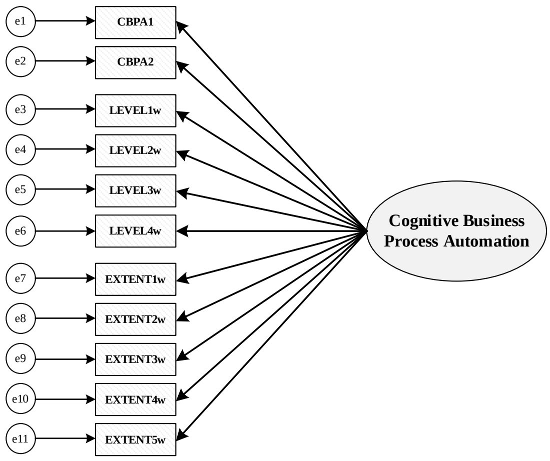
#	Items	Median	IA	AP (%)	CVI (%)	CVR	VI_k	Action
1	My company incorporates AI or Cognitive technologies and methods to automate business processes.	1.50	4.00	100.00	25.00	1.00	0.50	Exclude
2	It is difficult to automate processes in my company.	1.50	2.00	100.00	0.00	1.00	0.38	Exclude
3	Our organization continuously implements business process automation using AI or Cognitive technologies.	4.00	3.00	100.00	75.00	1.00	0.88	
4	Our organization has automated many business processes using AI or Cognitive technologies over the past three years.	4.00	3.00	100.00	75.00	1.00	0.88	
	What is the relative level of process automation enabled by cognitive technologies in your organization?							
5	Manual: the automation agent offers no assistance.	4.00	2.00	100.00	100.00	1.00	0.94	
6	Decision Support: the automation agent cannot perform the action but can provide support to the human.	4.00	2.00	100.00	0.00	1.00	0.94	
7	Decision Selection: the automation agent selects one decision and executes it with human approval.	4.00	1.00	100.00	100.00	1.00	1.00	
8	Supervisory Control: The automation agent carries out the action; the human may intervene if required.	4.00	2.00	100.00	100.00	1.00	0.94	
9	Full automation: The automation agent carries out the action autonomously.	4.00	2.00	100.00	100.00	1.00	0.94	
	What is the extent of automation enabled by cognitive technologies in your organization?							
10	Structured (static) business processes are automated.	4.00	2.00	100.00	100.00	1.00	0.94	
11	Structured with ad hoc exceptions, business processes are automated.	4.00	2.00	100.00	100.00	1.00	0.94	
12	Unstructured with predefined fragment business processes are automated.	4.00	2.00	100.00	100.00	0.50	0.94	
13	Loosely structured business processes are automated.	4.00	2.00	100.00	100.00	1.00	0.94	
14	Unstructured business processes are automated.	4.00	2.00	100.00	100.00	1.00	0.94	

Source: Own work.

4.4 Formal Measurement Model Specification

The reflective indicator measurement model (Figure 15) captures the expected relationships between the generated indicators (Table 51) and the focal construct they are intended to represent.

Figure 15: CBPA – Latent Construct Measurement Model



Source: Own work.

4.5 Scale Purification and Refinement

Similar to Section 3.7, we analyzed the data in three steps. In step 1, we performed a preliminary analysis of the scale by EFA. Step 2 consisted of further validating the factor structure using CFA. For CFA, we used IBM SPSS AMOS version 28. The sample used in the pilot study is described in Section 3.7.1.

4.5.1 Exploratory Factor Analysis

EFA, using the maximum likelihood method with Promax rotation, was used for analyzing the factor structure and correlation between items included in the scale.

A weighted average, otherwise known as a weighted mean, was used for Level and Extent items representing different values relative to each other. A higher Level or Extent has higher values. Weights (values) are presented in Table 51.

Table 45: Pattern Matrix for 2-Factor Solution

Item	Factor 1	Factor 2
CBPA1		0.982
CBPA2		0.942
LEVEL2^{w}	0.148	0.375
LEVEL3^{w}	0.441	0.335
LEVEL4^{w}	0.473	0.199
LEVEL5^{w}	0.452	
EXTENT1^{w}	0.280	0.531
EXTENT2^{w}	0.321	0.499
EXTENT3^{w}	0.773	0.188
EXTENT4^{w}	0.881	
EXTENT5^{w}	0.983	-0.141

Note. ^{w} *= Weighted value*

Source: Own work.

All extracted communalities are at or above 0.35, except item Level 1. The diagonals of the anti-image correlation matrix were all over 0.50, except for item Level 1. Therefore, item Level 1 was removed because of the wording concerning Levels 2 – 5, where Level 1 measures the state of no intelligent agent support. 2 factors were extracted. However, there is a high level of cross-loadings (Table 45), and the Factor Correlation Matrix shows a high correlation between factors > 0,70 (Table 46). Therefore, we accepted a 1-factor solution.

Table 46: Factor Correlation Matrix for 2-Factor Solution

Factor	1	2
1	1.000	0,714
2	0,714	1.000

Source: Own work.

The results of the abridged 1-factor matrix are provided in the following tables.

Table 47: KMO and Bartlett's Test

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy		0.827
Bartlett's Test of Sphericity	Approx. Chi-Square	715.573
	df	55
	Sig.	< 0.001

Source: Own work.

According to Table 47, the KMO value is above 0.50, indicating that sampling adequacy is met. The Bartlett test of sphericity is statistically significant ($p < 0.05$), so it shows that our correlation matrix is statistically different from an identity matrix as desired (Table 47). Extracted communalities are presented in Table 48 and are above 0.40. Exceptions are Level 2 and Level 5, which have low communalities, 0.249 and 0.219. We did not remove them as they are part of the Level Weighted Average Scale.

Table 48: Extracted Communalities

	Communalities	
	Initial	**Extraction**
CBPA1	0.828	0.582
CBPA2	0.797	0.540
LEVEL2^w	0.444	0.249
LEVEL3^w	0.644	0.550
LEVEL4^w	0.703	0.424
LEVEL5^w	0.564	0.219
EXTENT1^w	0.754	0.576
EXTENT2^w	0.748	0.591
EXTENT3^w	0.820	0.808
EXTENT4^w	0.849	0.790
EXTENT5^w	0.791	0.641

Note. ^{w} = Weighted value

Source: Own work.

The diagonals of the anti-image correlation matrix were all over 0.5 (Table 49).

Table 49: Anti-Image Correlation

	CBPA1	CBPA2	LEVEL 2^{w}	LEVEL 3^{w}	LEVEL 4^{w}	LEVEL 5^{w}	EXTENT 1^{w}	EXTENT 2^{w}	EXTENT 3^{w}	EXTENT 4^{w}	EXTENT 5^{w}
CBPA1	**0.756**	-0.762	-0.084	0.067	-0.301	0.301	0.039	-0.042	-0.144	-0.362	0.398
CBPA2	-0.762	**0.768**	0.087	-0.185	0.228	-0.216	-0.130	-0.042	-0.031	0.339	-0.333
LEVEL1^{w}	-0.084	0.087	**0.849**	-0.275	-0.274	0.084	-0.209	0.157	-0.148	0.007	0.205
LEVEL2^{w}	0.067	-0.185	-0.275	**0.934**	-0.155	-0.193	-0.183	0.113	-0.115	-0.031	-0.047
LEVEL3^{w}	-0.301	0.228	-0.274	-0.155	**0.789**	-0.575	0.019	-0.152	0.219	0.073	-0.357
LEVEL4^{w}	0.301	-0.216	0.084	-0.193	-0.575	**0.743**	0.126	-0.048	-0.135	-0.043	0.141
EXTENT1^{w}	0.039	-0.130	-0.209	-0.183	0.019	0.126	**0.850**	-0.659	0.132	-0.176	0.026
EXTENT2^{w}	-0.042	-0.042	0.157	0.113	-0.152	-0.048	-0.659	**0.856**	-0.233	-0.021	0.108
EXTENT3^{w}	-0.144	-0.031	-0.148	-0.115	0.219	-0.135	0.132	-0.233	**0.898**	-0.414	-0.296
EXTENT4^{w}	-0.362	0.339	0.007	-0.031	0.073	-0.043	-0.176	-0.021	-0.414	**0.841**	-0.531
EXTENT5^{w}	0.398	-0.333	0.205	-0.047	-0.357	0.141	0.026	0.108	-0.296	-0.531	**0.791**

Note. ^{w} = Weighted value

Source: Own work.

The results of the exploratory factor analysis presented in Table 50 show that the solution is based on 1 factor, as expected. The one-factor solution explains 54.291% of the total variance with Cronbach's Alpha measure for reliability 0.815.

Table 50: 1-Factor Matrix

	1-Factor
CBPA1	0.763
CBPA2	0.735
LEVEL1^{w}	0.499
LEVEL2^{w}	0.742
LEVEL3^{w}	0.651
LEVEL4^{w}	0.468
EXTENT1^{w}	0.759
EXTENT2^{w}	0.769
EXTENT3^{w}	0.899
EXTENT4^{w}	0.889
EXTENT5^{w}	0.801

Note. ^{w} = Weighted value

Source: Own work.

The results of the EFA show that our factor has a good level of validity.

Table 51: Generated Indicators

Factor	Indicators		Scale
Cognitive Automation Utilization	CBPA1	*Our organization continuously implements business process automation using AI or Cognitive technologies.*	5-point Likert Scale; Scored as 1 - Strongly Disagree, 2 – Disagree, 3 – Neutral., 4 – Agree, 5 - Strongly Agree
	CBPA2	*During the past three years, our organization has automated many business processes using AI or Cognitive technologies.*	5-point Likert Scale; Scored as 1 - Strongly Disagree, 2 – Disagree, 3 – Neutral., 4 – Agree, 5 - Strongly Agree
Level of automation	***What is the relative level of process automation enabled by cognitive technologies in your organization?***		
	LEVEL	*Level of automation (Weighted Average)*	Calculate Weighted Average = LEVEL1 * 0.10 + LEVEL2 * 0.2 + LEVEL3 * 0.3 + LEVEL4 * 0.4
	LEVEL1	*Manual: the automation agent offers no assistance.*	5-point Likert Scale; Scored as 1 - Strongly Disagree, 2 – Disagree, 3 – Neutral., 4 – Agree, 5 - Strongly Agree
	LEVEL2	*Decision Support: the automation agent cannot perform the action but can provide support to the human.*	
	LEVEL3	*Decision Selection: the automation agent selects one decision and executes it with human approval.*	
	LEVEL4	*Supervisory Control: The automation agent carries out the action; the human may intervene if required.*	
	LEVEL5	*Full automation: The automation agent carries out the action autonomously.*	

To be continued

Table 51: Generated Indicators (cont.)

Factor	Indicators		Scale
Extent of Automation	***What is the extent of automation enabled by cognitive technologies in your organization?***		
	EXTENT	*Extent of automation (Weighted Average)*	Calculate Weighted Average = EXTENT1 * 0.05 + EXTENT2 * 0.15 + EXTENT3 * 0.20 + EXTENT4 * 0.25 + EXTENT5 * 0.35
	EXTENT1	*Structured (static) business processes are automated.*	5-point Likert Scale; Scored as 1 - Strongly Disagree, 2 – Disagree, 3 – Neutral., 4 – Agree, 5 - Strongly Agree
	EXTENT2	*Structured with ad hoc exceptions, business processes are automated.*	
	EXTENT3	*Unstructured with predefined fragment business processes is automated.*	
	EXTENT4	*Loosely structured business processes are automated.*	
	EXTENT5	*Unstructured business processes are automated.*	

Source: Own work.

For further validation, we will discuss the CFA results in the following section.

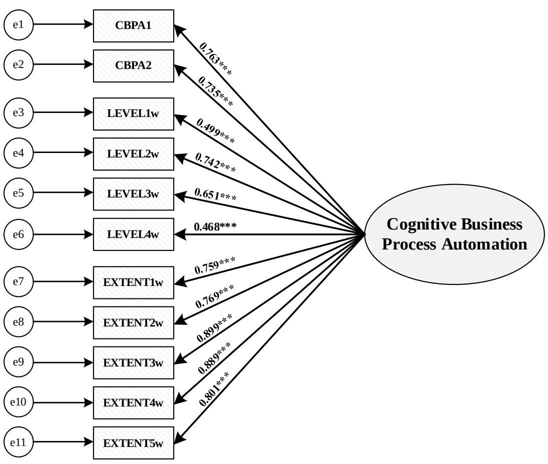
4.5.2 Confirmatory Factor Analysis

We assessed the model for reliability and convergent validity. The graphical representation of the CFA initial model and the final calculated model is followed by results in Table 52.

4.5.2.1 Initial CFA

The results show that the initial CFA model (Figure 16) had a poor model fit: $\chi2/df = 5.402$, GFI = 0.658, AGFI = 0.487, TLI = 0.656, CFI = 0.725, RMSEA = 0.236 (p-close = 0.000), and SRMR = 0.0966 (for the description of Fit Indices, refer to Table 74 or Table 83).

Figure 16: Initial CFA



Source: Own work.

4.5.2.2 *Eliminating Problematic Indicators*

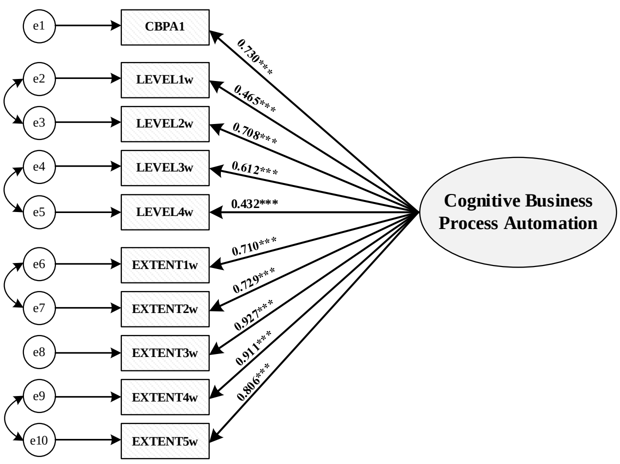
We examined the possibility of removing indicators. Similar to Section 3.7.3.2, we follow the recommendations of MacKenzie et al. (2011).

All loadings are significant and more or near 0.50. Based on Modification indices indicating the change in the Chi-square of model fit, we identified large and significant measurement error covariances between items CBPA1 and CBPA2. As they are very close in wording, we decided to remove CBPA2, as Landis, Edwards, and Cortina (2009) recommended. Also, significant measurement error covariances exist between items LEVEL2-3, LEVEL4-5, EXTENT1-2, and EXTENT4-5. According to Bollen and Lennox (1991), correlated errors are possible among items using similar wordings or appearing near each other on the questionnaire. The items LEVEL and EXTENT are related and part of a progressive scale. Also, they are meant to be parcelled using Weighted Averages. Therefore, we correlated the error terms.

4.5.2.3 *Abridged CFA*

The results show that the abridged CFA model (Figure 17) has a good model fit: $\chi2/df$ = 2.306, GFI = 0.853, AGFI = 0.739, TLI = 0.900, CFI = 0.931, RMSEA = 0.129 (p-close = 0.001), and SRMR = 0.0737. The elevated value of the RMSEA measure is due to the small sample size (Kenny et al., 2015). Consequently, we prefer the abridged model to the initially proposed measurement model.

Figure 17: Abridged CFA



Source: Own work.

4.5.2.4 Assessing Reliability of the Set of Indicators at the Construct Level

All items' standardized factor loading was above 0.40, and AVE was above 0.50. These indicate good convergent validity (Hair Jr et al., 2017). Internal consistency reliability (Cronbach, 1951) is higher than 0,70, and the index of construct reliability is higher than 0,7 (MacKenzie et al., 2011). Results are presented in Table 52.

Table 52: Abridged Model Loadings, Cronbach's alpha, CR, AVE

Construct/ Indicators	Standardized Factor Loadings	Cronbach Alpha	CR	AVE
CBPA		**0.782**	**0.911**	**0.519**
CBPA1	0.730			
LEVEL1[w]	0.465			
LEVEL2[w]	0.708			
LEVEL3[w]	0.612			
LEVEL4[w]	0.432			
EXTENT1[w]	0.710			
EXTENT2[w]	0.729			
EXTENT3[w]	0.927			
EXTENT4[w]	0.911			
EXTENT5[w]	0.806			
Model Fit: $\chi2/df$ = 2.306, GFI = 0.853, AGFI = 0.739, TLI = 0.900, CFI = 0.931, RMSEA = 0.129 (p-close = 0.001), and SRMR = 0.0737				

Source: Own work.

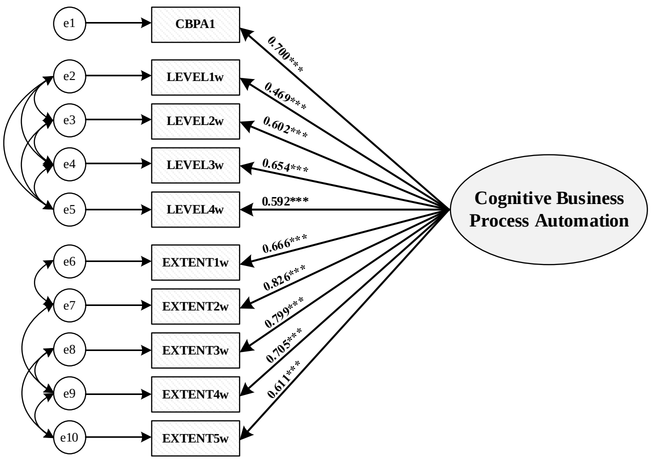
4.6 Validation

Validation was performed on the data collected in the main study. The collected and processed sample consists of 448 EU organizations. A summary of the characteristics of the sample is presented in Table 60.

4.6.1 Confirmatory Factor Analysis

The results show that the abridged CFA model (Figure 18) has a good model fit: $\chi2/df$ = 2.175, GFI = 0.977, AGFI = 0.948, TLI = 0.981, CFI = 0.990, RMSEA = 0.051 (p-close = 0.428), and SRMR = 0.0258. We identified additional significant measurement error covariances between items LEVEL2-4, LEVEL2-5, LEVEL3-4, LEVEL3-5, EXTENT2-4, EXTENT3-4, and EXTENT3-5. According to Bollen and Lennox (1991), correlated errors are possible among items using similar wordings or appearing near each other on the questionnaire. The items LEVEL and EXTENT are related and part of a progressive scale. Also, they are meant to be parcelled using Weighted Averages. Therefore, we correlated the error terms.

Figure 18: Final CFA



Source: Own work.

All items' standardized factor loading was above 0.46, and AVE was 0.449 (Table 53). These indicate good convergent validity (Hair Jr et al., 2017). Internal consistency reliability (Cronbach, 1951) is higher than 0.70, and the index of construct reliability is higher than 0.70 (MacKenzie et al., 2011).

Table 53: Final Model Factor Loadings, Cronbach's alpha, CR, AVE

Construct/ Indicators	Standardized Factor Loadings	Cronbach Alpha	CR	AVE
CBPA		**0.753**	**0.888**	**0.449**
CBPA1	0.700			
LEVEL1^{w}	0.469			
LEVEL2^{w}	0.602			
LEVEL3^{w}	0.654			
LEVEL4^{w}	0.592			
EXTENT1^{w}	0.666			
EXTENT2^{w}	0.826			
EXTENT3^{w}	0.799			
EXTENT4^{w}	0.705			
EXTENT5^{w}	0.611			
Model Fit: $\chi 2$/df = 2.175, GFI = 0.977, AGFI = 0.948, TLI = 0.981, CFI = 0.990, RMSEA = 0.051 (p-close = 0.428), and SRMR = 0.0258				

Source: Own work.

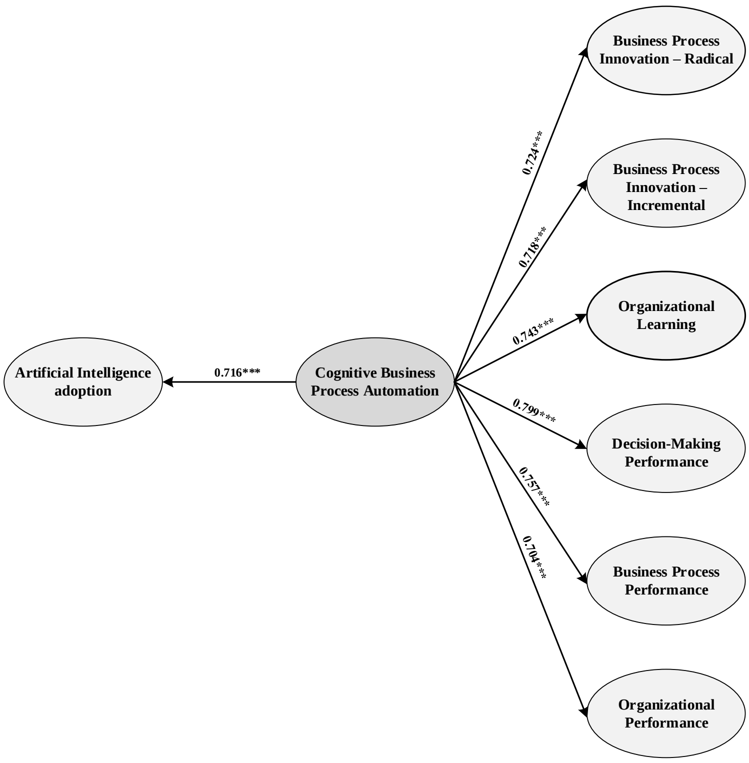
4.6.2 Validity, Reliability and Measurement Model Fit

We assessed the discriminant validity of the construct by testing whether the focal construct is less than perfectly correlated with conceptually similar constructs. Results are presented in Section 6.4.2.

4.6.3 Nomological Validity

Nomological validity was analyzed through SEM between CBPA and other constructs hypothesized to be in its nomological network (Figure 19).

Figure 19: The Results of the Test of Nomological Validity



Source: Own work.

The 90% CI values were scrutinized to assess significance (Hair Jr et al., 2017). The results provide support for nomological validity. CBPA is significantly and positively related to *AI*, *OL*, *BPII*, *BPIR*, *DMP*, *BPP*, and *OP* (Table 54).

Table 54: Nomological Validity Analysis

Path	β	[90% CI]
CBPA → AI	0.716	[0.650, 0.780]
CBPA → BPIR	0.724	[0.653, 0.786]
CBPA → BPII	0.718	[0.657, 0.773]
CBPA → OL	0.743	[0.680, 0.796]
CBPA → DMP	0.799	[0.739, 0.849]
CBPA → BPP	0.757	[0.686, 0.812]
CBPA → OP	0.704	[0.623, 0.773]

Source: Own work.

5 RESEARCH DESIGN AND METHODOLOGY

5.1 Research Design

We empirically examine the research problem using a single primary data source, self-reporting, and a cross-sectional design. The data are collected using an anonymous questionnaire survey that is distributed electronically. The unit of analysis is the organization.

5.2 Sampling Strategy

According to Eurostat (2020), there are 27.9 million active companies in the EU-28. The survey sampling frame consists of participants from the population of companies in the EU-27/28 that use AI in their business processes. In 2020, 7% of enterprises in the EU with at least ten employees used AI applications (Eurostat, 2022). We estimate the sample frame to be 8% (or 2.2 million) active enterprises. We identify a required sample size of 385 with a confidence level of 95% and a margin of error of 5% using proportionate country-stratified random sampling.

Table 55: Proportional Country-Stratified Sampling

Country	**Share in %**
Belgium	2.14
Bulgaria	1.07
Czechia	3.30
Denmark	0.72
Germany	8.38
Estonia	0.29
Ireland	0.83
Greece	2.53
Spain	9.50
France	13.05
Croatia	0.56
Italy	11.51
Cyprus	0.19
Latvia	0.35
Lithuania	0.68
Luxembourg	0.11
Hungary	1.97
Malta	0.12
Netherlands	4.04
Austria	1.29
Poland	6.33
Portugal	2.88
Romania	2.30
Slovenia	0.46
Slovakia	1.60
Finland	0.94
Sweden	2.43
Norway	0.91
Switzerland	1.23
United Kingdom	7.92

To be continued

Table 55: Proportional Country-Stratified Sampling (cont.)

Country	Share in %
Serbia	1.24
Turkey	9.14
Total	*100.00*

Note. Based on the number of active companies (Eurostat, 2020)

Source: Own work.

5.3 Operational Definition of Variables

We measure the adoption of AI using a five-point Likert scale ranging from 1 ("never") to 5 ("always"). The main constructs and moderators – *CBPA, BPI, OL, DMP, BPP, OP DDC, BPMM*, and *Environmental Uncertainty* – are measured on a five-point scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). *DM* (digital maturity) is measured on a five-point scale as follows: 1 ("absence of digital initiatives"), 2 ("planned"), 3 ("just started"), 4 ("under development") and 5 ("developed and ongoing"). We measure *OC* (organizational culture) by asking participants to rate their organizational culture by dividing 100 points over four alternatives corresponding to the four culture types.

5.3.1 Main Constructs

Next, we present the operational definitions of our main research constructs. Specifically, we provide clear definitions of the independent and dependent variables, and mediators.

5.3.1.1 AI Adoption

Conceptual definition: *The implementation, deployment, and use of AI resources (data, AI infrastructure, skills, capabilities) in business processes.*

We conceptualize and operationalize the concept of AI adoption (second-order focal construct with reflective sub-dimensions and reflective indicators) with five underlying sub-constructs: data acquisition and processing, cognitive insight, cognitive engagement, cognitive decision assistance, and cognitive technologies. Items are generated through the literature review, theoretical definitions, interviews with experts, and 1,860 AI-related projects from businesses (MacKenzie et al., 2011). The interviews and literature review yield 28 items representing the key components of AI adoption. After the validation procedure, we retain 15 items, three for each sub-construct.

5.3.1.2 Cognitive Business Process Automation

Conceptual definition: *The automation of knowledge-intensive business processes using cognitive technologies.*

We conceptualize and operationalize CBPA (first-order construct with reflective indicators) with items generated from reviews of the literature (Di Ciccio et al., 2015; Sindhgatta et al., 2020a; Szelagowski & Lupeikiene, 2020; Vagia et al., 2016; van der Aalst, Becker, et al., 2018), interviews with experts, and existing measures of the construct (MacKenzie et al., 2011).

5.3.1.3 Organizational Learning

Conceptual definition: "The organization's capability to maintain or improve performance through the creation, acquisition, sharing, and utilization of knowledge."

Our measure of organizational learning is based on the four items developed by García-Morales et al. (2012). The unidimensional measure emphasizes an organization's capability to maintain or improve performance and includes a measure of knowledge acquisition, sharing, and utilization (DiBella, Nevis, & Gould, 1996). Numerous studies use the scale to measure the effect of organizational learning on organizational performance (Birasnav, Chaudhary, & Scillitoe, 2019; García-Morales et al., 2012; Kılıç & Uludağ, 2021). The measurement scale is only available in English.

The measurement of the organizational learning construct has high validity. The scale development process includes CFA ($\chi2$ = 4.04, RMSEA = 0.05, NFI = 0.99, NNFI = 0.99, CFI = 0.99) and reliability testing (Cronbach's alpha = 0.919).

5.3.1.4 Business Process Innovation - Incremental

Conceptual definition: "The organization's ability to exploit existing processes continuously, consistently, gradually, and on a small scale by improving existing components and architectures."

We adapt the definition and scale from Ng, Rungtusanatham, Zhao, and Lee (2015) to measure incremental business process innovation (*BPII*). The bi-dimensional measure emphasizes the duality of process exploitation, which is characterized by refinement, choice, efficiency, implementation, and execution (Baum, Li, & Usher, 2000; Benner & Tushman, 2001; Dixon, Meyer, & Day, 2007), along with the pursuit of first-order learning (March, 1991). Two subdimensions are "incremental process improvement infrastructure," which is concerned with fostering an atmosphere of improvement, and "incremental process improvement tactics," which are associated with process quality and delivery. The main objective of this study is to investigate the influence of AI on business processes, with a specific emphasis on the impact of AI on process exploitation, which aligns perfectly with our focus. Our scale has been used in studies on business process exploitation, exploration, and organizational performance (Helbin, 2019; Vilkas, Stankevice, Duobiene, & Rauleckas, 2021).

The measurement scale is only available in English. The scale development process followed the standard recommendations for measurement scale development. The authors reported on a check against the content domain, content validity, face validity with subject-matter experts, pilot study, convergent validity, reliability, discriminant validity, criterion validity, exploratory factor analysis (EFA), and CFA.

The construct's measurement has high validity (loadings > 0.55) and reliability (Cronbach's alpha exceeds the suggested value of 0.60; composite reliability greater than 0.72).

5.3.1.5 Business Process Innovation - Radical

Conceptual definition: "The organization's ability to explore new processes by designing and implementing radical new processes at a rapid pace and substantial scale, resulting in significant and transformative change."

We adapt the conceptual definition and the measurement scale from Ng et al. (2015) to measure the BPIR construct. The scope captured in the unidimensional measure emphasizes activities such as search, variation, risk-taking, experimentation, flexibility, discovery, and innovation (Baum et al., 2000; March, 1991). This can lead to second-order learning (March, 1991) that develops entirely new routines (Dixon et al., 2007). This study examines the impact of AI on business processes, particularly in relation to process exploration and the potential for significant improvements. As a result, the proposed measure is a suitable fit for the study's objectives. The scale is used in studies on business process exploitation, exploration, and organizational performance (Helbin, 2019; Vilkas et al., 2021). The measurement scale is only available in English.

The scale development process follows the standard recommendations for measurement scale development reporting on a check against the content domain, content validity, face validity with subject-matter experts, pilot study, convergent validity, reliability, discriminant validity, criterion validity, EFA and CFA.

The construct's measurement has high validity (loadings > 0.55) and reliability (Cronbach's alpha exceeds the suggested value of 0.60; composite reliability greater than 0.72).

5.3.1.6 Decision-Making Performance

Conceptual definition: "The efficiency and effectiveness of the decision-making in an organization."

We measure *DMP* using six items developed by Aydiner, Tatoglu, Bayraktar, and Zaim (2019). They have drawn the construct from previous literature (Gable, Sedera, & Chan, 2008; Huber, 1990; McLaren, Head, Yuan, & Chan, 2011; Mithas et al., 2011; Tippins & Sohi, 2003). The scope captured in the unidimensional measure evaluates the efficiency and effectiveness of the decision-making in an organization. The scale was previously used in decision-making and organizational performance studies (Kullenda, 2020; Yoshikuni & Dwivedi, 2022; Zelenkov, 2022; Zhang, Zhu, et al., 2021).

The measurement scale is available only in the English language.

Measurement of construct DMP has high validity. Aydiner, Tatoglu, Bayraktar, and Zaim (2019) report loading > 0.65, reliability (Cronbach's alpha) 0.85, composite reliability 0.86, and AVE > 0.50.

5.3.1.7 Business Process Performance

Conceptual definition: "The level of efficiency, quality, and flexibility of business processes."

We adopt an existing measurement scale as in Bosilj Vukšić, Pejić Bach, Grublješič, Jaklič, and Stjepić (2017) and Hernaus (2016) to measure the BPP construct. The scale is based on the Devil's Quadrangle (Dumas et al., 2018), which defines the construct's dimensions with lead indicators of efficiency (time, cost), quality, and flexibility. It was developed utilizing items from previous studies about business process orientation (Hernaus, 2012; McCormack et al., 2009; Škrinjar et al., 2008; Škrinjar et al., 2010) and Process Performance Index - PPI ("The Process Performance Index," 2022). We trace the scale development to the original study by McCormack McCormack and Johnson (2001). The scale was further refined by Škrinjar et al. (2008) and is theoretically based on the balanced scorecard model (Kaplan & Norton, 1996).

All studies utilizing the scale were focused on subjective, qualitative measurement of BPM, business process orientation, organizational performance, and process performance in organizations, linking BPM and organizational performance (Hernaus, 2012, 2016; Hernaus, Škerlavaj, & Dimovski, 2008; Hribar & Mendling, 2014; Kohlbacher, 2010; McCormack et al., 2009; McCormack & Johnson, 2001; Miri-Lavassani, 2018; Škrinjar et al., 2008; Škrinjar et al., 2010). As this study researches the same broad BPM context as my thesis, using the existing refined scale is sensible and justified. The measurement scale is only available in English.

The scale development process follows the standard recommendations for scale development reporting on content validity evaluation, pilot studies, sampling and data collection, reliability, EFA, and CFA. Construct BPP measurement has high validity (loadings higher than 0.8) and reliability (Cronbach's alpha around 0.9).

5.3.1.8 Organizational Performance

Conceptual definition: "The organization's operational performance and market performance in relation to its competitors, where operational performance refers to productivity, profitability, and financial indicators, while market performance refers to success in entering new markets and introducing new products or services."

We measure organizational performance using an existing measurement scale developed by Wang et al. (2012) and adapted from Ravichandran, Lertwongsatien, and Lertwongsatien (2005) and Capon, Farley, Lehmann, and Hulbert (1992). This second-order construct consists of two first-order reflective constructs: operational performance and market performance. The measurement of each first-order construct consists of four items. Each item pertains to the extent to which the focal organization exceeds its main competitors in a specific area.

Other studies utilizing the scale are focused on how technology affects organizational performance (Bhatti, Santoro, Khan, & Rizzato, 2021; Gupta & George, 2016; Mehandjiev, 2019; Pinochet, Amorim, Júnior, & de Souza, 2021; Srimarut & Mekhum, 2020; Wamba et al., 2017). IT is central to this study, so using the existing scale is sensible and justified.

Most sampled organizations are predicted to be privately held or state-owned. Our prior experience makes gathering unbiased accounting data on an organization's performance challenging. We, therefore, employed arbitrary, self-reported performance measures. Research on information systems and strategic management establishes a strong correlation between subjective and objective corporate performance metrics (Capon et al., 1992; Ravichandran et al., 2005). Additionally, since our sample includes companies from more than ten industries, the explicit comparison of the performance of competitors offers a way to account for performance variations resulting from industry and strategic group effects (Wang et al., 2012). The measurement scale is only available in English.

Wang et al. (2012) did not report in detail on the scale development process. The authors follow Hinkin (1998) scale development process. The face validity of the items is assessed by an expert panel of three scholars of information systems, five chief information officers, and senior business managers.

Measurement of the construct has high validity (loadings higher than 0.830). The sub-dimension of *Operational Performance* has a Cronbach's alpha coefficient equal to 0.886, composite reliability equal to 0.821, and AVE of 0.537. The *Market Performance* sub-dimension has a Cronbach's alpha coefficient equal to 0.922, composite reliability equal to 0.929, and AVE of 0.765. The authors also report on the CFA; model fit is adequate: $\chi2$ = 46.197, df = 19, $\chi2$/df = 2.431, RMSEA = 0.072, NFI = 0.893, CFI = 0.901, TLI = 0.876, SRMR = 0.068.

5.3.2 Moderators

This section presents an operational definition of the moderators investigated in this study.

5.3.2.1 Digital Maturity

Conceptual definition: "The extent of the learned ability to adapt to ongoing digital changes and digital transformation efforts in an appropriate manner."

We measure *DM* using ten items developed by Salviotti et al. (2019). The result is a quantitative score expressed by the respondent according to the level of development of digital initiatives in the organization. Using a symmetric 5-point Likert scale, each item can assume "1" as the lowest value corresponding to the "absence of digital initiatives" in the activity performed by the organization. Instead, the highest value, "5," corresponds to "developed and ongoing." The measure was not often used in the research. However, it was only published in 2019. The small number of items was the main reason we used the scale to limit the questionnaire length. The measurement scale is only available in English. The process of scale development is not reported in detail. EFA and internal reliability are reported; Cronbach's alpha equals 0.826.

5.3.2.2 Data-Driven Culture

Conceptual definition: A pattern of behavior and practice by a group of people who share a belief that having, understanding, and using certain kinds of data and information plays a critical role in the success of their organization.

We measure whether an organization's culture is data-driven using five items developed by Duan et al. (2020) and based on the existing literature (Davenport, Harris, De Long, & Jacobson, 2001; Kiron et al., 2012; Kiron & Shockley, 2011; LaValle et al., 2011). The unidimensional measure captures the organizational belief, attitude, and behavior toward using insight and information generated from data. The scale is used in studies exploring the relationship between a data-driven culture and performance (Almazmomi, Ilmudeen, & Qaffas, 2021; Chatterjee, Chaudhuri, et al., 2021; Chaudhuri et al., 2021; Kassies, 2021).

The measurement scale is available only in English language. The process of scale development is not reported in detail. We follow the recommendations in Hair Jr et al. (2017) and emphasize high validity. However, data on validity and reliability measures are not presented—other research (Almazmomi et al., 2021; Chatterjee, Chaudhuri, et al., 2021) utilizing the same scale report high validity and reliability.

5.3.2.3 BPM Maturity

Conceptual definition: "The evaluation of the professionalism of an organization's business processes management."

We measure BPM maturity using 15 items developed by Dijkman et al. (2016). They have based the construct on the business process maturity model (Weber, Curtis, & Gardiner, 2008). The measure captures five distinct maturity levels: processes are continuously improved (Level 5 – innovating), processes are managed quantitatively to establish predictable results (Level 4 – predictable), standardized processes are identified throughout the organization (Level 3 - Standardized), management ensures that work within work-units can be performed in a repeatable manner (Level 2 – managed), and work is performed in inconsistent and ad hoc ways (Level 1 – initial). The measurement scale is only available in English.

The scale development process follows the recommendations of Straub, Boudreau, and Gefen (2004). The authors report in detail on a check against the content domain, content validity, face validity pilot study, convergent validity, reliability, discriminant validity, criterion validity, EFA, and CFA. Measurement of the BPM maturity construct has high validity (loadings > 0.77), reliability (Cronbach's alpha exceeds the suggested value of 0.60; composite reliability equal or greater than 0.84), and convergent validity (AVE greater than 0.57).

5.3.2.4 Organizational Culture

Conceptual definition: "The values, beliefs, hidden assumptions, customs, behaviors, and artifacts characterize an organization and influence how its members interact with one another and external stakeholders."

We measure organizational culture using the Organizational Culture Assessment Instrument (OCAI), which has been used in over a thousand organizations and effectively predicts organizational performance (Cameron & Quinn, 2011). The OCAI consists of six questions concerning the following: dominant characteristics, organizational leadership, management of employees, organizational glue, strategic emphases, and criteria of success. Each question has four alternatives (A=Clan, B=Adhocracy, C=Market, D=Hierarchy). Individuals completing the OCAI are asked to divide 100 points among the four alternatives, depending on how each alternative is similar to the organization being assessed. Results of the OCAI survey are obtained by computing the average response scores for each alternative. We examine the resulting cultural dimensions that provide insight into the organization's underlying culture.

The OCAI is available in 19 different languages.

Measurement of the OC construct has high validity. The authors report in detail on reliability and convergent and discriminant validity. Numerous researchers have used the instrument in studies of many different types of organizations. During their analyses, these studies tested the instrument's reliability and validity (Cameron & Quinn, 2011).

5.3.3 Control Variables

Control variables are held constant to eliminate or reduce the influence of alternative explanations for the observed relationship between the independent and dependent variables. The operational definitions of control variables are presented next.

5.3.3.1 Firm Age

Age is measured by the number of years since the organization's establishment.

5.3.3.2 Firm Size

Firm size is measured by the number of employees.

5.3.3.3 Industry

We create a variable based on the NACE-R2 1st-level categories (Eurostat, 2008).

5.3.3.4 Country

We measure Country variable determined by the organization's principal place of business as the EU-27, including Serbia, Norway, Switzerland, the United Kingdom, and Turkey.

5.3.3.5 Environmental Uncertainty

Conceptual definition: "The degree to which a business environment is stable or unstable, simple or complex, and concentrated or dispersed."

We measure the variable *Environmental Uncertainty* using eight items proposed by Rowe, Besson, and Hemon (2017). The authors develop the construct using the construct in Karimi, Somers, and Gupta (2004) which is derived from Miller and Friesen (1983). The construct is presented as unidimensional, although it has three components: 1) dynamism (stability vs. turbulence), which characterizes the rate of change of innovation in production techniques and services as well as in client behavior and needs, 2) heterogeneity (complexity and dispersion) of resources and 3) hostility of the environment (Karimi et al., 2004). The scale is used in studies examining the relationship between environmental uncertainty and IT

(Chang; Liang, Wang, Xue, & Ge, 2017; Zhuang, Zhu, & Sarkis, 2021). The measurement scale is only available in English.

We report convergent validity by assessing factor loadings, internal consistency or CR, and AVE. The measurement of the construct has high validity (loadings higher than 0.860). The sub-dimension has a Cronbach's alpha coefficient greater than 0.80, composite reliability equal to 0.913, and AVE of 0.827.

5.4 Instrument

The survey instrument, a structured online questionnaire, was prepared to measure the constructs from the presented model. Based on previous experiences and recommendations from Brace (2018), we set and followed the following approach.

5.4.1 Design

The key guideline regarding design was one question per page. It has been shown (Van Schaik & Ling, 2007) that respondents complete the questionnaire more quickly with a single question per page. Next, we avoided horizontal scrolling altogether by using a responsive web design. Finally, we only used closed-question styles with strict input validation to reduce missing values. The only missing values come when the respondent gives up and walks away. To minimize the number of clicks, the selection of options is bound to the complete cell area of the matrix. Even if the click of the respondent is not precise, the correct option selection is made. This reduces interface user frustrations and increases the flow of filling in the questionnaire.

5.4.2 Accessibility

The accessibility guidelines (ETSI, 2021; W3C, 2018) we followed ensure the online survey is accessible for different user profiles and on various devices (mobile, tablets, PC) and optimized for maximum user experience. Dialogues were developed on four core principles of accessibility guidelines (W3C, 2018): dialogues must be perceivable, operable, understandable, and robust.

5.4.2.1 Perceivable

For content to be perceivable, users must be able to perceive that the content exists. We achieved this by:

- clear and descriptive headings,
- all text is easily resizable,

- we used descriptive labels and inline[14] instructions,
- we used simple and consistent (previous-next question) navigation,
- we provided text alternatives for any non-text content on the page,
- content is displayed in different ways and different layouts without losing information when showing on various devices and
- when presenting information such as errors while a user fills out a form, we use a combination of color and icons so users can easily distinguish the contextual and error messages.

5.4.2.2 Operable

For a user interface to be operable, users must be able to operate and navigate the site, regardless of whether they use a mouse, keyboard, or touchscreen. We accomplished this by using: Responsive Design[15] and Input Modalities[16].

5.4.2.3 Understandable

For information to be understandable, users must understand the content on the page and how to operate the page. To achieve this, we implemented the following:

- Call-To-Action[17] elements (navigation buttons) with description included,
- Preserve states between, allowing users to navigate between already filled-in dialogue pages,
- additional explanations for all options of questions, provided in the form of a tooltip[18],
- predictable behavior for all website functions, and
- input assistance, such as labels on all inputs, appropriate placeholder text, and filter input to help users avoid and correct mistakes when filling out forms.

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[14] Inline content refers to any content within a document or webpage that is formatted to flow within a line of text.

[15] Responsive design is a web design approach that enables a website to adapt to the screen size and device type of the user. A website designed with responsive design will automatically adjust its layout, content, and functionality to provide an optimal viewing experience for users on different devices.

[16] Users should be able to operate inputs with their keyboard on a desktop/laptop as well as with a touch screen on a mobile device or tablet.

[17] Call-To-Action elements are graphical or textual prompts that encourage users to take a specific action, such as filling out a form. They are designed to be eye-catching and attention-grabbing, using bold colours, prominent placement, and persuasive language to persuade users to act. We use Call-To-Action elements in the form of navigation buttons, links and popups.

[18] A tooltip is a graphical user interface element that provides additional information about an item when the user hovers the cursor over it.

5.4.2.4 Robust

To ensure a website is robust, users must be able to access it on various devices, screen sizes, and browsers, including when using assistive technology. We ensure this robustness by implementing the following features:

- adopting the website layout for different devices and screen sizes: mobile, tablets, or monitors,
- cross-browser support, ensuring the website works on all main web browsers (Edge, Chrome, Firefox, Safari, and Opera) for at least the two previous versions,
- validating HTML, CSS, and JavaScript code to ensure the website is free of errors or inconsistencies,
- using secure protocols (automatically redirecting from HTTP to HTTPS URL address) to protect user data and ensure a secure connection between the user and the server,
- implementing error handling and logging mechanisms to detect and diagnose issues on the website and
- implementing caching mechanisms to improve website performance and reduce server load.

5.5 Methodological Assumptions, Limitations, and Delimitations

The assumptions of the research study, sampling method, and methodology are made before the beginning of data collection. The assumptions represent what the researcher expects to occur or to be true. Limitations represent constraints that restrict the resolution of the results. Delimitations define the scope of the research study and clarify what aspects of the research problem will be included or excluded from the study (Simon, 2011).

5.5.1 Assumptions

We have considered several assumptions recommended by Verma and Abdel-Salam (2019).

a.) The assumption was that participants would be willing to respond openly, honestly, and accurately to structured questions regarding their experiences with adopting AI technology.
b.) The assumption is that the survey sample is representative of the target population and that the results can be generalized to the larger population.
c.) The assumption is that participants' responses will be kept confidential and that individual responses will not be identifiable to anyone outside the research team.
d.) The assumption is that a sufficient number of participants will respond to the survey to obtain meaningful results.
e.) The assumption is that survey questions are clear and understandable to participants and that the meaning of the questions is consistent across participants.

f.) The assumption is that survey questions are relevant to the research question and will provide meaningful data.
g.) The assumption is that survey questions are not biased towards any particular response and that the survey does not influence the participant's responses.
h.) The assumption is that the respondents hardly read the instructions in the questionnaire; hence, the questions should be framed so that the message can be effectively conveyed to the respondents.
i.) The assumption is that the respondents have prior knowledge of the acronyms and jargon used in the survey.
j.) The assumption is that the respondents will receive the survey's feedback, or at least they should be able to see it in the publication.
k.) The assumption is that there is the least nonresponse error.

5.5.2 Limitations

We have considered several limitations that may limit survey results' accuracy, reliability, or generalizability.

a.) Non-response bias can occur when a significant number of survey participants do not respond, and the responses of those who do respond may not represent the target population.
b.) Sampling bias can occur when the survey sample is not representative of the target population, either because of a sampling method that does not accurately reflect the people or because of self-selection bias.
c.) Social desirability bias can occur when participants provide responses that they believe are socially acceptable or desirable rather than reflecting their true thoughts or experiences.
d.) Response bias can occur when participants respond to survey questions in a certain way, such as selecting the same response for multiple questions, regardless of their experiences or opinions.
e.) Measurement bias can occur when the survey questions or response options are not valid or reliable measures of the measured underlying construct.
f.) Question-wording bias can occur when survey questions are worded in a way that influences participants' responses or misrepresents the underlying measured construct.
g.) Limited response options can limit the accuracy and depth of participants' responses and may not fully capture the complexity of their experiences or opinions.
h.) Due to participants not answering all questions, incomplete data can limit the analysis and interpretation of survey results. This might interfere with the representativeness of the sample, mainly if it happened frequently within a study (Coughlan, Cronin, & Ryan, 2009).
i.) Poor response rates in self-administered questionnaires: poor response rates can restrict the generalization of the findings to the population (Coughlan et al., 2009).

Steps were taken to minimize and account for the limitations in the research design and analysis, thus increasing the accuracy and generalizability of the findings.

5.5.3 Delimitations

We have considered several delimitations.

a.) Geographic delimitation: we limited the survey to the EU.
b.) Time delimitation: we limited the survey to a specific period, the year 2022.
c.) Sample delimitation: we limited the sample to EU organizations using AI in their business operations.
d.) Topic delimitation: we limited the sample to organizations using AI in their processes.
e.) Instrument delimitation: we limited the survey to include Likert scale closed questions.
f.) Language delimitation: we limited the survey only to English as validation of the instrument for various European languages would not be feasible. Invitations were sent in specific languages, according to EU countries.
g.) Contextual delimitation: no contextual delimitations were set.

By these delimitations, we clarified the focus and scope of the research.

5.5.4 Visibility

The web page was shared on search engines (i.e., listed in site directories, search engine indexing allowed via robots.txt, and linking from other already indexed sites) and social sites (i.e., LinkedIn, Facebook). We followed the search engine optimization guidelines published by Spencer, Enge, and Stricchiola (2022). Although the original plan was to increase visibility through search engine ads (e.g., Google AdWords), the response on social media sites was substantial enough, eliminating the need for such ads.

The questionnaire is accessible at the URL address: https://www.aibusinessresearch.eu.

5.5.5 Content

We followed the guidelines from Brace (2018) for the design and layout of the questions.

a.) Ask one question at a time using direct language
b.) Keep them short and easy to understand
c.) Speak your respondents' language
d.) Explain random questions
e.) Don't use leading questions
f.) Avoid double-barreled questions
g.) Avoid prestige bias
h.) Don't use absolutes

i.) Don’t mix your question types
j.) Question sequence: follow a logical order; start with broad and general questions that qualify the respondent and introduce the topic, move into more specific questions

After the initial questionnaire test, we reduced the length using shorter scales for *OL* and *DM*.

5.5.6 Communication and Navigation

On the landing page, we outlined the survey’s purpose to respondents and set and advertised expectations for the survey duration to 30 minutes.

The percentage progress indicator is shown throughout the whole questionnaire (all pages). To increase the response rate, we split the questionnaire into two parts. The first part included demographics and main construct measures. The second part consists of the moderators and control variable Environmental Uncertainty. The progress indicator gets reset after the first part. After the first part, an additional invite page is displayed to engage respondents in completing the questionnaire. Respondents can navigate between questions backward but not forward. They can change their responses at any time until they complete the questionnaire.

Direct communication was also provided: respondents can read about the research and contact the researcher via LinkedIn and email.

5.5.7 Engagement: Personalization and Gamification

The questionnaire is anonymous. However, we personalize the result report. After respondents finish the questionnaire, we prepare a PDF preliminary report with personalized results (an example included in Appendix 2) on AI maturity (Büschgens, Bausch, & Balkin, 2013; Jaaksi, Koskinen, & Jalava, 2018; Pringle & Zoller, 2018) of the organization. The report is presented as an incentive for respondents to complete the questionnaire. The report is sent to the respondent's email address or can be downloaded on the thank you page.

A motivational message with animation is displayed after every set of content-related pages to keep the respondents engaged. Also, we included game design elements (Prott & Ebner, 2020; Schacht, Keusch, Bergmann, & Morana, 2017), specifically badges and visual representations of achievement of completing a questionnaire section. Badges have motivational value, allowing the respondents to align themselves with the researcher's goal to get a completed questionnaire. They also indicate how the questionnaire is structured and present an alternative progress indicator.

To prevent respondents from leaving the questionnaire page, we used Exit Intent. An Exit Intent is an event in a web browser triggered when the user moves the mouse to the upper corner to close the tab or window. When triggered, a message with a modal dialogue and a motivational message to complete the questionnaire or resume it later is displayed.

Also, respondents have options on every questionnaire page to save the location and resume later. To continue, they can send the URL to their email address or copy the URL response.

5.5.8 Privacy and General Data Protection Regulation

In the published document about privacy and General Data Protection Regulation (GDPR; document included in Appendix 2), we justify requests for sensitive information (email address) and ensure the respondents about GDPR compliance. The document contains information about cookies, personal data, use and storage of data, data processing, transfer of data to third parties or countries, data protection, deletion, correction, or access to personal and survey data, and contact information in the case of privacy issues.

Next, we present the complete questionnaire.

5.5.9 Measurement of Survey-Based Constructs

The questionnaire is in English language. The online questionnaire was divided into two parts to increase the number of fully completed questionnaires and motivate participants. The first part focuses on survey-based constructs relevant to the serial multiple-mediation model (Table 56), followed by a thank you message and an invitation to continue to the second part, which pertains to survey-based constructs relevant to the moderating and control variables (Table 57).

Table 56: Measurement of Survey-Based Constructs (1st Part)

Construct	**Items**	**Source(s)**
Artificial Intelligence adoption (*AI*)	*Please identify the relative use of AI applications in your organization using a 5-points Likert scale (ranging from 1= "never" to 5 = "always").*	Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019); Bawack et al. (2019); Davenport and Ronanki (2018); Dunston and Wang (2005); Farshid et al. (2018); Heimbach et al. (2015); Kelly (2015); Kuhn and Johnson (2013); Phillips-Wren (2012); Prieto (2019); Roeglinger et al. (2018); Schatsky et al. (2014); Suvetha et al. (2018); Tavana et al. (2016); Taylor (2011); Zasada (2019)
Data acquisition and processing (*DACQ*)	Data warehousing	
	Data Lake	
	Data Capturing System	
Cognitive Insight (*CI*)	Marketing Automation	
	Marketing Intelligence System	
	CRM and CX System	
Cognitive Engagement (*CE*)	Conversational AI	
	Personalization and Recommendation System	
	Computer Vision	
Cognitive Decision Assistance (*CDA*)	Decision Automation System	
	Knowledge Engineering and Expert Systems	
	Decision Support System	
Cognitive Technologies (*CT*)	Predictive Modeling and Analytics	
	Anomaly and Deviant Behavior Detection	
	Machine learning	

To be continued

Table 56: Measurement of Survey-Based Constructs (1st Part) (cont.)

Construct	Items	Source(s)
Cognitive Business Process Automation (*CBPA*)	*What is the relative level & extent of Cognitive/AI technologies used in your organization? A 5-points Likert scale (1 = "strongly disagree" to 5 = "strongly agree")*	Di Ciccio et al. (2015); Sindhgatta et al. (2020a); Szelagowski and Lupeikiene (2020); Vagia et al. (2016); van der Aalst, Becker, et al. (2018)
Level	Decision Support: the automation agent cannot perform the action but can provide support to the human	
	Decision Selection: the automation agent selects one decision and executes it with human approval	
	Supervisory Control: The automation agent carries out the action; the human may intervene if required	
	Full automation: The automation agent carries out the action autonomously	
Extent	Structured (static) business processes are automated	
	Structured with ad hoc exceptions business processes are automated	
	Unstructured with predefined fragment business processes are automated	
	Loosely structured business processes are automated	
	Unstructured business processes are automated	
Organizational Learning (*OL*)	*Please, indicate to what extent you agree/disagree with the following statements using a 5-point Likert scale (1 = "strongly disagree"to 5 = "strongly agree").*	García-Morales et al. (2012)
	Our organization has acquired and used much new and relevant knowledge that has provided a competitive advantage over the last 3 years.	
	Our organization's members have acquired some critical capacities and skills that have provided a competitive advantage over the last 3 years.	
	Organizational improvements have been influenced fundamentally by new knowledge entering our organization over the last 3 years.	
	Our organization is a learning organization.	
Business Process Innovation – Incremental (*BPII*)	*Please, indicate to what extent you agree/disagree with the following statements using a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Adopted from Ng et al. (2015)
Incremental process improvement I	We run process improvement projects on a continual basis.	
	We encourage front-line employees to participate in process improvement teams.	
	We implement process improvement in a gradual way.	
Incremental process improvement II	We seek ways to simplify existing processes.	
	We continuously reduce process variation, even if it is already at an acceptable level.	
Business Process Innovation – Radical (*BPIR*)	*Please indicate to what extent you agree/disagree with the following statements using a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Adopted from Ng et al. (2015)
	When improving, we usually design and implement a totally new process.	
	We implement radical and newly designed processes.	
Decision-making Performance (*DMP*)	*Please indicate to what extent you agree/disagree with the following statements using a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Aydiner, Tatoglu, Bayraktar, and Zaim (2019)
Decision efficiency	Our organization has a culture to facilitate long-term strategic planning.	
	Our organization reduces the time required to make a decision.	
	Our organization's organizational intelligence is designed to ensure accurate and comprehensive information on time.	
Decision effectiveness (quality)	Our organization makes strategic decisions effectively.	
	Decisions are more consistent between various departments in our organization.	
	Our organization communicates the results of organizational-level analysis to workgroup and/or functional level operations to enable effective support for decision-making.	

To be continued

Table 56: Measurement of Survey-Based Constructs (1st Part) (cont.)

Construct	Items	Source(s)
Business Process Performance (*BPP*)	*Please indicate to what extent you agree/disagree with the following statements using a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Bosilj Vukšić et al. (2017)
	The efficiency of our processes is high above the average of the industry.	
	The quality of our processes is well above the average of the industry.	
	The flexibility of our processes is high above the average of the industry.	
Organizational Performance (*OP*)	*Please indicate to what extent you agree/disagree with the following statements using a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Wang et al. (2012)
Operational Performance	... our productivity has exceeded that of our competitors.	
	... our profit rate has exceeded that of our competitors.	
	... our ROI (return on investment) has exceeded that of our competitors.	
	... our sales revenue has exceeded that of our competitors.	
Market Performance	... we have entered new markets more quickly than our competitors.	
	... we have introduced new products or services to the market faster than our competitors.	
	... our level of success with new products or services has been higher than our competitors.	
	... our market share has exceeded that of our competitors.	

Source: Own work.

Table 57: Measurement of Survey-Based Constructs (2nd Part)

Construct	Items	Source(s)
Digital Maturity (*DM*)	*Our organization has initiated or planned digitization initiatives, and in which phase are they positioned? A 5 points Likert scale (1 = "Absence of digital initiatives", 2 = "Planned", 3 = "Just started", 4 = "Under development", 5 = "Developed and ongoing").*	Salviotti et al. (2019)
	IT Infrastructure	
	Human resource management	
	Research and Development	
	Administration, finance and control	
	Procurement	
	Inbound logistics	
	Operations	
	Outbound logistics	
	Marketing and sales	
	Post-sales services	
Data-Driven Culture (*DDC*)	*Please, indicate to what extent you agree/disagree with the following statements using a 5 points Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Duan et al. (2020)
	We believe that having, understanding and using data and information plays a critical role.	
	We are open to new ideas and approaches that challenge current practices on the basis of new information.	
	We depend on data-based insights to support decision-making.	
	We use data-based insights for the creation of new services or products.	
	Individuals need data to make decisions.	

To be continued

Table 57: Measurement of Survey-Based Constructs (2nd Part) (cont.)

Construct	Items	Source(s)
Business Process Management Maturity (*BPMM*)	*Please, indicate to what extent you agree/disagree with the following statements using a 5 points Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Dijkman et al. (2016)
Level 1 (Initial)	Formal procedures for the execution of processes do not exist in our organization.	
	If procedures are defined, they are rarely followed	
	Everybody executes tasks in their own way; in other words: everybody has their own methods.	
Level 2 (Managed)	At the beginning of a project, we agree on which methods and technology we will use.	
	If we make agreements about work methods, they will be documented so that they can be executed similarly at another time.	
	We use planning and management procedures to control our projects.	
Level 3 (Standardized)	Procedures are standardized for the whole organization.	
	Work procedures and objectives are well documented in our whole organization.	
	Processes are defined such that they will be in the same way by different work groups.	
Level 4 (Predictable)	Performance is managed statistically (e.g. by measuring KPIs) to understand performance and to control variation.	
	Processes/tasks are managed in such a way that they meet agreed-upon performance and quality goals.	
	If processes do not perform according to predefined standards, they are corrected to meet the quantitative goals.	
Level 5 (Innovating)	Our organization understands its critical business issues and areas of concern by using feedback from performance measurements.	
	Our organization sets quantitative improvement goals to reorganize processes when perceived as necessary constantly.	
	We constantly pilot new ideas and new technologies to improve our processes.	
Organizational Culture (*OC*)	*Divide 100 points among these four alternatives depending on how much each alternative is similar to your organization. Give more points to the option that is most similar to your organization.*	Cameron and Quinn (2011)
Dominant Characteristics	The organization is a very personal place. It is like an extended family. People seem to share a lot of themselves.	
	The organization is a dynamic and entrepreneurial place. People are willing to stick their necks out and take risks.	
	The organization is very results oriented. A major concern is with getting the job done. People are very competitive and achievement-oriented.	
	The organization is a very controlled and structured place. Formal procedures generally govern what people do.	
Organizational Leadership	The leadership in the organization is generally considered to exemplify mentoring, facilitating, or nurturing.	
	The leadership in the organization is generally considered to exemplify entrepreneurship, innovation, or risk-taking.	
	The leadership in the organization is generally considered to exemplify a no-nonsense, aggressive, results-oriented focus.	
	The leadership in the organization is generally considered to exemplify coordinating, organizing, or smooth-running efficiency.	
Management of Employees	The management style in the organization is characterized by teamwork, consensus, and participation.	
	The management style in the organization is characterized by individual risk-taking, innovation, freedom, and uniqueness.	
	Hard-driving competitiveness, high demands, and achievement characterize the management style in the organization.	
	The management style in the organization is characterized by the security of employment, conformity, predictability, and stability in relationships.	

To be continued

Table 57: Measurement of Survey-Based Constructs (2^{nd} Part) (cont.)

Construct	Items	Source(s)
Organizational Glue	The glue that holds the organization together is loyalty and mutual trust. Commitment to this organization runs high.	Cameron and Quinn (2011)
	Its commitment to innovation and development is the glue that holds the organization together. There is an emphasis on being on the cutting edge.	
	The glue that holds the organization together emphasises achievement and goal accomplishment.	
	The glue that holds the organization together is formal rules and policies. Maintaining a smooth-running organization is important.	
Strategic Emphases	The organization emphasizes human development. High trust, openness, and participation persist.	
	The organization emphasizes acquiring new resources and creating new challenges. Trying new things and prospecting for opportunities are valued.	
	The organization emphasizes competitive actions and achievement. Hitting stretch targets and winning in the marketplace are dominant.	
	The organization emphasizes permanence and stability. Efficiency, control and smooth operations are important.	
Criteria of Success	The organization defines success based on human resources development, teamwork, employee commitment, and concern for people.	
	The organization defines success based on having the most unique or newest products. It is a product leader and innovator.	
	The organization defines success based on winning in the marketplace and outpacing the competition. Competitive market leadership is key.	
	The organization defines success based on efficiency. Dependable delivery, smooth scheduling and low-cost production are critical.	
Environmental Uncertainty (*EU*)	*Please, indicate to what extent you agree/disagree with the following statements using a 5 points Likert scale (1 = "strongly disagree" to 5 = "strongly agree").*	Rowe et al. (2017)
Environmental dynamism	Your competitive environment has become far more unpredictable.	
	Clients' tastes and preferences in your main economic sectors have become far more unstable.	
	Your primary sector's innovation rate for new operational processes, products, and services has increased considerably.	
	Your principal economic sector's downswings and upswings have become far more unpredictable.	
Hostility	Your competitive environment has become far more hostile.	
	Multidimensional competition (prices, supply chain, talent, services, image, reputation) threatens your company's survival.	
Heterogeneity	Diversity in your production/service methods required to deal effectively with your clients has increased considerably.	
	The diversity in your marketing tactics required to deal effectively with your clients has increased considerably.	

Source: Own work.

5.6 Data Collection

We use a single-source, self-reporting, cross-sectional design to gather the data used in the analysis. The data are collected through an anonymous questionnaire (in English) distributed electronically. The participants were identified using the LinkedIn Pro Subscription and ZoneFiles.io Active Business Domains by Country Code.

5.6.1 LinkedIn Pro Subscription Source

On LinkedIn, we targeted chief experience officers, senior business managers, IT directors and managers, business process architects, BPM consultants, business analysts, chief process officers, chief digital and data officers, and other senior business decision-makers or people directly involved with executing AI strategy in the organization. We target only individuals related to EU organizations using LinkedIn Pro Subscription Search services. Filtering by other organization characteristics (size, age, revenue) was unavailable in search services and was not necessary according to the sampling frame. Using the LinkedIn profile of the thesis author (Aleš Zebec), we sent 1,815 direct connection requests (Table 58). Eventually, we connected with 1,400 individuals and sent direct message invitations to participate in English. The 1,400 invitations are included in the overall proportional country-stratified sampling percentages (Table 55). We could not calculate the response rate or separate the responses by this source as the questionnaire is anonymous; we did not include any identification data.

Table 58: LinkedIn Pro Subscription Individual Requests

Country	**Num. of requests**
Austria	93
Belgium	95
Bulgaria	45
Croatia	49
Cyprus	58
Czech Republic	70
Denmark	261
Estonia	6
Finland	93
France	53
Germany	111
Greece	99
Hungary	33
Ireland	13
Italy	148
Latvia	5
Lithuania	33
Luxembourg	8
Malta	39
Netherlands	46
Poland	80
Portugal	83
Romania	114
Serbia	4
Slovakia	10
Spain	89
Sweden	64
Norway	1
Switzerland	5
United Kingdom	3
Other	4
Total	*1,815*

Source: Own work.

5.6.2 ZoneFiles.io Source

From ZoneFiles.io, we compiled a list of domain names for EU countries (.at, .be, .bg, .cy, .cz, .de, .dk, .ee, .es, .fi, .fr, .gr, .hr, .hu, .ie, .it, .lt, .lu, .lv, .mt, .nl, .pl, .pt, .ro, .rs, .se, .sk, .tr) in addition to .eu, .ai, .io, and .digital. Excluded were domains not having a valid MX record (related to a mail server). Invitations were sent to public email addresses of the organizational domain names. Table 59 shows a proportional country-stratified sampling of randomly selected email invites (domains). Although domains were selected randomly, additional randomization comes from the inability to receive emails or rejections (user unknown or non-response). Email invitations were sent indiscriminately because we could not isolate the sampling frame (organizations adopting AI). Therefore, from 4,324,606 sent invites, 8% ~ 345,968 could be considered related to the sampling frame (Section 5.2), i.e., the Eurostat (2022) report identified 7% (we used adjusted 8%) of EU organizations use AI in their business processes.

Table 59: Domain-Based Random Selection of Sent Invites

Domain	Public email addresses	Invite language	Randomly selected sent invites
eu	admin, billing, careers, contact, hello, info, partners, press, support	English	356.402
ai	contact, hello, info, press, support	English	119.590
io	contact, hello, info, press, support	English	88.977
digital	info	English	27.493
at	info	*German*	43.900
		English	23.350
be	info	English	95.225
bg	info	English	14.602
cy	info	English	1.524
cz	info	English	122.067
de	info	*German*	585.708
		English	499.908
dk	info	*Danish*	52.305
		English	27.761
ee	info	English	19.951
es	info	*English*	99.479
		Spanish	95.441
fi	info	English	52.405
fr	contact, contact, info, support	*French*	633.601
		English	24
gr	info	English	34.922
hr	info	English	17.824
hu	info	*Hungarian*	49.517
		English	3.202
ie	info	English	54.512
it	amministrazione, info	*English*	73.768
		Italian	170.026
lt	info	English	30.281
lu	info	English	7.936
lv	info	English	13.363
mt	info	English	1.076
nl	contact, info, planning, sales, secretariaat, service, support	*English*	223.272
		Dutch	171.381
pl	info	*Polish*	98.290
		English	52.586
pt	info	*English*	27.779
		Portuguese	19.590
ro	info	English	96.224
rs	info	English	18.062
se	info	*Swedish*	93.443
		English	50.414

To be continued

Table 59: Domain-Based Random Selection of Sent Invites (cont).

Domain	Public email addresses	Invite language	Randomly selected sent invites
sk	info	*Slovak*	28.180
		English	1.957
tr	info	*Turkish*	17.604
		English	9.392

Source: Own work.

5.6.3 Email Invitations

Email invites (copy included in Appendix 2) were sent in four waves from March 2022 to June 2022 at the start of the month. Levene's test for equality (or homogeneity) of variances indicates that there is not a significant difference in terms of homogeneity of variances between the early and late responses (details in Section 6.4.6).

Reminders were sent only to the LinkedIn contacts. Email invites were translated into 12 different languages and distributed accordingly: Danish, Dutch, French, German, Hungarian, Italian, Polish, Portuguese, Slovak, Spanish, Swedish, and Turkish. Due to the invitations being sent to public email addresses, we asked the contact person to forward the invite to the Business Intelligence, Analytics, or IT department or a specific person like the Chief Information Officer, Chief Digital or Data Officers, Head of IT, Business Intelligence, Analytics, or AI department, etc. Accordingly, the primary informants of the questionnaires submitted were senior, executive, and middle managers since they were most familiar with the current state of AI adoption. There were 1,392 questionnaires submitted, of which 448 were usable, i.e., fully completed.

5.7 Sample Characteristics

The collected and processed sample consists of 448 EU organizations[19]. A summary of the sample's characteristics is presented in Table 60. Sample representativeness was accessed with business size, industry sector (NACE_R2), years in business (age), and country/GEO.

According to the information in Table 60, we conclude the sample is representative of the sample frame and the population. 76.34% of respondents were senior/executive managers, and 18.75% were middle/first-line managers. The remaining 4.91% were engineers or consultants. 28.35% were at the organizations longer than 14 years, and 18.75% were present for less than two years. The rest were present for more than three years. This indicates the respondents had considerable knowledge of the organization's operations due to their tenure. The sample characteristics suggest that larger organizations may have more resources and

[19] Since the survey was anonymous and compliant with GDPR (Sections 5.5.8 and 5.8), no identifiable data was included in the invitations. Consequently, it was not possible to distinguish between participants from LinkedIn and ZoneFiles.io.

incentives to invest in AI. Still, they face more challenges and complexity in scaling up AI across their functions. Kazakova et al. (2020) identify strict standards for data exchange (e.g., data protection laws) and lack of access to high-quality private data as major barriers. Smaller organizations may have fewer resources and incentives, but they also have more flexibility and agility to experiment with AI solutions and leverage cloud-based platforms and services. The leverage of cloud-based platforms and services is likely the reason (Kazakova et al., 2020) that in our sample, 47.10% were represented by organizations with less than ten employees, where 90.5% of the respondents were executive managers. The majority of them, 25.1% from IT, 30.8%, 19.9% from services, scientific and technical activities (e.g., legal and accounting services, architectural and engineering services, technical testing and analysis services, advertising and market research services, scientific research and development services, veterinary services, computer programming, and consultancy services, translation and interpretation services, photography and graphic design services, and consulting and management services). 59.38% of organizations have been in business for more than ten years. 40.62% less than ten years and 20.98% less than five years. This can be considered a mix of established and relatively new organizations. Similarly, 55.4% make less than 1 million in revenue and 44.6% more, consistent with the organization's size distribution. The number of respondents per country is consistent with the Proportional Country-Stratified Sampling percentages used in the study.

Table 60: Characteristics of the Sample

Characteristics		**Number**	**%**
Respondent's position	Senior/executive manager	342	76.34
	Middle/first line manager	84	18.75
	Other: *Data Analyst, AI Engineer, Data Engineer, Software Developer, IT Specialist, Scientist, Consultant, Statistician*	22	4.91
Respondent's time at the organization	0 - 2 years	84	18.75
	3 - 5 years	99	22.10
	6 - 9 years	80	17.86
	10 - 14 years	58	12.95
	More than 14 years	127	28.35
Organization size	Micro: with less than 10 persons employed	211	47.10
	Small: with 10-49 persons employed	112	25.00
	Medium-sized: with 50-499 persons employed	79	17.63
	Large: with 500 or more persons employed	46	10.27
Organization age (years of operation)	< 5 years	94	20.98
	5 - 10	88	19.64
	11 - 30	153	34.15
	31 - 50	60	13.39
	> 50	53	11.83
Annual revenue (EUR)	< €10.000	32	7.14
	€10.000 - €24.999	27	6.03
	€25.000 - €49.999	27	6.03
	€50.000 - €99.999	21	4.69
	€100.000 - €199.999	44	9.82
	€200.000 - €499.999	52	11.61
	€500.000 - €599.999	13	2.90
	€600.000 - €999.999	32	7.14
	€1 million - €2.5 million	43	9.60
	€2.5 million - €5 million	37	8.26
	€5 million - €10 million	16	3.57
	€10 million - €20 million	14	3.13
	€20 million - €30 million	6	1.34
	€30 million - €50 million	11	2.46
	> €50 million	31	6.92

To be continued

Table 60: Characteristics of the Sample (cont).

Characteristics		Number	%
	Not sure	42	9.38
Industry sector	Agriculture, forestry and fishing	14	3.13
	Mining and quarrying	3	0.67
	Manufacturing	25	5.58
	Electricity, gas, steam and air conditioning supply	8	1.79
	Water supply; sewerage, waste management and remediation activities	4	0.89
	Construction	13	2.90
	Wholesale and retail trade; repair of motor vehicles and motorcycles	25	5.58
	Transportation and storage	9	2.01
	Accommodation and food service activities	10	2.23
	Information and communication	94	20.98
	Financial and insurance activities	33	7.37
	Real estate activities	7	1.56
	Professional, scientific and technical activities	58	12.95
	Administrative and support service activities	12	2.68
	Public administration and defence; compulsory social security	11	2.46
	Education	15	3.35
	Human health and social work activities	19	4.24
	Arts, entertainment and recreation	16	3.57
	Other service activities	72	16.07
Country/GEO	Austria	11	2.46
	Belgium	9	2.01
	Bulgaria	8	1.79
	Croatia	15	3.35
	Cyprus	2	0.45
	Czech Republic	16	3.57
	Denmark	3	0.67
	Estonia	7	1.56
	Finland	7	1.56
	France	31	6.92
	Germany	96	21.43
	Greece	12	2.68
	Hungary	10	2.23
	Ireland	11	2.46
	Italy	49	10.94
	Latvia	1	0.22
	Luxembourg	2	0.45
	Malta	3	0.67
	Netherlands	47	10.49
	Poland	15	3.35
	Portugal	8	1.79
	Romania	6	1.34
	Serbia	12	2.68
	Slovakia	13	2.90
	Slovenia	4	0.89
	Spain	13	2.90
	Sweden	4	0.89
	Norway	2	0.45
	Switzerland	2	0.45
	United Kingdom	5	1.12
	Turkey	7	1.56
	Other	17	3.79

Source: Own work.

5.8 Ethical Considerations

This study complied with the University of Ljubljana, School of Economics and Business) research ethics policy ("Code of ethics of the Faculty of Economics of the University of Ljubljana," 2012).

The survey instrument was anonymous and included a Data Protection Notice. The notice explained collecting personal data, storing and processing data, data protection and deletion. The notice is included in Appendix 2. The invitation letter (also included in Appendix 2) and the introduction page of the survey described the study, including the expected duration and the number of pages. Participants could decline participation in the study and withdraw at any time during the survey.

6 ANALYSIS

The section includes a description and the results of the statistical data analysis. It covers various aspects, such as data screening, variable selection, exploratory data analysis, confirmatory factor analysis, and structural model evaluation.

6.1 Case Screening

We evaluated cases for relevance based on specific criteria and considered issues such as missing data, unengaged responses, and outliers.

6.1.1 Missing Data in Rows

From 1,392 cases, we removed 933 due to missing data over 20%.

6.1.2 Unengaged Responses

Using the STDEV.P function (Calculates standard deviation based on the entire population), we removed 8 cases due to being unengaged (they answered somewhat the same to every Likert scale item) with values less than 0.45.

6.1.3 Outliers

We are not using any continuous variables. Therefore, there are no outliers.

6.2 Variable Screening

The section provides results on evaluating data for missing values in columns and skewness and kurtosis.

6.2.1 Missing Data in Columns

We observed six missing values in the Country/GEO column. We extracted the values from resolving public IP addresses of the participants to impute the missing values.

6.2.2 Skewness and Kurtosis

To check the normality, this study applied the statistical method of Skewness and Kurtosis (Hair, Black, Babin, & Anderson, 2013; Kline, 2015; Tabachnick & Fidell, 2012). However, Tabachnick and Fidell (2012) state that deviation from the normality of Skewness and Kurtosis often makes no substantive difference in the analysis when the samples are more than 200. Additionally, following an argument of Kline (2015), the absolute value of Skewness greater than 3 and a Kurtosis value greater than 10 may indicate a problem, and values above 20 may indicate a more severe problem. Hence, it was suggested that the absolute value of Skewness and Kurtosis should not be greater than 3 and 10. Based on this recommendation, the absolute values of the Skewness and Kurtosis of all the items in this study are within the acceptable range of < 3 and < 10, respectively. Skewness values ranged from -1.587 to 1.909, and for kurtosis, between -1.549 and 3.712.

6.3 Exploratory Factor Analysis

EFA using the Maximum Likelihood method with oblique rotation type Promax was used to analyze the factor structure and correlation between items from latent variables. The Maximum Likelihood method maximizes differences between factors and provides a Model Fit estimate. The same method is used in IBM SPSS AMOS SEM. Therefore, it is recommended to use it for EFA (Gaskin, 2021b). We used Promax oblique rotation to assess the items for the unique relationship between each factor and the items (removing relationships shared by multiple factors) because factor intercorrelations are the norm in social sciences (Costello & Osborne, 2005).

6.3.1 Adequacy and Reliability

The KMO value is above 0.50, indicating that the sampling adequacy criteria are met (Table 62). The Bartlett test of sphericity is statistically significant ($p < 0.05$), showing that our correlation matrix is statistically different from an identity matrix as desired. The diagonals of the anti-image correlation matrix (Measures of Sampling Adequacy - MSA) were also all over 0.50 (Appendix 4). We used composites of first-order latent constructs for the latent variables *AI*, *CBPA*, *BPII*, *DMP*, and *OP*. All extracted communalities were above 0.40, except for *AI*: CI item (0.331), a first-order composite and is not a candidate for removal. The results of the exploratory factor analysis presented in Table 63 show that the solution is based on 8 factors, as expected. Initial eigenvalues indicated that the seven factors explained 67.725% of the total variance with reliability Cronbach's Alpha between 0.744 and 0.890 (Table 61). Based on the results, no items were removed.

Table 61: Initial Cronbach's Alpha and Variance Extracted

Factor	**Cronbach's Alpha**	**Variance Extracted**
AI Adoption (*AI*)	0.842	19.135
Cognitive Business Process Automation (*CBPA*)	0.791	2.377
Organizational Learning (*OL*)	0.879	16.780
Business Process Innovation Incremental (*BPII*)	0.867	9.838
Business Process Innovation Radical (*BPIR*)	0.744	3.687
Decision Making Performance (*DMP*)	0.890	2.609
Business Process Performance (*BPP*)	0.855	10.443
Organizational Performance (*OP*)	0.832	2.857

Source: Own work.

Table 62: Initial KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.913
Bartlett's Test of Sphericity	Approx. Chi-Square	6291.229
	df	253
	Sig.	0.000

Source: Own work.

6.3.2 Convergent Validity

The results of the rotated factor matrix are provided in Table 63. According to Hair et al. (2013), the sufficient factor loading for a sample size of over 350 is 0.30. All loadings exceed 0.50, except for the CBPA1 item in the *CBPA* factor (0.316). This item has a significant cross-loading of 0.393 on the AI factor; therefore, we removed it. The average loading for the factors is over 0.60.

Table 63: Initial Factor Loadings and Communalities

	Factor loadings								
Items	***AI***	***CBPA***	***OL***	***BPII***	***BPIR***	***DMP***	***BPP***	***OP***	**Communalities**
AI: DACQ	0.751								0.487
AI: CI	0.578								0.331
AI: CE	0.810								0.597
AI: CDA	0.745								0.626
AI: CT	0.838								0.705
CBPA: CBPA1	*0.393*[a]	0.316							0.606
CBPA: LEVEL		0.868							0.682
CBPA: EXTENT		0.682							0.618
OL1			0.814						0.750
OL2			0.950						0.808
OL3			0.781						0.623
OL4			0.524						0.546
BPII: IPII				1.025					0.978
BPII: IPIII				0.700					0.634
BPIR: RAD1					0.484				0.411
BPIR: RAD2					1.050				1.000
DMP: EFFC						0.855			0.831
DMP: EFFT						0.807			0.782
BPP1							0.718		0.705
BPP2							1.019		0.878
BPP3							0.601		0.524

To be continued

Table 63: Initial Factor Loadings and Communalities (cont.)

Items	Factor loadings								Communalities
	AI	*CBPA*	*OL*	*BPII*	*BPIR*	*DMP*	*BPP*	*OP*	
OP: OPER								0.834	0.796
OP: MP								0.757	0.663
	0.686	0.622	0.767	0.862	0.767	0.831	0.779	0.795	
	Average loading per factor								

Notes.
Extraction Method: Maximum Likelihood.
Rotation Method: Promax (Kappa = 4) with Kaiser Normalization.
[a] *Cross-loading*

Source: Own work.

6.3.3 Reexamining Adequacy, Reliability, and Convergent Validity

6.3.3.1 Adequacy and Reliability

The KMO value is above 0.50, indicating that the sampling adequacy criteria are met (Table 65). The Bartlett test of sphericity is statistically significant ($p < 0.05$), showing that our correlation matrix is statistically different from an identity matrix as desired. The diagonals of the anti-image correlation matrix (Measures of Sampling Adequacy – MSA) were also all over 0.50 (Appendix 5). The results of the exploratory factor analysis presented in Table 66 show that the solution is based on 8 factors, as expected. Initial eigenvalues indicated that the seven factors explained 68.073% of the total variance with reliability Cronbach's Alpha between 0.744 and 0.890 (Table 64). Based on the results, no items were removed.

Table 64: Final Cronbach's Alpha and Variance Extracted

Factor	**Cronbach's Alpha**	**Variance Extracted**
AI Adoption (*AI*)	0.842	19.622
Cognitive Business Process Automation (*CBPA*)	0.776	2.445
Organizational Learning (*OL*)	0.879	19.848
Business Process Innovation Incremental (*BPII*)	0.867	9.370
Business Process Innovation Radical (*BPIR*)	0.744	2.866
Decision Making Performance (*DMP*)	0.890	2.683
Business Process Performance (*BPP*)	0.855	7.217
Organizational Performance (*OP*)	0.832	4.022

Source: Own work.

Table 65: Final KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.908
Bartlett's Test of Sphericity	Approx. Chi-Square	5893.441
	df	231
	Sig.	0.000

Source: Own work.

6.3.3.2 *Convergent Validity*

The results of the rotated factor matrix are provided in Table 66. According to Hair et al. (2013), the sufficient factor loading for a sample with over 350 cases is 0.30. All loadings are higher than 0.475. The average loading for the factors is over 0.70.

Table 66: Final Factor Loadings and Communalities

Items	Factor loadings								Communalities
	AI	***CBPA***	***OL***	***BPII***	***BPIR***	***DMP***	***BPP***	***OP***	
AI: DACQ	0.716								0.493
AI: CI	0.510								0.319
AI: CE	0.776								0.609
AI: CDA	0.717								0.631
AI: CT	0.813								0.693
CBPA: LEVEL		0.665							0.530
CBPA: EXTENT		0.852							0.764
OL1			0.817						0.750
OL2			0.950						0.807
OL3			0.780						0.623
OL4			0.518						0.544
BPII: IPII				0.996					0.961
BPII: IPIII				0.701					0.643
BPIR: RAD1					0.475				0.415
BPIR: RAD2					1.042				0.999
DMP: EFFC						0.846			0.823
DMP: EFFT						0.815			0.789
BPP1							0.708		0.702
BPP2							1.014		0.884
BPP3							0.591		0.522
OP: OPER								0.898	0.844
OP: MP								0.727	0.631
	0.713	0.758	0.766	0.848	0.759	0.830	0.771	0.812	
	Average loading per factor								

Notes.
Extraction Method: Maximum Likelihood.
Rotation Method: Promax (Kappa = 4) with Kaiser Normalization.

Source: Own work.

6.3.4 Discriminant Validity

To test discriminant validity, we examine the factor correlation matrix. Correlations between factors should not exceed 0.70 (Gaskin, 2021b). A correlation greater than 0.70 indicates a majority of shared variance. As we can see from the factor correlation matrix in Table 67, no factor exceeds the threshold value.

Table 67: Factor Correlation Matrix

	AI	***CBPA***	***OL***	***BPII***	***BPIR***	***DMP***	***BPP***	***OP***
AI	**1,000**	0,642	0,422	0,447	0,402	0,437	0,406	0,380
CBPA	0,642	**1,000**	0,336	0,379	0,442	0,413	0,331	0,354
OL	0,422	0,336	**1,000**	0,524	0,488	0,631	0,642	0,528
BPII	0,447	0,379	0,524	**1,000**	0,488	0,612	0,468	0,408
BPIR	0,402	0,442	0,488	0,488	**1,000**	0,481	0,534	0,450
DMP	0,437	0,413	0,631	0,612	0,481	**1,000**	0,604	0,496

To be continued

Table 67: Factor Correlation Matrix (cont.)

	AI	CBPA	OL	BPII	BPIR	DMP	BPP	OP
BPP	0,406	0,331	0,642	0,468	0,534	0,604	**1,000**	0,631
OP	0,380	0,354	0,528	0,408	0,450	0,496	0,631	**1,000**

Note. The extraction method is Maximum Likelihood. Rotation Method: Promax (Kappa = 4) with Kaiser Normalization.

Source: Own work.

6.4 Confirmatory Factor Analysis

We used IBM SPSS AMOS version 28 to perform the confirmatory factor analysis using the maximum likelihood method.

6.4.1 Item Parceling

Following the recommendation on item parceling (Hau & Marsh, 2004; Little, Rhemtulla, Gibson, & Schoemann, 2013; Matsunaga, 2008), we parcelled the items of constructs pertaining to subdimensions. Table 68 presents the CFA results:

Table 68: CFA Results

Construct	Item	Model SRW	AVE	CR	α
Artificial Intelligence adoption (*AI*)	DACQ	0.670	**0.534**	**0.849**	**0.842**
	CI	0.553			
	CE	0.780			
	CDA	0.797			
	CT	0.819			
Cognitive Business Process Automation (*CBPA*)	LEVEL	0.747	**0.639**	**0.779**	**0.776**
	EXTENT	0.849			
Organizational Learning (*OL*)	OL1	0.857	**0.655**	**0.883**	**0.879**
	OL2	0.879			
	OL3	0.792			
	OL4	0.698			
Business Process Innovation – Incremental (*BPII*)	IPII	0.912	**0.769**	**0.869**	**0.867**
	IPIII	0.840			
Business Process Innovation – Radical (*BPIR*)	RAD1	0.710	**0.607**	**0.754**	**0.744**
	RAD2	0.842			
Decision-making Performance (*DMP*)	EFFT	0.890	**0.803**	**0.891**	**0.890**
	EFFC	0.902			
Business Process Performance (*BPP*)	BPP1	0.871	**0.678**	**0.862**	**0.855**
	BPP2	0.878			
	BPP3	0.710			
Organizational Performance (*OP*)	OPER	0.882	**0.715**	**0.834**	**0.832**
	MP	0.808			

Notes. SRW = Model standardized regression weights are significant at $p < 0.0001$; AVE = Average variance extracted; CR = Composite reliability; α = Cronbach's Alpha

Source: Own work.

6.4.2 Validity, Reliability, and Measurement Model Fit

In Table 69, we observed convergent and discriminant validity as evidenced by (convergent is AVE above 0.50, the discriminant is the square root of AVE greater than correlations) and reliability (the CR value above 0.70).

Table 69: Inter-Correlations, Assessment of Reliability, and Validity

	Construct	1	2	3	4	5	6	7	8
1	*AI*	**0.731**							
2	*CBPA*	0.705	**0.800**						
3	*OL*	0.452	0.366	**0.810**					
4	*BPII*	0.476	0.431	0.584	**0.877**				
5	*BPIR*	0.469	0.486	0.560	0.584	**0.779**			
6	*DMP*	0.499	0.471	0.557	0.682	0.557	**0.896**		
7	*BPP*	0.439	0.361	0.616	0.505	0.616	0.643	**0.823**	
8	*OP*	0.406	0.355	0.585	0.448	0.516	0.574	0.704	**0.846**
	Mean	2.141	2.377	3.651	3.561	2.792	3.350	3.350	3.093
	Standard Deviation	0.888	0.892	0.926	0.894	0.960	0.844	0.902	0.766
	α	0.842	0.776	0.879	0.867	0.744	0.890	0.855	0.832
	CR	0.849	0.779	0.883	0.869	0.754	0.891	0.862	0.834
	AVE	0.534	0.639	0.655	0.769	0.607	0.803	0.678	0.715
	MSV	0.497	0.497	0.449	0.465	0.379	0.465	0.496	0.496
	MaxR(H)	0.868	0.794	0.898	0.880	0.775	0.891	0.883	0.843

Notes. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; MaxR(H) = McDonald Construct Reliability

Source: Own work.

6.4.3 Pair-Wise Construct Comparison for Discriminant Validity

In the pair-wise construct comparison method (Anderson & Gerbing, 1988; Bagozzi & Phillips, 1982; Bagozzi & Yi, 1988), we separately compare all 21 possible pairs for the seven factors. For each pair, the chi-square value of the full model was compared with the value of the collapsed model (one pair of constructs was collapsed). Anderson and Gerbing (1988) suggested that if the collapsed model is significant and its chi-square value is more than the values of the full model by four or more, then the free model reflects a better fit than the collapsed one. This indicates that collapsed factors do not measure the same concept and hence increase the chi-square value, i.e., collapsed factors are discriminant from each other. As shown in

Table 70, for each possible combination of 28 collapsed models, the chi-square value has increased by more than four, hence all factors are discriminant (from each other).

Table 70: Pair-Wise Construct Comparison for Discriminant Validity

Model	ϰ2 Value (df)	Difference
Original full model	376.758 (181)	
AI → CBPA	563.965 (182)	187.207
AI → OL	454.38 (182)	77.622
AI → BPII	459.918 (182)	83.16
AI → BPIR	448.521 (182)	71.763
AI → DMP	472.692 (182)	95.934
AI → BPP	448.407 (182)	71.649
AI → OP	434.257 (182)	57.499
CBPA → OL	421.504 (182)	44.746
CBPA → BPII	438.678 (182)	61.92
CBPA → BPIR	445.668 (182)	68.91
CBPA → DMP	453.225 (182)	76.467
CBPA → BPP	419.66 (182)	42.902
CBPA → OP	414.765 (182)	38.007
OL → BPII	506.75 (182)	129.992
OL → BPIR	485.876 (182)	109.118

To be continued

Table 70: Pair-Wise Construct Comparison for Discriminant Validity (cont.)

Model	ϰ2 Value (df)	Difference
OL → DMP	575.324 (182)	198.566
OL → BPP	573.562 (182)	196.804
OL → OP	510.839 (182)	134.081
BPII → BPIR	495.613 (182)	118.855
BPII → DMP	574.9 (182)	198.142
BPII → BPP	475.864 (182)	99.106
BPII → OP	449.165 (182)	72.407
BPIR → DMP	484.893 (182)	108.135
BPIR → BPP	509.548 (182)	132.79
BPIR → OP	460.911 (182)	84.153
DMP → BPP	549.022 (182)	172.264
DMP → OP	503.368 (182)	126.61
BPP → OP	578.257 (182)	201.499

Source: Own work.

6.4.4 Heterotrait-Monotrait Ratio for Assessing Discriminant Validity

Henseler, Ringle, and Sarstedt (2015) argue Heterotrait–Monotrait ratio (HTMT) is a more robust criterion to assess discriminant validity. The HTMT is calculated based on the average of the correlations of indicators across latent constructs, measuring different aspects of the model relative to the average of the correlations of indicators within the same construct. The results presented in Table 71 confirm sufficient discriminant validity, where the threshold of 0.85 is not exceeded.

Table 71: Heterotrait-Monotrait Ratio

	AI	*CBPA*	*OL*	*BPII*	*BPIR*	*DMP*	*BPP*	*OP*
AI								
CBPA	0.701							
OL	0.450	0.368						
BPII	0.469	0.420	0.582					
BPIR	0.468	0.502	0.552	0.589				
DMP	0.497	0.473	0.702	0.689	0.553			
BPP	0.420	0.360	0.701	0.502	0.612	0.660		
OP	0.432	0.380	0.587	0.445	0.536	0.572	0.700	

Source: Own work.

6.4.5 Common Method Variance

We conducted Harman's one-factor test with an unrotated factor solution. The test revealed an explained variance of 37.780%, well below the threshold of 50% suggested by Podsakoff, MacKenzie, Lee, and Podsakoff (2003). Next, we conducted Harman's single-factor test using CFA. Method biases are assumed to be substantial if the hypothesized model fits the data (Malhotra, Kim, & Patil, 2006). Our single-factor model showed a poor data fit ($\chi2$/df = 11.214, GFI = 0.621, AGFI = 0.541, TLI = 0.591, CFI = 0.630, RMSEA = 0.151 (p-close < 0.001), SRMR = 0.1050), which confirms the nonexistence of Common Method Variance (CMV). Finally, we used a CLF test and compared the standardized regression weights of all items for models with and without CLF. The differences in these regression weights presented in Table 72 were found to be a maximum of 0.153 (< 0.200), which confirmed that CMV is not a significant issue in our data (Gaskin, 2021a).

Table 72: Difference in CLF Regression Weights

Relations	**Standardized weights**	**Standardized weights with CLF**	**Difference**
AI → DACQ	0.670	0.603	0.067
AI → CI	0.553	0.444	0.109
AI → CE	0.780	0.684	0.096
AI → CDA	0.797	0.721	0.076
AI → CT	0.819	0.768	0.051
CBPA → LEVEL	0.747	0.643	0.104
CBPA → EXTENT	0.849	0.763	0.086
OL → OL1	0.857	0.782	0.075
OL → OL2	0.879	0.815	0.064
OL → OL3	0.792	0.72	0.072
OL → OL4	0.698	0.606	0.092
BPI → IPII	0.912	0.826	0.086
BPI → IPIII	0.840	0.740	0.100
BPR → RAD1	0.710	0.573	0.137
BPR → RAD2	0.842	0.835	0.007
DMP → EFFT	0.890	0.773	0.117
DMP → EFFC	0.902	0.806	0.096
BPP → BPP1	0.871	0.802	0.069
BPP → BPP2	0.878	0.793	0.085
BPP → BPP3	0.710	0.621	0.089
OP → OPER	0.882	0.777	0.105
OP → MP	*0.808*	*0.655*	*0.153*

Source: Own work.

6.4.6 Non-Response Bias

Non-response bias arises from differences between those who respond and those who do not, leading to skewed results that do not accurately represent the target population (Lambert & Harrington, 1990; Maitland et al., 2017). We employed Armstrong and Overton (1977) extrapolation method based on the assumption that late respondents closely resemble non-respondents (Pace, 1939). Our sample included 165 early respondents (36%) and 286 late respondents (64%). Further, we randomly selected 200 non-responders from 933 incomplete cases (Section 6.1.1).

Following the guidelines of Armstrong and Overton (1977), an independent sample t-test (Table 73) was performed to assess the potential presence of non-response bias in this study. Levene’s test for equality (or homogeneity) of variances indicates that there is not a significant difference in terms of homogeneity of variances between the early and late responses for each variable. The p-value of equality of means is statistically nonsignificant for all latent constructs, indicating no significant difference in early and late responses (Pallant, 2016). Also, the magnitude of the differences in the means (eta squared) for all latent constructs is small, < 0.03, acceptable according to Cohen (1988). A comparison of a randomly selected group of 200 non-respondents with 451 respondents revealed no significant differences and minimal effect size for any organizational level indicators (industry, size, age, revenue). We conclude the usable sample is not affected by non-response bias; hence, both early and late respondents of this study represent the same target population.

Table 73: Assessment of Non-Response Bias Using Independent Samples t-Test

					Levene's Test for Equality of Variances		**t-test for Equality of Means**			**Effect Size**
Latent Variables	**Response Type**	**N**	**Mean**	**SD**	**F**	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Eta squared**
AI	Early Response	165	2.323	0.929	2.273	0.132	3.340	449.000	0.001	0.0242
	Late Response	286	2.036	0.848			3.260	317.532	0.001	
CBPA	Early Response	165	2.542	0.936	0.717	0.398	3.002	449.000	0.003	0.0197
	Late Response	286	2.282	0.854			2.929	317.081	0.004	
OL	Early Response	165	3.779	0.959	0.813	0.368	2.239	449.000	0.026	0.0110
	Late Response	286	3.577	0.901			2.202	325.160	0.028	
BPII	Early Response	165	3.648	0.927	0.001	0.975	1.591	449.000	0.112	0.0056
	Late Response	286	3.510	0.871			1.565	325.326	0.119	
BPIR	Early Response	165	2.906	0.960	0.021	0.884	1.929	449.000	0.054	0.0082
	Late Response	286	2.726	0.956			1.926	340.807	0.055	
DMP	Early Response	165	3.436	0.825	0.009	0.925	1.662	449.000	0.097	0.0061
	Late Response	286	3.300	0.851			1.676	351.052	0.095	
BPP	Early Response	165	3.430	0.908	0.042	0.837	1.432	449.000	0.153	0.0045
	Late Response	286	3.304	0.896			1.428	338.747	0.154	
OP	Early Response	165	3.177	0.748	0.012	0.913	1.788	449.000	0.075	0.0071
	Late Response	286	3.044	0.774			1.804	351.698	0.072	
Industry	Respondents	451	11.729	5.065	0.138	0.711	-0.680	649.000	0.496	0.0007
	Non-respondents	200	12.020	4.936			-0.687	390.570	0.492	0.0007
Size	Respondents	451	2.641	2.100	0.462	0.497	0.371	649.000	0.711	0.0002
	Non-respondents	200	2.575	2.056			0.374	388.921	0.708	0.0002
Age	Respondents	451	2.754	1.256	0.062	0.804	0.878	649.000	0.380	0.0012
	Non-respondents	200	2.660	1.266			0.875	378.710	0.382	0.0012
Revenue	Respondents	451	8.029	4.594	1.784	0.182	-1.227	649.000	0.220	0.0023
	Non-respondents	200	8.515	4.814			-1.205	365.789	0.229	0.0073

Source: Own work.

6.4.7 Measurement Model Fit

Table 74 summarizes the results of the measurement model goodness of fit indices. Firstly, the Chi-square value of the measurement model is 376.758, with 181 degrees of freedom. The Normed Chi-Square value (ratio of Chi-Square to Degrees of Freedom) is acceptable at 2.082 (Hoe, 2008; Kline, 2015). The GFI value of the measurement model is 0.930 and acceptable, according to Hooper, Coughlan, and Mullen (2008). Also, the RMSEA value of the model is 0.049, which is between 0.05 and 0.08, and an acceptable fit interval, according to Brown (2015); Hu and Bentler (1999). As the last absolute fit index, AGFI is 0.902, indicating an acceptable model fit (Hooper et al., 2008). As shown, the incremental fit indices of the model (NFI, TLI, and CFI) are in acceptable intervals, according to Hair et al. (2013). Lastly, the parsimony-adjusted PCFI value of 0.757 is close to 1 and acceptable for the fit index (Byrne, 2016).

Table 74: Measurement Model Fit Summary

Fit Measure	Obtained fit	Acceptable Fit Interval	Reference
Chi-square ($\chi 2$)	376.758 (df = 181)		Brown (2015); Kline (2015)
Normed Chi-square	2.082	$\chi 2$ / df ≤ 3 Good model fit	Hoe (2008); Kline (2015)
Absolute Fit Indices			
Goodness-of-fit index (GFI)	0.930	0.80 < GFI < 0.95 Acceptable model fit	Baumgartner and Homburg (1996); Doll, Xia, and Torkzadeh (1994); Hooper et al. (2008)
Root mean square error of approximation (RMSEA)	0.049 (p-close = 0.581)	RMSEA < 0.06 Good model fit	Brown (2015); Hu and Bentler (1999)
Adjusted goodness-of-fit index (AGFI)	0.902	0.80 < AGFI < 0.95 Acceptable model fit	Baumgartner and Homburg (1996); Doll et al. (1994); Hooper et al. (2008)
Standardized Root Mean Squared Residual (SRMR)	0.0349	SRMR < 0.08 Good model fit	Hu and Bentler (1999); Tabachnick and Fidell (2012)
Incremental Fit Indices			
Normed fit index (NFI)	0.937	NFI > 0.90 Acceptable model fit	Bentler and Bonett (1980)
Non-normed Fit Index (NNFI) or Tucker-Lewis Index (TLI)	0.957	TLI > 0.95 Good model fit	Brown (2015); Hoe (2008)
Comparative fit index (CFI)	0.966	CFI > 0.90 Acceptable model fit	Brown (2015); Hoe (2008)
Parsimony Fit Indices			
Parsimony-Adjusted Comparative fit index (PCFI)	0.757	PCFI ≥ 0.60 is considered to indicate an Acceptable model fit	Byrne (2016); Mulaik et al. (1989)

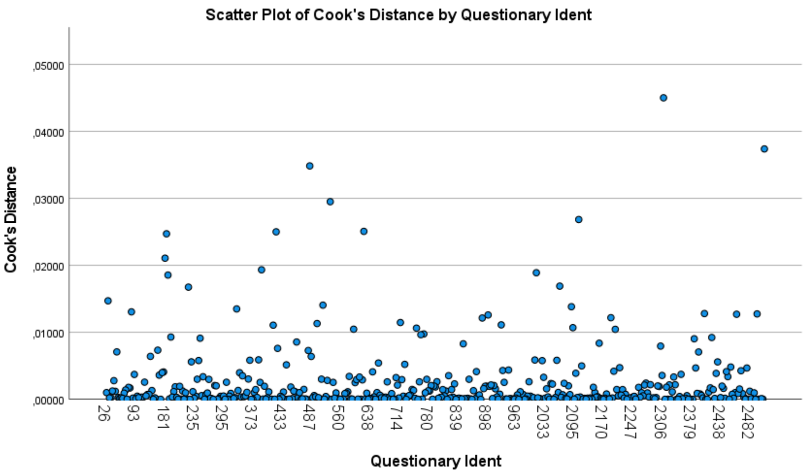
Source: Own work.

6.5 Structural Models

6.5.1 Multivariate Assumptions (Outliers, Influentials and Multicollinearity)

We ran a Cook's distance analysis to determine if any (multivariate) influential outliers existed. In no case did we observe a Cook's distance greater than 1. Most cases were far less than 0.05. We removed 3 cases (case numbers 482, 2310, and 2509) with the Cook's distance over 0.03 (Figure 20).

Figure 20: Cook's Distance



Source: Own work.

We examined Variable Inflation Factors (VIF) for all predictors of our dependent variables. The analysis reveals the absence of multicollinearity, which is supported by the values of the two measures of multicollinearity (Tolerance and VIF). As presented in Table 75, all tolerance values are larger than 0.1 (the lowest is 0.437). A VIF value greater than 10 is usually problematic. In this respect, the highest in the table is 2.287, which complies with the set thresholds (Linton et al., 2020).

Table 75: Collinearity Statistics

	Collinearity Statistics	
Independent variables	**Tolerance**	**VIF**
AI	0.543	1.842
CBPA	0.618	1.619
OL	0.480	2.083
BPII	0.542	1.846
BPIR	0.609	1.641
DMP	0.437	2.287
BPP	0.505	1.981
Control variables		
Age	0.682	1.466
Size	0.642	1.558
Industry	0.951	1.052
Country	0.952	1.050
Environmental Uncertainty	0.877	1.140

Source: Own work.

6.5.2 Control Variables

We included firm age as a control variable (CV) since prior research indicates that firm age can affect both short and long-term performance (Coad, Holm, Krafft, & Quatraro, 2018). Firm age was measured by the number of years since the establishment of the firm. New organizations comprise those with ages equal to or less than 5 years. Young organizations between 5 and 10 years. Middle-age firms include those whose ages vary between 11 and 30. Mature organizations are the ones whose ages are more than 30 years and over 50 years old. Frequencies are presented in Table 76.

Table 76: Firm Age Frequencies

Firm age	**Frequency**	**Percent**
< 5 years (new)	94	21.0
5 – 10 (young)	88	19.6
11 – 30 (middle-age)	153	34.2
31 – 50 (mature)	60	13.4
> 50 (old)	53	11.8
Total	*448*	*100.0*

Source: Own work.

Additionally, firm size (number of employees) is a common control variable in IS research and was included in this study, as it has also been shown to affect performance (Bhatt & Grover, 2005). Organizations are classified into nine categories, presented in Table 77.

Table 77: Firm Size Frequencies

Firm size	**Frequency**	**Percent**
< 10	211	47.1
10 - 19	57	12.7
20 - 49	55	12.3
50 - 99	36	8.0
100 - 499	43	9.6
500 - 999	11	2.5
1,000 – 4,999	19	4.2
5,000 – 9,999	5	1.1
10,000+	11	2.5
Total	*448*	*100.0*

Source: Own work.

Additionally, in prior research, the industry sector has been shown to affect performance (Mallinguh, Wasike, & Zoltan, 2020; Nielsen & Raswant, 2018). To control for the effect of the industry sector, we created a variable based on NACE-R2 1st-level categories, presented in Table 78.

Table 78: Industry Sector Frequencies

Firm size	**Frequency**	**Percent**
Agriculture, forestry and fishing	14	3.1
Mining and quarrying	3	0.7
Manufacturing	25	5.6
Electricity, gas, steam and air conditioning supply	8	1.8
Water supply; sewerage, waste management and remediation activities	4	0.9
Construction	13	2.9
Wholesale and retail trade; repair of motor vehicles and motorcycles	25	5.6
Transportation and storage	9	2.0
Accommodation and food service activities	10	2.2
Information and communication	94	21.0
Financial and insurance activities	33	7.4
Real estate activities	7	1.6
Professional, scientific and technical activities	58	12.9
Administrative and support service activities	12	2.7
Public administration and defence; compulsory social security	11	2.5
Education	15	3.3
Human health and social work activities	19	4.2
Arts, entertainment and recreation	16	3.6
Other service activities	72	16.1
Total	*448*	*100.0*

Source: Own work.

According to Nielsen and Raswant (2018), researchers should include contextual control variables in multi-country studies. Results should be interpreted in terms of these contextual control variables. Therefore, we had the country as a control variable. It was measured by the organization's principal place of business, EU-27, including Serbia, Norway, Switzerland, the United Kingdom, Turkey, and others. Frequencies are presented in Table 79.

Table 79: Country Frequencies

Country	**Frequency**	**Percent**
Austria	11	2.46
Belgium	9	2.01
Bulgaria	8	1.79
Croatia	15	3.35
Cyprus	2	0.45
Czech Republic	16	3.57
Denmark	3	0.67
Estonia	7	1.56
Finland	7	1.56
France	31	6.92
Germany	96	21.43
Greece	12	2.68
Hungary	10	2.23
Ireland	11	2.46
Italy	49	10.94
Latvia	1	0.22
Luxembourg	2	0.45
Malta	3	0.67
Netherlands	47	10.49
Poland	15	3.35
Portugal	8	1.79
Romania	6	1.34
Serbia	12	2.68
Slovakia	13	2.90
Slovenia	4	0.89
Spain	13	2.90
Sweden	4	0.89
Norway	2	0.45
Switzerland	2	0.45
United Kingdom	5	1.12
Turkey	7	1.56
Other	17	3.79
Total	*448*	*100.0*

Source: Own work.

Nielsen and Raswant (2018) posit that multi-country studies are susceptible to omitted variable problems due to the complexity of multiple environmental contexts (i.e., political, economic, socio-cultural, and institutional). With the rising frequency of environmental dynamism and complexity in business operations, firms are operating in environments that are becoming increasingly unpredictable (Yu, Wang, & Brouthers, 2016). Therefore, we included Environmental Uncertainty as a control variable. The variable was measured with a three-dimensional scale (Environmental dynamism, Hostility, Heterogeneity) developed by Miller and Friesen (1983) and used in various studies.

Next, means, standard deviations, and correlations between CVs and all other variables (independent, mediator, and dependent variables) are presented in Table 80. VIFs for all independent variables, including controls, are shown in Table 75.

Table 80: Correlation Matrix for IV, DV, Mediators and Control Variables

IV	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
AI	2.144	0.890	1.000												
DV and Mediators															
CBPA	2.386	0.889	0.565**	1.000											
OL	3.650	0.929	0.391**	0.308**	1.000										
BPII	3.566	0.886	0.413**	0.349**	0.523**	1.000									
BPIR	2.792	0.958	0.373**	0.383**	0.459**	0.478**	1.000								
DMP	3.349	0.840	0.436**	0.401**	0.623**	0.610**	0.466**	1.000							
BPP	3.350	0.898	0.362**	0.299**	0.609**	0.453**	0.514**	0.579**	1.000						
OP	3.089	0.758	0.372**	0.318**	0.509**	0.412**	0.437**	0.518**	0.602**	1.000					
Control variables															
Age	2.754	1.259	-0.069	-0.118*	-0.200**	-0.106*	-0.195**	-0.178**	-0.185**	-0.027	1.000				
Size	2.650	2.104	0.122**	-0.080	-0.158**	-0.049	-0.098*	-0.176**	-0.195**	0.008	0.524**	1.000			
Industry	11.730	5.062	-0.061	-0.052	-0.036	-0.025	-0.025	-0.083	-0.088	-0.013	-0.020	-0.074	1.000		
Country	15.188	8.040	0.102*	0.086	-0.004	0.069	0.010	0.059	0.083	0.046	-0.107*	-0.014	.0059	1.000	
Env. uncerta.	3.208	0.653	0.264**	0.200**	0.217**	0.232**	0.146**	0.187**	0.176**	0.177**	0.034	0.063	-0.155**	0.053	1.000

*Notes: IV = Independent variable; DV = Dependent variable; SD = Standard Deviation; ** Correlation is significant at the 0.01 level; * Correlation is significant at the 0.05 level*

Source: Own work.

Control variable Size significantly influences the *OP* and *OL* variables. Larger organizations had a higher level of *OP* than smaller firms. However, larger organizations had a lower level of *OL* than smaller firms. Other control variables were found to be nonsignificant and had no influence. Control variable loadings are presented in Table 81.

Table 81: Control Variables Loadings

Control variable → OP	**β**	**t-value**	**p-value**
Age	0.063	1.401	0.227
Size	*0.113*	*2.485*	*0.022*
Industry	0.049	1.296	0.169
Country	-0.019	-0.498	0.573
Env. Uncertainty	0.019	0.483	0.655
Control variable → OL			
Size	*-0.224*	*-5.034*	*< 0.001*

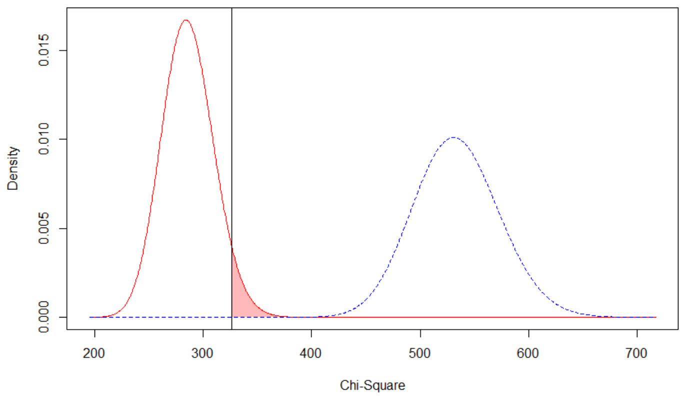
Source: Own work.

6.5.3 Post-hoc Structural Equation Modeling Power Analysis

We conducted post hoc SEM power analyses using the semPower R-package (Moshagen & Erdfelder, 2016) to confirm that the sample size for the structural equation model was adequate. Our model is based on an N of 448, 286 degrees of freedom (df), and an RMSEA of 0.044. Using an alpha level of 0.05, the power to reject an incorrect model was above 0.99.

Table 82: Post-Hoc Structural Equation Modeling Power Analysis Results

Results	**Values**
F0	0.554
RMSEA	0.044
Mc	0.758
df	286
Num Observations	448
NCP	247.502
Critical Chi-Square	326.443
Alpha	0.05
Beta	9.358695×10^{-10}
Power (1-Beta)	> 0.9999
Implied Alpha/Beta Ratio	5.342625×10^{7}



Source: Own work.

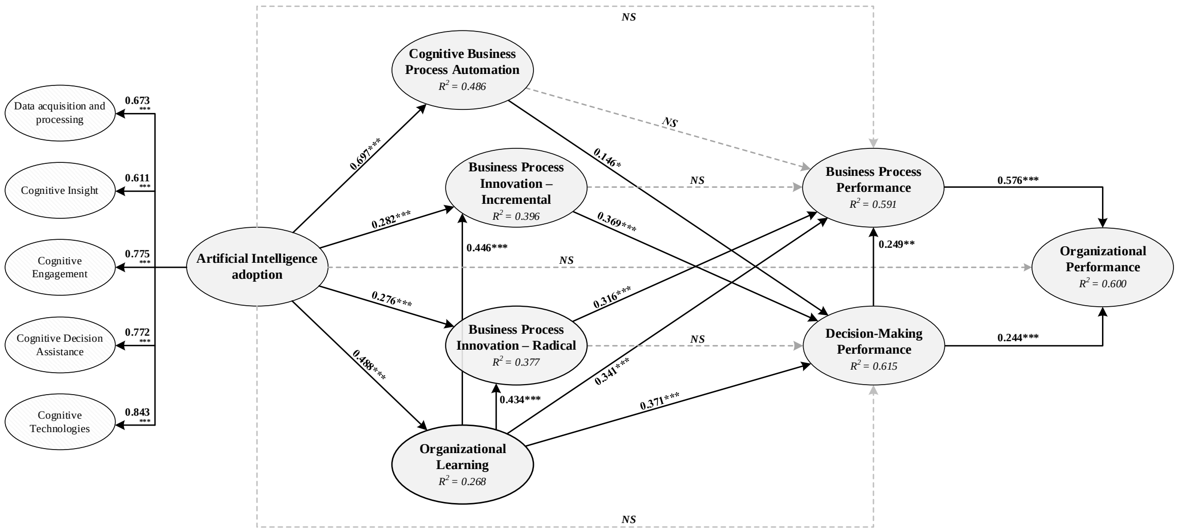
When power is requested to compare a hypothesized model to the saturated model, the model df is given by $df = \frac{p(p+1)}{2} - q$ where p is the number of observed variables, and q is the number of free parameters of the hypothesized model. We use 27 observed variables (including control variables) and 92 free parameters (40 weights, 17 covariances, and 35 variances) for the model.

An in-depth tutorial on power analyses in SEM using semPower is also provided in the following paper: Jobst, Bader, and Moshagen (2021).

6.5.4 Hypotheses Testing

The study examines the structural relationships between the constructs through a path analysis by considering the multiple mediating and moderating effects. Path analyses with the IBM SPSS AMOS software (Collier, 2020) were used to test the hypotheses in the conceptual model. The maximum likelihood method uses the bootstrap (Bootstrap Sample = 5,000 with replacement) method to simulate the sampling distributions of the estimated parameters selected to calculate the model parameters. The model includes six mediating variables (i.e., *CBPA*, *OL*, *BPII*, *BPIR*, *DMP*, and *BPP*) in addition to *AI* and *OP* constructs.

Figure 21: Structural Model Results



Notes.
+: Standardized regression weights are shown.
**p<0.05, **p<0.01; ***p<0.001; NS: Not significant.*

Source: Own work.

Structural equation model fit is within the acceptable levels. Table 83 summarizes the results of the measurement model goodness of fit values. The results confirm that the model fits the data well.

Table 83: Structural Model Fit Summary

Fit Measure	Obtained fit	Acceptable Fit Interval	Reference
Chi-square ($\chi 2$)	535.908 (df=286)		Brown (2015); Kline (2015)
Normed Chi-square	1.874	$\chi 2$ / df ≤ 3 Good model fit	Hoe (2008); Kline (2015)
Absolute Fit Indices			
Goodness-of-fit index (GFI)	0.917	0.80 < GFI < 0.95 Acceptable model fit	Baumgartner and Homburg (1996); Doll et al. (1994); Hooper et al. (2008)
Root mean square error of approximation (RMSEA)	0.044 (p-close=0.951)	RMSEA < 0.06 Good model fit	Brown (2015); Hu and Bentler (1999)
Adjusted goodness-of-fit index (AGFI)	0.891	0.80 < AGFI < 0.95 Acceptable model fit	Baumgartner and Homburg (1996); Doll et al. (1994); Hooper et al. (2008)
Standardized Root Mean Squared Residual (SRMR)	0.0443	SRMR < 0.08 Good model fit	Hu and Bentler (1999); Tabachnick and Fidell (2012)
Incremental Fit Indices			
Normed fit index (NFI)	0.917	NFI > 0.90 Acceptable model fit	Bentler and Bonett (1980)
Non-normed Fit Index (NNFI) or Tucker-Lewis Index (TLI)	0.950	TLI > 0.95 Good model fit	Brown (2015); Hoe (2008)
Comparative fit index (CFI)	0.959	CFI > 0.90 Acceptable model fit	Brown (2015); Hoe (2008)
Parsimony Fit Indices			
Parsimony-Adjusted Comparative fit index (PCFI)	0.781	PCFI ≥ 0.60 is considered to indicate an Acceptable model fit	Byrne (2016); Mulaik et al. (1989)

Source: Own work.

6.5.4.1 Direct Effects

H1: *AI adoption directly positively influences organizational performance.*

H1 was not supported ($\beta = 0.036$, $t = 0.691$, $p > 0.05$), indicating that *AI* has no direct association with *OP*. However, the relationship is significant in the absence of the mediating variables.

H2: *Business process performance positively influences organizational performance.*

Support for H2 ($\beta = 0.576$, $t = 9.488$, $p < 0.001$) is aligned with prior studies that point to *BPP* as the link to *OP* (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Melville et al., 2004).

H3a: *Decision-making performance positively influences business process performance.*

H3b*: Decision-making performance positively influences organizational performance.*

Support was found for H3a ($\beta = 0.249$, $t = 3.532$, $p < 0.001$) and H3b ($\beta = 0.244$, $t = 4.050$, $p < 0.001$), confirming the expected impact of *DMP* on *BPP* and *OP* (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Fredrickson & Mitchell, 1984).

H8a: *OL positively influences BPII.*

H8b: *OL positively influences BPIR.*

Finally, strong support was found for H8a ($\beta = 0.446$, $t = 8.442$, $p < 0.001$) and H8b ($\beta = 0.434$, $t = 7.001$, $p < 0.001$), indicating that *OL* has a significant direct association with process innovation, i.e., *BPII* and *BPIR*.

6.5.4.2 Indirect Effects

Next, we examine the indirect effects. We used the revised method to assess the indirect effect by examining the product of the A path and the B path while controlling for the direct impact of the C path (Collier, 2020). Hence, the indirect effect is quantified as the product of the unstandardized regression weight of mediation paths, as shown in Table 84 (Collier, 2020; Hayes, 2018; Taylor, MacKinnon, & Tein, 2008). Since the Sobel test (Sobel, 1982) is flawed for this type of test, the more accepted approach in mediation testing is to use a bootstrap technique to determine significance (Bootstrap Sample = 5,000 with replacement).

The full model was run to identify the mediating, indirect effects. According to the results in Table 84, *CBPA* mediates the positive impact of *AI* adoption on *DMP* (support for H4a) but not on *BPP* (no support for H4b). Positioned as a key augmentation capability, results in Table 84 show *OL* mediates the positive impact of *AI* adoption on *DMP* and *BPP* (support for H5a and H5b). To test the effects of *AI* on process innovation, two parallel constructs of *BPII* and *BPIR* were inserted, and relationships were tested. The results in Table 84 show that *BPII* mediates the positive impact of *AI* adoption on *DMP* (support for H6a). However, *BPII* does not mediate the path between *AI* and *BPP* (no support for H6b). In contrast, *BPIR* does not mediate the impact of *AI* adoption on *DMP* (no support for H7a) but does on *BPP* (support for H7b).

Table 84: Results of the Single Mediation Analysis, i.e., Indirect Effects

Path	**Relations**	**Unstandardized weights**	**Indirect effect**	**Z-score**	**Mediation**
AI → CBPA → DMP	*AI → CBPA*	0.715 (0.063)	0.104* (0.050)	2.271ξ*	Support for H4a, the mediation role of *CBPA* between *AI* and *DMP* (the direct effect is not significant).
	CBPA → DMP	0.146 (0.063)			
AI → CBPA → BPP	*AI → CBPA*	0.715 (0.063)	-0.042 (0.059)	-0.793ξ	No support for H4b.
	CBPA → BPP	-0.058 (0.073)			
AI → OL → DMP	*AI → OL*	0.576 (0.065)	0.185*** (0.040)	5.482ξ***	Support for H5a, the mediation role of *OL* between *AI* and *DMP*.
	OL → DMP	0.321 (0.046)			
AI → OL → BPP	*AI → OL*	0.576 (0.065)	0.190*** (0.045)	4.673ξ***	Support for H5b, the mediation role of *OL* between *AI* and *BPP* (the direct effect is not significant).
	OL → BPP	0.330 (0.060)			
AI → BPII → DMP	*AI → BPII*	0.304 (0.058)	0.106*** (0.034)	4.076ξ***	Support for H6a, the mediation role of *BPII* between *AI* and *DMP*.
	BPII → DMP	0.350 (0.054)			
AI → BPII → BPP	*AI → BPII*	0.304 (0.058)	-0.013 (0.023)	-0.622ξ	No support for H6b.
	BPII → BPP	-0.042 (0.067)			

To be continued

Table 84: Results of the Single Mediation Analysis, i.e., Indirect Effects (cont.)

Path	Relations	Unstandardized weights	Indirect effect	Z-score	Mediation
AI → BPIR → DMP	*AI → BPIR*	0.241 (0.052)	0.021 (0.023)	1.237ξ	No support for H7a.
	BPIR → DMP	0.086 (0.067)			
AI → BPIR → BPP	*AI → BPIR*	0.241 (0.052)	0.099*** (0.031)	3.410ξ***	Support for H7b, the mediation role of *BPIR* between *AI* and *BPP*.
	BPIR → BPP	0.413 (0.082)			

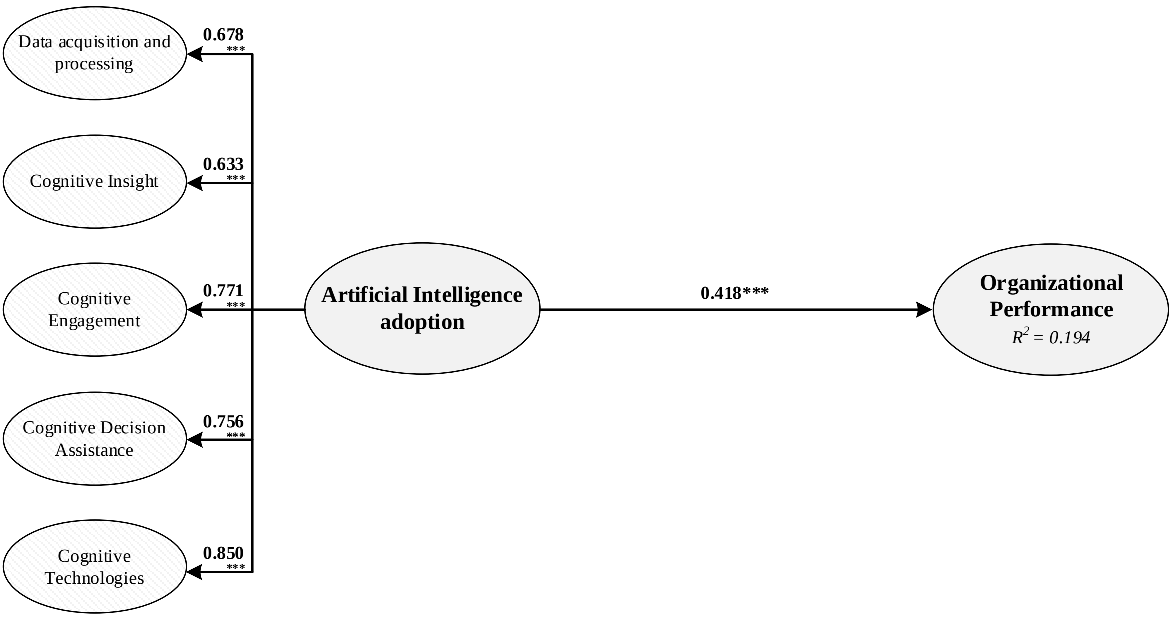
*Notes. + Boot Standard errors are indicated within the parentheses. *p<0.05, **p<0.01, ***p<0.001. ξ2-tail z-score =* $\frac{a*b}{\sqrt{b^2*SEa^2+a^2*SEb^2}}$ *for single mediation effect.*

Source: Own work.

6.5.4.3 Full Mediation

Without the mediators, the total effect of *AI* on *OP* was tested. The relationship is significant, and the standardized total effect is 0.418 (t = 6.584, p < 0.001, 95% CI: LL = 0.314 to UL = 0.521). Model Fitness is $\chi 2$/df = 1.719, GFI = 0.977, AGFI = 0.952, TLI = 0.969, CFI = 0.982, RMSEA = 0.040 (p-close = 0.829), and SRMR = 0.0288.

Figure 22: Total Effect



*Note: Standardized effects are presented. ***p<0.001*

Source: Own work.

The full parallel, serial mediating model was run to identify the mediating effects. The direct relationship between *AI* and *OP* was nonsignificant (p = 0.541, 95% CI: LL = -0.074 to UL = 0.139). Thus, these findings support the full parallel, serial mediating role of *CBPA*, *BPII*, *BPIR*, *OL*, *DMP* and *BPP*.

6.5.4.4 Summary of Hypothesis Testing

We observe in Table 86 that the distinctive serial (chain) relationships of *CBPA*, *OL*, *BPII*, *BPIR*, *DMP*, and *BPP* together establish the link between *AI* and *OP*. The nonsignificant direct relationship defined by H1 indicates the relationship between *AI* and *OP* is fully mediated.

Table 85: Summary of Support for the Hypotheses

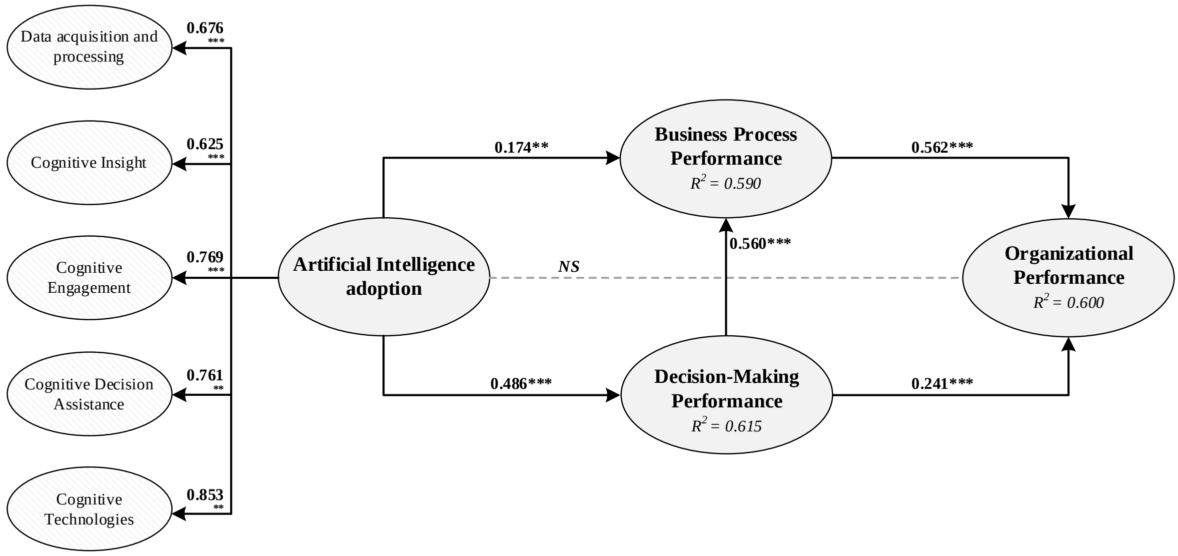
Hypotheses	Definition	Level of support
H1	*AI adoption directly positively influences organizational performance.*	Not supported
H2	*Business process performance positively influences organizational performance.*	Supported
H3a	*Decision-making performance positively influences business process performance.*	Supported
H3b	*Decision-making performance positively influences organizational performance.*	Supported
H4a	*Cognitive business process automation mediates the positive impact of AI adoption on decision-making performance.*	Supported
H4b	*Cognitive business process automation mediates the positive impact of AI adoption on business process performance.*	Not supported
H5a	*Organizational learning mediates the positive impact of AI adoption on decision-making performance.*	Supported
H5b	*Organizational learning mediates the positive impact of AI adoption on business process performance.*	Supported
H6a	*Incremental business process innovation mediates the positive impact of AI adoption on decision-making performance.*	Supported
H6b	*Incremental business process innovation mediates the positive impact of AI adoption on business process performance.*	Not supported
H7a	*Radical business process innovation mediates the positive impact of AI adoption on decision-making performance.*	Not supported
H7b	*Radical business process innovation mediates the positive impact of AI adoption on business process performance.*	Supported
H8a	*Organizational learning positively influences incremental business process innovation.*	Supported
H8b	*Organizational learning positively influences radical business process innovation.*	Supported

Source: Own work.

6.5.5 Testing Additional Paths

Without the *CBPA*, *OL*, *BPII*, and *BPIR* mediators, the impact of *DMP* on *BPP* and *OP* is positive and significant (Figure 23). However, running the full model shows no significant direct effect of *AI* adoption on *DMP*. Nevertheless, we can observe in Table 86 that the mediating impact of *DMP* is positive when positioned as a secondary mediator in serial multiple-mediation relationships. Therefore, *DMP* plays a mediating role and is fully mediated.

Figure 23: Structural Model Without Mediators



Notes.
+: Standardized regression weights are shown.
**p<0.05, **p<0.01; ***p<0.001; NS: Not significant.*

Source: Own work.

Similarly, excluding the *CBPA*, *OL*, *BPII*, *BPIR*, and *DMP* mediators, the impact of *AI* on *OP* mediated through *BPP* is positive and significant (Figure 23), but not when running the entire model. We can observe in Table 86 that the mediating effect of *BPP* is positive when positioned as a secondary mediator in serial multiple-mediation relationships. Hence, *BPP* plays a mediating role and is fully mediated.

Table 86: Results of the Serial Multiple-Mediation Analysis, i.e., Serial Indirect Effects

Path	Relations	Unstandardized weights	Indirect effect	Z-score	Mediation
AI → *CBPA* → *DMP* → *OP*	*AI* → *CBPA*	0.715 (0.063)	0.022* (0.012)	1.981ξξ*	Support for the serial multiple-mediation role of *CBPA* and *DMP* between *AI* and *OP*.
	CBPA → *DMP*	0.146 (0.063)			
	DMP → *OP*	0.215 (0.053)			
AI → *CBPA* → *DMP* → *BPP* → *OP*	*AI* → *CBPA*	0.715 (0.063)	0.013* (0.008)		Support for the serial multiple-mediation role of *CBPA*, *DMP*, and *BPP* between *AI* and *OP*.
	CBPA → *DMP*	0.146 (0.063)			
	DMP → *BPP*	0.278 (0.079)			
	BPP → *OP*	0.455 (0.048)			
AI → *CBPA* → *BPP* → *OP*	*AI* → *CBPA*	0.715 (0.063)	-0.019 (0.028)	-0.790ξξ	No support.
	CBPA → *BPP*	-0.058 (0.073)			
	BPP → *OP*	0.455 (0.048)			

To be continued

Table 86: Results of the Serial Multiple-Mediation Analysis, i.e., Serial Indirect Effects (cont.)

Path	**Relations**	**Unstandardized weights**	**Indirect effect**	**Z-score**	**Mediation**
AI → OL → DMP → OP	*AI → OL*	0.576 (0.065)	0.040^{***} (0.013)	$3.261^{\xi\xi***}$	Support for the serial multiple-mediation role of *OL* and *DMP* between *AI* and *OP*.
	OL → DMP	0.321 (0.046)			
	DMP → OP	0.215 (0.053)			
AI → OL → DMP → BPP → OP	*AI → OL*	0.576 (0.065)	0.023^{**} (0.010)		Support for the serial multiple-mediation role of *OL*, *DMP*, and *BPP* between *AI* and *OP*.
	OL → DMP	0.321 (0.046)			
	DMP → BPP	0.278 (0.079)			
	BPP → OP	0.455 (0.048)			
AI → OL → BPP → OP	*AI → OL*	0.576 (0.065)	0.086^{***} (0.024)	$4.191^{\xi\xi***}$	Support for the serial multiple-mediation role of *OL* and *BPP* between *AI* and *OP*.
	OL → BPP	0.330 (0.060)			
	BPP → OP	0.455 (0.048)			
AI → OL → BPII → DMP → OP	*AI → OL*	0.576 (0.065)	0.018^{***} (0.007)		Support for the serial multiple-mediation role of *OL*, *BPII*, and *DMP* between *AI* and *OP*.
	OL → BPII	0.407 (0.048)			
	BPII → DMP	0.350 (0.054)			
	DMP → OP	0.215 (0.053)			
AI → OL → BPII → DMP → BPP → OP	*AI → OL*	0.576 (0.065)	0.010^{***} (0.005)		Support for the serial multiple-mediation role of *OL*, *BPII*, *DMP*, and *BPP* between *AI* and *OP*.
	OL → BPII	0.407 (0.048)			
	BPII → DMP	0.350 (0.054)			
	DMP → BPP	0.278 (0.079)			
	BPP → OP	0.455 (0.048)			
AI → OL → BPII → BPP → OP	*AI → OL*	0.576 (0.065)	-0.005 (0.009)		No support.
	OL → BPII	0.407 (0.048)			
	BPII → BPP	-0.042 (0.067)			
	BPP → OP	0.455 (0.048)			
AI → OL → BPIR → DMP → OP	*AI → OL*	0.576 (0.065)	0.003 (0.004)		No support.
	OL → BPIR	0.320 (0.046)			
	BPIR → DMP	0.086 (0.067)			
	DMP → OP	0.215 (0.053)			
AI → OL → BPIR → DMP → BPP → OP	*AI → OL*	0.576 (0.065)	0.002 (0.002)		No support.
	OL → BPIR	0.320 (0.046)			
	BPIR → DMP	0.086 (0.067)			
	DMP → BPP	0.278 (0.079)			
	BPP → OP	0.455 (0.048)			
AI → OL → BPIR → BPP → OP	*AI → OL*	0.576 (0.065)	0.035^{***} (0.010)		Support for the serial multiple-mediation role of *OL*, *BPIR* and *BPP* between *AI* and *OP*.
	OL → BPIR	0.320 (0.046)			
	BPIR → BPP	0.413 (0.082)			
	BPP → OP	0.455 (0.048)			

To be continued

Table 86: Results of the Serial Multiple-Mediation Analysis, i.e., Serial Indirect Effects (cont.)

Path	**Relations**	**Unstandardized weights**	**Indirect effect**	**Z-score**	**Mediation**
AI → BPII → DMP → OP	*AI → BPII*	0.304 (0.058)	0.023^{***} (0.010)	$2.875^{\xi\xi**}$	Support for the serial multiple-mediation role of *BPII* and *DMP* between *AI* and *OP*.
	BPII → DMP	0.350 (0.054)			
	DMP → OP	0.215 (0.053)			
AI → BPII → DMP → BPP → OP	*AI → BPII*	0.304 (0.058)	0.013^{***} (0.006)		Support for the serial multiple-mediation role of *BPII*, *DMP* and *BPP* between *AI* and *OP*.
	BPII → DMP	0.350 (0.054)			
	DMP → BPP	0.278 (0.079)			
	BPP → OP	0.455 (0.048)			
AI → BPII → BPP → OP	*AI → BPII*	0.304 (0.058)	-0.006 (0.011)	$-0.621^{\xi\xi}$	No support.
	BPII → BPP	-0.042 (0.067)			
	BPP → OP	0.455 (0.048)			
AI → BPIR → DMP → OP	*AI → BPIR*	0.241 (0.052)	0.004 (0.005)	$1.183^{\xi\xi}$	No support.
	BPIR → DMP	0.086 (0.067)			
	DMP → OP	0.215 (0.053)			
AI → BPIR → DMP → BPP → OP	*AI → BPIR*	0.241 (0.052)	0.003 (0.003)		No support.
	BPIR → DMP	0.086 (0.067)			
	DMP → BPP	0.278 (0.079)			
	BPP → OP	0.455 (0.048)			
AI → BPIR → BPP → OP	*AI → BPIR*	0.241 (0.052)	0.045^{***} (0.016)	$3.209^{\xi\xi***}$	Support for the serial multiple-mediation role of *BPIR* and *BPP* between *AI* and *OP*.
	BPIR → BPP	0.413 (0.082)			
	BPP → OP	0.455 (0.048)			

*Notes. + Boot Standard errors are indicated within the parentheses. *p<0.05, **p<0.01, ***p<0.001.*

$^{\xi\xi}$ *2-tail z-score =* $\frac{a*b*c}{\sqrt{a^2*b^2*SEc^2+a^2*c^2*SEb^2+b^2*c^2*SEa^2}}$ *for serial multiple-mediation effect.*

Source: Own work.

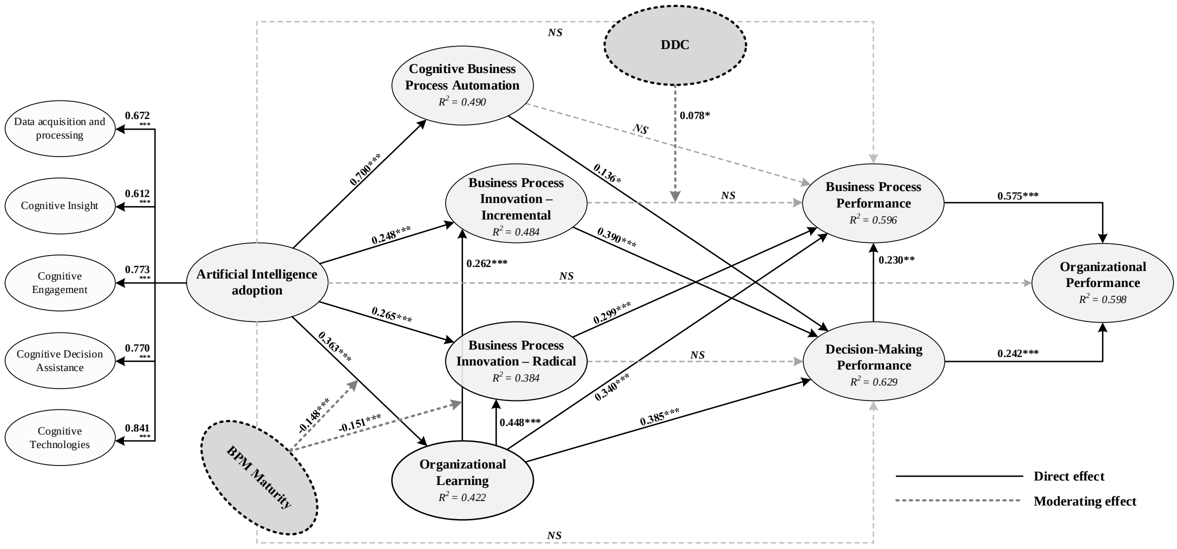
6.5.6 Moderated Effects

We assessed the moderating role of BPM Maturity, Digital Maturity, Data-driven Culture, and Organizational Culture (clan, adhocracy, market, hierarchy) on all the hypothesized paths between latent variables.

First, we assessed all the paths using Hayes Process Macro v4.1 Model 1 (IBM SPSS). Next, the significant paths were assessed using the mixed model method for testing moderation in a structural model (IBM SPSS AMOS), as Collier (2020) recommended. The mixed model method includes latent unobservable variables with a model's independent and dependent variables but includes a composite moderator variable and a composite interaction term. The mixed method approach accounts for the measurement error in the independent and dependent variables but fails to run a latent interaction test. Subsequently, it does not account for measurement error in the moderator.

After excluding the nonsignificant interaction, we next present the significant moderated effects.

Figure 24: Structural Model With Moderators



Model Fitness: $\chi2/df = 2.052$, GFI = 0.900, AGFI = 0.863, TLI = 0.929, CFI = 0.945, RMSEA = 0.049 (p-close = 0.688), and SRMR = 0.0493.

Source: Own work.

6.5.6.1 Moderating Role of BPM Maturity on the Relationship Between AI Adoption and Organizational Learning

The study assessed the moderating role of *BPMM* on the relationship between *AI* and *OL*. The results revealed a negative and significant moderating impact of *BPMM* on the relationship between *AI* and *OL* ($\beta = -0.148$, $t = -3.579$, $p < 0.001$). The moderation analysis summary is presented in Table 87.

Table 87: Moderation Test Results for BPMM on the Relationship Between AI and OL

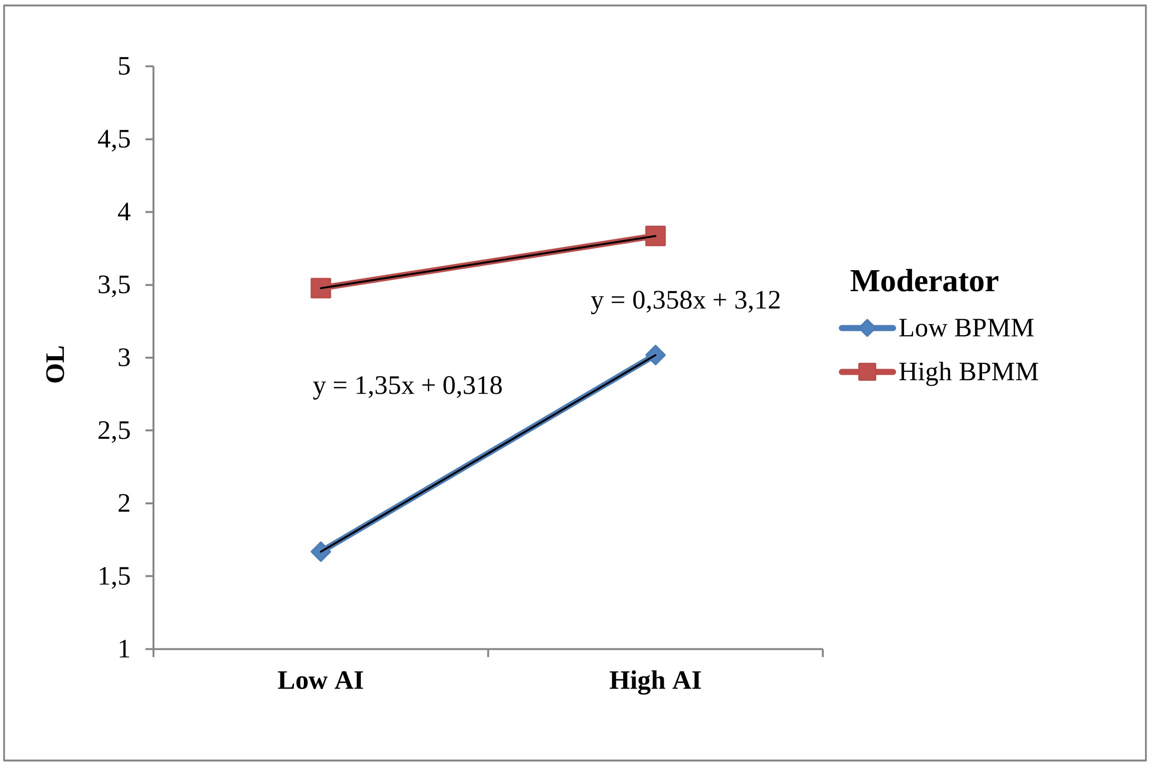
Relationship	Unstandardized weights	t-value	p-value
AI → OL	*0.427*	*6.736*	*< 0.001*
BPMM → OL	*0.657*	*8.070*	*< 0.001*
*AI*BPMM → OL*	*-0.248*	*-3,579*	*< 0.001*

Probing the Interaction of *BPMM*			
Low level: *AI → OL*	0.619	6.136	< 0.001
Mean Level: *AI → OL*	0.427	6.736	< 0.001
High level: *AI → OL*	0.242	3.654	< 0.001

Source: Own work.

Figure 25 shows the results of a simple slope analysis conducted to better understand the nature of the moderating effects. As can be seen, the line is much steeper for Low *BPMM*, which indicates that at a low level of *BPMM*, the impact of *AI* on *OL* is much stronger compared to High *BPMM*. As the level of *BPMM* increased, the strength of the relationship between *AI* and *OL* decreased.

Figure 25: BPMM Dampens the Positive Relationship Between AI and OL



Source: Own work.

6.5.6.2 *Moderating Role of BPM Maturity on the Relationship Between Organizational Learning and Business Process Innovation - Incremental*

The study assessed the moderating role of *BPMM* on the relationship between *OL* and *BPII*. The results revealed a negative and significant moderating impact of *BPMM* on the relationship between *OL* and *BPII* (β = -0.151, t = -3.628, p < 0.001). The moderation analysis summary is presented in Table 88.

Table 88: Moderating impact of BPMM on the Relationship Between OL and BPII

Relationship	**Unstandardized weights**	**t-value**	**p-value**
OL → BPII	0.235	4.764	< 0.001
BPMM → BPII	0.424	5.394	< 0.001
*OL*BPMM → BPII*	-0.164	-3,628	< 0.001

To be continued

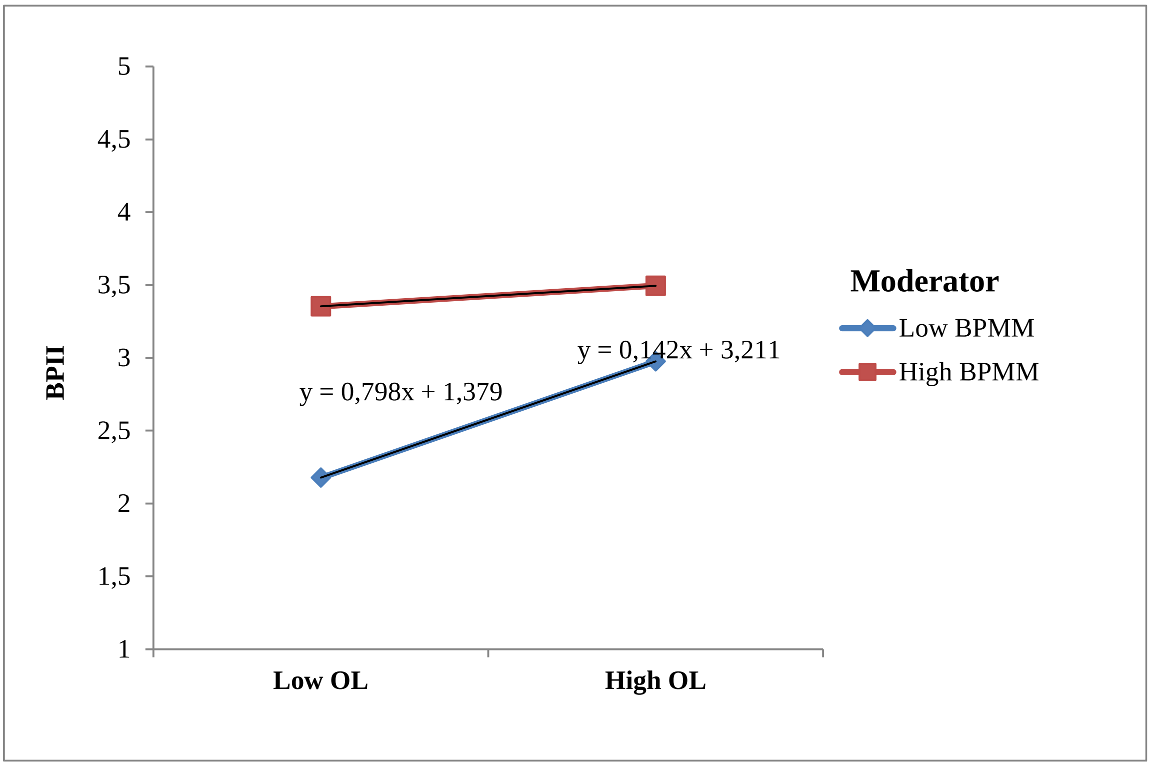
Table 88: Moderating impact of BPMM on the Relationship Between OL and BPII (cont.)

Relationship	**Unstandardized weights**	**t-value**	**p-value**
Probing the Interaction of *BPMM*			
Low level: *OL* → *BPII*	0.338	6.818	< 0.001
Mean Level: *OL* → *BPII*	0.235	4.764	< 0.001
High level: *OL* → *BPII*	0.141	2.935	< 0.01

Source: Own work.

Figure 26 shows the results of a simple slope analysis conducted to better understand the nature of the moderating effects. As can be seen, the line is much steeper for Low *BPMM*, and this indicates that at a low level of *BPMM*, the impact of *OL* on *BPII* is much stronger compared to High *BPMM*. As the level of *BPMM* increased, the strength of the relationship between *AI* and *OL* decreased.

Figure 26: BPMM Dampens the Positive Relationship Between OL and BPII



Source: Own work.

6.5.6.3 Moderating Role of Data-Driven Culture on the Relationship Between Incremental Business Process Innovation and Business Process Performance

The study assessed the moderating role of *DDC* on the relationship between *BPII* and *BPP*. The results revealed a positive and significant moderating impact of *DDC* on the relationship between *BPII* and *BPP* (β = 0.098, t = 2.422, $p < 0.05$). The moderation analysis summary is presented in Table 89.

Table 89: The Moderating Impact of DDC on the Relationship Between BPII and BPP

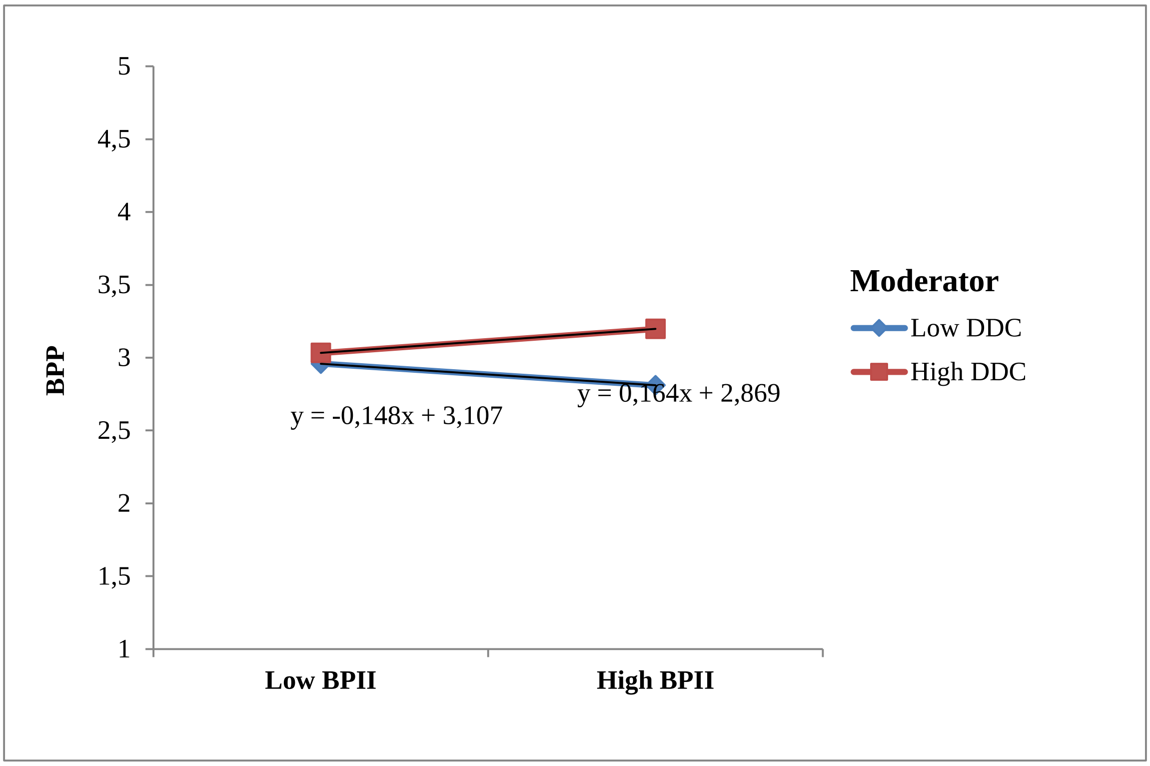
Relationship	**Unstandardized weights**	**t-value**	**p-value**
BPII → BPP	0.004	0.055	= 0.956
DDC → BPP	0.115	2.335	= 0.020
*BPII*DDC → BPP*	0.078	2.422	= 0.015

Probing the Interaction of *DDC*			
Low level: *BPII → BPP*	-0.084	-1.207	= 0.227
Mean Level: *BPII → BPP*	0.004	0.055	= 0.956
High level: *BPII → BPP*	0.105	1.525	= 0.127

Source: Own work.

Figure 27 shows the results of a simple slope analysis conducted to better understand the nature of the moderating effects. As can be seen, the line is much steeper for High *DDC*, which indicates that at a high level of *DDC*, the impact of *BPII* on *BPP* is stronger than for Low *DDC*. As the level of *DDC* increases, the relationship between *BPII* and *BPP* strengthens, although the relationship stays nonsignificant.

Figure 27: DDC Strengthens the Positive Relationship Between BPII and BPP



Source: Own work.

6.5.6.4 Moderated Mediation

The moderating role of *BPMM* on the relationships between *AI* and *OL*, *OL* and *BPII*, and *BPII* and *BPP* changes the indirect effects. Next, we present the indexes of moderated mediation following Collier (2020) recommendations for reporting moderated mediation.

AI → OL* → DMP → OP

Table 90: Moderated Mediation AI → OL → DMP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → DMP	0.332	7.062
DMP → OP	0.214	4.011
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579

Moderated Indirect Relationship	**Direct Effect**	**Indirect Effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → DMP → OP*	0.038 (0.805)	0.030	0.014/0.058	< 0.001
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		0.044	0.020/0.086	< 0.001
High Levels of *BPMM*		0.017	0.007/0.038	< 0.001
Index of Moderated Mediation		-0.018	-0.037/-0.007	< 0.001

*Note: * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL* → DMP → BPP → OP

Table 91: Moderated Mediation AI → OL → DMP → BPP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → DMP	0.332	7.062
DMP → BPP	0.258	3.204
BPP → OP	0.453	9.514
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579

Moderated Indirect Relationship	**Direct Effect**	**Indirect Effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → DMP → BPP → OP*	0.038 (0.805)	0.017	0.006/0.036	< 0.003
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		0.025	0.009/0.057	< 0.003
High Levels of *BPMM*		0.009	0.002/0.022	< 0.004
Index of Moderated Mediation		-0.010	-0.024/-0.003	< 0.002

*Note: * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL → BPP → OP*

Table 92: Moderated Mediation AI → OL → BPP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → BPP	0.328	5.292
BPP → OP	0.453	9.514
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579

Moderated Indirect Relationship	**Direct Effect**	**Indirect Effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → BPP → OP*	0.038 (0.805)	0.064	0.032/0.111	< 0.001
Probing Moderated Indirect Relationships				
Low Levels of BPMM		0.092	0.045/0.168	< 0.001
High Levels of *BPMM*		0.036	0.015/0.072	< 0.001
Index of Moderated Mediation		-0.037	-0.071/-0.015	< 0.001

*Notes. * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL → BPII* → DMP → OP*

Table 93: Moderated Mediation AI → OL → BPII* → DMP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → BPII	0.235	4.764
BPII → DMP	0.376	7.115
DMP → OP	0.214	4.011
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579
BPMM → BPII	0.424	5.394
*OL*BPMM → BPII*	-0.164	-3.628

Moderated Indirect Relationship	**Direct Effect**	**Indirect Effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → BPII* → DMP → OP*	0.038 (0.805)	0.008	0.003/0.019	< 0.001
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		0.016	0.007/0.037	< 0.001
High Levels of *BPMM*		0.003	0.001/0.009	< 0.009
Index of Moderated Mediation		0.003	0.001/0.008	< 0.001

*Notes. * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL → BPII* → DMP → BPP → OP*

Table 94: Moderated Mediation AI → OL → BPII* → DMP → BPP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → BPII	0.235	4.764
BPII → DMP	0.376	7.115
DMP → BPP	0.258	3.204
BPP → OP	0.453	9.514
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579
BPMM → BPII	0.424	5.394
*OL*BPMM → BPII*	-0.164	-3.628

Moderated Indirect Relationship	**Direct Effect**	**Indirect Effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → BPII* → DMP → BPP → OP*	0.038 (0.805)	0.004	0.001/0.012	< 0.002
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		0.009	0.003/0.025	< 0.002
High Levels of *BPMM*		0.001	0.000/0.005	< 0.014
Index of Moderated Mediation		0.002	0.000/0.005	< 0.002

*Notes. * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL → BPII* → BPP → OP*

Table 95: Moderated Mediation AI → OL → BPII* → BPP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → BPII	0.235	4.764
BPII → BPP	0.004	0.055
BPP → OP	0.453	9.514
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579
BPMM → BPII	0.424	5.394
*OL*BPMM → BPII*	-0.164	-3.628

Moderated Indirect Relationship	**Direct Effect**	**Indirect Effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → BPII* → BPP → OP*	0.038 (0.805)	-0.000	-0.008/0.007	> 0.05
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		-0.008	-0.030/0.006	> 0.05
High Levels of *BPMM*		0.002	-0.001/0.008	> 0.05
Index of Moderated Mediation		0.000	-0.003/0.003	> 0.05

*Notes. * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL → BPIR → DMP → OP*

Table 96: Moderated Mediation AI → OL → BPIR → DMP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → BPIR	0.329	7.132
BPIR → DMP	0.053	0,832
DMP → OP	0.214	4.011
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579

Moderated Indirect Relationship	**Direct Effect**	**Indirect Effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → BPIR → DMP → OP*	0.038 (0.805)	0.002	-0.003/0.008	> 0.05
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		0.003	-0.004/0.012	> 0.05
High Levels of *BPMM*		0.001	-0.002/0.005	> 0.05
Index of Moderated Mediation		-0.001	-0.005/0.001	> 0.05

*Notes. * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL → BPIR → DMP → BPP → OP*

Table 97: Moderated Mediation AI → OL → BPIR → DMP → BPP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → BPIR	0.329	7.132
BPIR → DMP	0.053	0,832
DMP → BPP	0.258	3.204
BPP → OP	0.453	9.514
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579

Moderated Indirect Relationship	**Direct Effect**	**Indirect effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → BPIR → DMP → BPP → OP*	0.038 (0.805)	0.001	-0.001/0.005	> 0.05
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		0.001	-0.002/0.008	> 0.05
High Levels of *BPMM*		0.000	-0.001/0.003	> 0.05
Index of Moderated Mediation		-0.001	-0.003/0.001	> 0.05

*Notes. * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

AI → OL* → BPIR → BPP → OP

Table 98: Moderated Mediation AI → OL → BPIR → BPP → OP*

Direct relationships	**Unstandardized weights**	**t-values**
AI → OL	0.427	6.736
OL → BPIR	0.329	7.132
BPIR → BPP	0.394	5.003
BPP → OP	0.453	9.514
BPMM → OL	0.657	8.070
*AI*BPMM → OL*	-0.248	-3.579

Moderated Indirect Relationship	**Direct Effect**	**Indirect effect**	**Confidence Interval Low/High**	**p-value**
AI → OL → BPIR → BPP → OP*	0.038 (0.805)	0.025	0.013/0.046	< 0.001
Probing Moderated Indirect Relationships				
Low Levels of *BPMM*		0.038	0.019/0.071	< 0.001
High Levels of *BPMM*		0.014	0.006/0.030	< 0.001
Index of Moderated Mediation		-0.015	-0.030/-0.007	< 0.001

*Notes. * = The construct of BPMM moderates the indirect effect. Unstandardized coefficients are reported. The value in parentheses is t- value. Bootstrap Sample = 5,000 with replacement.*

Source: Own work.

7 DISCUSSION

Although AI has been around since the 1960s, it has reemerged as a key technology in realizing performance and competitive advantage (Davenport & Ronanki, 2018). This study was primarily motivated by managers' and academics' renewed interest in the business value of AI. There is much theoretical discussion on its business value potential. However, the scholarly literature has lagged in its examination of the value-generation process and empirically verifying if and under what conditions the AI investments perform.

This study is built on the resource-based view and dynamic capability view, contextualized by the integrative IT business value model, and incorporates the knowledge management perspective and recent research on AI business value.

The proposed serial multiple-mediation model proves that multiple constructs can be linked in series to obtain the desired output. The results generally confirm the existence of full serial multiple-mediations in the proposed framework, highlighting the relationship between AI resources, BPM capabilities, and organizational performance. This chapter examines these results and discusses how AI affects performance.

7.1 Answering the Research Question

This study investigates the relationship of the proposed serial multiple-mediation AI business value model with AI as the independent variable (as defined in Section 2.2). We test how several mediating and moderating variables affect the relationship between AI adoption and organizational performance. Our overarching research question, formulated in line with these objectives, is as follows: How do AI technologies create business value, and what form of business value is expected? Although previous studies examine the relationship between AI and firm performance (Table 1), there is no comprehensive assessment of the value-generation process.

This study's theoretical framework and background are based on a review of existing literature on IT business value and AI. The findings from the literature review are supplemented with interviews (Section 3.4.2). The broader scope of AI adoption was discussed in nine in-depth semi-structured interviews, and the interviewees shared their experiences with AI implementation, deployment, use, and impact. Based on the findings, we propose a serial multiple-mediation model where multiple constructs are linked serially to explain the impact of AI on performance. Several relevant mediating variables are proposed (defined variable in parenthesis): cognitive business process automation (*CBPA*), business process innovation (*BPI*), organizational learning (*OL*), decision-making performance (*DMP*), and business process performance (*BPP*). Additionally, we include the constructs of digital maturity (*DM*), data-driven culture (*DDC*), BPM maturity (*BPMM*), and organizational culture (*OC*) to account for organizational context and *Environmental Uncertainty* in the competitive environment.

We empirically examine the research question utilizing a survey design. In addition to the literature review and exploratory interviews, we conceptualize and operationalize the concepts of AI adoption and CBPA and merge these with the existing measures in a structured questionnaire. After the pilot run and the refinement procedures, we employ the questionnaire in the main survey to collect data; we use a single primary data source, self-reporting, and cross-sectional design. The analysis is performed on a data sample of 448 cases of EU organizations utilizing AI in their business processes. We answer the subsidiary research questions by testing the proposed hypotheses.

7.1.1 AI Adoption Impact on Organizational Performance

Does AI adoption have a direct positive influence on organizational performance?

This sub-question is intended to identify if there is a relationship between AI and organizational performance. As this study is based on a survey, the respondent's opinions of the relationship are examined using structural equation modeling (SEM). This represents the reexamination of the base proposition of the AI business value model established by previous research (Table 1). Establishing the causal link between these two variables confirms that AI business value generation is an important area for consideration in the academic literature.

Big Data has become ubiquitous in the business environment and is now classified as a factor of production (Chetty, 2019; Manyika et al., 2011). The accellerated growth and low storage costs have led organizations to focus on AI technology to extract value from Big Data. AI-enabled data processing facilitates new IT capabilities that directly or indirectly impact the operational and dynamic capabilities by automating or augmenting them, resulting in improved decision-making and process performance. We examine these IT capabilities using five distinct sub-dimension of AI adoption.

7.1.1.1 Results for Five Distinct Sub-Dimensions of AI Adoption

This study outlines AI adoption using five distinct sub-dimensions, the components of AI adoption. By maximizing market and operational efficiencies, businesses can achieve superior performance. The AI-enabled capabilities of automation and augmentation are grounded in the resource-based, dynamic capabilities, and knowledge-based views. They are expected to increase competitive advantage and firm performance. According to the resource-based view, organizations can produce sustained competitive advantage when the resources they deploy are valuable, rare, inimitable, and non-substitutable. On the dynamic capabilities view, there is a recognition of the organization's ability to adapt to changing business environments and effectively manage its resources to sustain a competitive advantage over time. The knowledge-based view emphasizes the role of knowledge and knowledge management in creating and sustaining competitive advantage for firms.

The measurement of the AI-adoption latent construct is based on a Likert-scale-derived research survey. Therefore, the mean can be used as an acceptable measure of central tendency. The mean value for *AI adoption* is 2.144, with a standard deviation of 0.890. We employ a five-point Likert scale, and this mean value is low, indicating that, overall, the respondents view their organization's AI adoption as lacking. In the business context, this implies that the organizations in this study are underdeveloped in their adoption of AI technologies and solutions. They nevertheless adopt and leverage AI technologies and realize performance gains (Mishra & Pani, 2020). These results reflect management's continuing difficulty leveraging technologies to gain a competitive edge.

The second-order AI-adoption construct is positively and moderately correlated with *DDC* ($r = 0.430$, $p < 0.001$),[20] *DM* ($r = 0.445$, $p < 0.001$), and *BPMM* ($r = 0.377$, $p < 0.001$). This implies an organizational environment with more extensive and higher-level informatization and digitalization, a more structured approach, and active data-driven management of business operations. The only culture type correlated with the latent construct ($r = 0.135$, $p = 0.004$), *Adhocracy Culture*, focuses on innovation and creativity. This indicates organizations should strive to achieve a culture of innovation and creativity to efficiently and successfully leverage AI technologies. As shown by the correlation with *Environmental Uncertainty* ($r = 0.264$, $p < 0.001$), organizations in more competitive and unstable business

[20] Pearson correlation (significance, two-tailed) is a statistical measure of the linear relationship between two continuous variables. It measures the degree to which two variables are related and the direction of that relationship.

environments tend to achieve a higher level of adoption. The correlation with *Country* ($r = 0.102$, $p = 0.030$) suggests differences in levels of adoption dependent on the EU country. The following discussion on AI adoption sub-dimensions offers a more detailed view.

The sub-dimension of data acquisition and preprocessing (*DACQ*) has a mean value of 2.354 with a standard deviation of 1.188, meaning responses are spread out and diverse. We employ a five-point Likert scale, and the mean value can thus be considered moderate. Only 13.6% of the organizations rated highly on this measure. Respondents overwhelmingly view their organizations as inadequate in data acquisition and preprocessing, attributing this to the ineffective leveraging of Big Data, an essential resource in the resource-based view. As a result, other sub-dimensions that build on this may also have lower values. Interestingly, there is a negative correlation between *DACQ* and *Clan Culture* ($r = -0.095$, $p = 0.045$); a culture focused on collaboration and teamwork will hinder AI adoption efforts.

In contrast, *Market Culture,* which focuses on competition and achieving measurable goals, will reinforce AI adoption ($r = 0.094$, $p = 0.48$). *DACQ* positively correlates with *Firm Size* ($r = 0.176$, $p < 0.001$), indicating higher adoption rates for larger organizations. It is plausible that larger organizations have more data and resources, including finances, expertise, and technology infrastructure, and tend to generate more data than smaller ones, as indicated by Interview 1. However, competitiveness and industry trends do not seem influential as *Firm Size* is not correlated with *Environmental Uncertainty*, which measures competitiveness and trends in the business environment.

DDC ($r = 0.284$–0.428, $p < 0.001$), *DM* ($r = 0.307$– 0.393, $p < 0.001$), and *BPMM* ($r = 0.274$–0.326, $p < 0.001$) all have a positive correlation with the sub-dimensions. Achieving a higher level and extent of AI adoption requires a greater focus on data and analytics, digital initiatives, and the management of business processes.

Although we expect *Environmental Uncertainty* to have an inhibitory effect (e.g., increased operational risks, financial risks, and hindering endogenous financing) on technological adoption (Chen, Wang, et al., 2022; Choon-Ling, Hock-Hai, Tan, & Kwok-Kee, 2004; Deng, Fang, Tian, & Luo, 2022), when environmental uncertainty rises, organizations will increase R&D activities, investment, and improve their ability to innovate to be more agile and responsive to new trends and technologies (Sun, Yu, Zhang, & Zhang, 2022). We can infer that a positive correlation responds to highly competitive industries or rapidly changing markets.

Cognitive Insight (*CI*), "the ability to use AI to detect patterns in data and interpret their meaning," is closely related to the dynamic capabilities of sensing and seizing opportunities in response to changing markets and the technological conditions represented by Big Data (see Section 3.4.4). It has a low mean value of 2.200 with a standard deviation of 1.196; responses are thus spread out. Only 11.2% of the organizations rated highly. The results suggest that the organizations are passing up potential benefits and insights. The results for

DACQ indicate that insufficient resources and data quality issues could influence the results. Also, resistance to change and, by extension, lack of awareness or understanding could hinder the adoption of AI. The moderate correlation ($r = 0.393$, $p < 0.001$) of *CI* with *DM* partially confirms this assumption. Interestingly, the sub-dimension does not significantly correlate with any culture type. Like *DACQ*, *CI* is positively correlated with *Firm Size* ($r = 0.127$, $p = 0.007$), indicating higher adoption rates for larger organizations.

Cognitive Engagement (*CE*), "the ability to support AI-enhanced human–computer interaction and collaboration," has the lowest mean in the study, with a value of 1.887 and a standard deviation of 0.985. Only 5.1% of the organizations rated highly. No specific reasons for the lower value are discernable from the results. The *CE* sub-dimension is moderately correlated with *DM* ($r = 0.382$, $p < 0.001$) and has the highest correlation, although it is still low, with *Country* ($r = 0.115$, $p = 0.015$), suggesting that there could be a language barrier. We speculate this could be because of the limited number of EU languages supported by AI systems (e.g., chatbots, virtual assistants, recommendation systems, NLP tools). The country variable is not correlated with any other control or contextual variable that would indicate a lack of infrastructure, limited resources, environmental uncertainty, cultural barriers, or low digital maturity. A negative correlation between *CE* and *Hierarchy Culture* ($r = -0.104$, $p = 0.024$), which is focused on structure and stability, shows this culture hinders integration efforts.

In decision-making processes, the ability to use AI, known as cognitive decision assistance (*CDA*), has a low mean value of 1.960 with a standard deviation of 1.111, indicating the responses are more spread out. Only 8.9% of the organizations rated highly. This sub-dimension has a moderate correlation with *DDC* ($r = 0.318$, $p < 0.001$), DM ($r = 0.342$, $p < 0.001$), and BPMM ($r = 0.313$, $p < 0.001$). A positive correlation with *Adhocracy Culture* ($r = 0.198$, $p < 0.001$) indicates that a culture focused on innovation and creativity will ensure higher AI adoption. Interestingly, the sub-dimension negatively correlates with *Firm Age* ($r = -0.115$, $p = 0.015$), indicating lower adoption rates for older organizations. We can only speculate, but reasons for this could include legacy systems, infrastructural limitations, resistance to change, higher risk aversion, and poor data quality. Older organizations may face more significant challenges integrating AI technologies into their existing IT infrastructure and operations. There may be cultural resistance to change, and older organizations may be more risk-averse, making them slower to adopt new technologies. This risk aversion may be the result of the fear of disrupting existing operations or a desire to avoid costly mistakes. AI systems require high-quality data to work effectively. Older organizations may have legacy data systems that are not optimized for AI, resulting in poor data quality. This can make it harder to implement AI-assisted decision-making systems. This scenario was confirmed during Interviews 1 and 3.

Cognitive technologies (*CT*), "the ability to integrate AI technologies with other IT resources, services, and devices," have a low to moderate mean value of 2.319 with a standard deviation of 1.184; responses are more spread out. Only 14.7% of the organizations rated highly. AI technologies moderately correlate with *DM* ($r = 0.330$, $p < 0.001$) and *BPMM* ($r = 0.326$, $p < 0.001$) integration. It has the highest correlation with *Environmental Uncertainty* ($r = 0.221$, $p < 0.001$) and *DDC* ($r = 0.428$, $p < 0.001$) from all sub-dimensions. A positive correlation with *Adhocracy Culture* ($r = 0.198$, $p < 0.001$) indicates that a culture focused on innovation and creativity will facilitate greater integration of AI technologies.

By contrast, a negative correlation between *CT* and *Hierarchy Culture* ($r = -0.107$, $p = 0.024$), which is a culture focused on structure and stability, will hinder integration efforts. As with cognitive decision assistance, the *CT* sub-dimension negatively correlates with *Firm Age* ($r = -0.122$, $p = 0.010$), indicating lower adoption rates for older organizations. The negative correlation with *Hierarchy Culture* could imply a siloed organizational structure where business units operate with limited communication or collaboration. There is limited knowledge sharing, a lack of coordination, and reduced agility in such a structure, hindering the organization's ability to work effectively and efficiently and presenting a barrier to the adoption of new technologies and approaches, including AI. The siloed organizational structure (*Hierarchy Culture*) could also be linked to *Firm Age* as they are positively correlated ($r = 0.283$, $p < 0.001$).

7.1.1.2 The Relationship Between AI Adoption and Organizational Performance

We test the proposed relationship between AI and organizational performance using SEM. The relationship is significant without the mediators, and the standardized total effect is 0.418. This indicates that there is a positive relationship between AI adoption and organizational performance, where an increase in AI adoption increases *MP* and *OP*. This finding (direction and approximate value) aligns with several studies on AI and firm performance presented in Table 1. The variation in data and the sample population can explain the measurable differences in the findings.

The standardized weights of the AI adoption sub-dimension are high, and range between 0.633 and 0.850, and the proportion of variance explained (R^2) ranges between 0.401 and 0.722. Similarly, standardized weights of the organizational performance sub-dimensions of the *MP* ($\beta = 0.856$) and *OP* ($\beta = 0.827$) are high. The proportion of variance explained by the latent variables is as follows: $R^2 = 0.732$ for *MP* and $R^2 = 0.684$ for *OP*.

However, the relatively small proportion of variance explained by *OP* ($R^2 = 0.194$) indicates that this effect could be mediated. Including mediators in the analysis makes the relationship insignificant, showing that it is indeed fully mediated by the proposed variables (Section 2.2) and, therefore, does not positively and directly influence organizational performance.

7.1.2 Business Process Performance Impact on Organizational Performance

Does BPP positively influence organizational performance?

According to Kaplan and Norton (1996), organizations need to balance financial and non-financial indicators to link performance measures to strategy and build competitive advantage (Hegazy, Hegazy, & Eldeeb, 2022). Kaplan and Norton (1996) introduce the balanced scorecard approach, a widely accepted framework that measures and links performance according to four perspectives: customer, financial, internal business, and learning and growth. Isolating internal processes from overall organizational performance metrics reveals their mediating role. Therefore, we argue that BPP mediates the impact of AI adoption on organizational performance as AI adoption results in more efficient, flexible, and better-quality processes. The separation allows a more detailed view of the value-generation process, as suggested by Melville et al. (2004) IT value-generation model. Enholm et al. (2021) propose that in the context of AI adoption, performace measures should be separated at the process and organizational level. However, empirical studies on AI and firm performance do not present BPP as a mediating factor (Table 1).

The analysis confirms that *BPP* positively influences organizational performance ($\beta = 0.576$, $t = 9.488$, $p < 0.001$). The results at the construct level show the impact of AI adoption comes in the form of improved process efficiency ($\beta = 0.871$, $p < 0.001$) and quality ($\beta = 0.875$, $p < 0.001$), and slightly less comes in the form of enhanced flexibility of processes ($\beta = 0.709$, $p < 0.001$). While AI adoption excels at streamlining existing processes and boosting efficiency and output quality, its impact on process flexibility might be less pronounced. AI is often designed to optimize specific tasks, prioritizing efficiency and accuracy. Enhancing flexibility usually involves trade-offs between efficiency and quality. The focus on efficiency and quality can limit its ability to adapt to unexpected situations or changing requirements. Moreover, current AI may lack the general reasoning necessary to understand complex process changes, and its effectiveness relies heavily on training data representative of all process variations. The results indicate that AI has the most significant impact on process quality ($\beta = 0.875$, $p < 0.001$). From a theoretical perspective, several potential reasons can be inferred. AI effectively automates repetitive tasks accurately, minimizing errors and process variability. In most exploratory interviews, this emerged as the primary rationale for adopting AI. Moreover, AI supports ongoing process quality enhancement and maintenance through continuous monitoring and optimization. By continuously learning from data, AI systems can propose process enhancements or adjustments, improving outcomes and ultimately contributing to higher process quality. This assertion aligns with findings from the British Petroleum case study (Section 2.8). We conclude that value is realized at the operational level through enhanced execution of processes achieved by improving information speed, scale, granularity, and accuracy. These results are consistent with prior studies on IT business value that position BPP as a mediator of the impact on organizational performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Melville et al., 2004).

However, *BPP* is positioned as a secondary mediator in the serial multiple-mediation relationships in the proposed model because the direct relationship between AI adoption and *BPP* is insignificant and is clearly mediated.

Additionally, *BPP* has a mean value of 3.350 with a standard deviation of 0.897, which indicates a moderate level of process performance. As expected, *BPP* is positively correlated with *BPMM* ($r = 0.488$, $p < 0.001$), indicating efforts to manage processes are related to BPP. The variables *DDC* ($r = 0.438$, $p < 0.001$) and *DM* ($r = 0.299$, $p < 0.001$) are also positively correlated with BPP, implying organizations use data to continuously monitor, analyze and improve the performance of business processes. A positive correlation of *BPP* with *Adhocracy Culture* ($r = 0.276$, $p < 0.001$) indicates that, in the AI context, a culture focused on innovation and creativity reinforces BPP. A negative correlation with *Hierarchy Culture* ($r = -0.146$, $p = 0.002$), which is focused on structure and stability, implies lower *BPP*. Also, BPP is negatively correlated with the *Firm Size* ($r = -0.195$, $p < 0.001$) and *Firm Age* ($r = -0.185$, $p < 0.001$), indicating that the performance of business processes in larger and older organizations will be lower. A possible reason for this could be a lack of innovation; growing and aging companies may focus more on maintaining their existing business than innovating. Over time, a lack of innovation can lead to a decline in performance. The negative correlation between *Radical Innovation* and *Firm Size* ($r = -0.098$, $p = 0.037$) and *Age* ($r = -0.195$, $p < 0.001$) and between *Incremental Innovation* and *Age* ($r = -0.106$, $p = 0.025$) confirms this assertion.

7.1.3 Decision-Making Performance Impact Business Processes and Organizational Performance

Does DMP positively influence BPP and organizational performance?

AI systems' enhancement of decision-making effectiveness (quality) and efficiency are expected. We measure the impact on decision-making at the process level and position *DMP* as an essential mediator linking AI adoption to *BPP* and organizational performance. The link to BPP is intended to confirm the impact of AI-enabled decision-making at the level of operational processes. At the same time, the link to organizational performance demonstrates the implications at the strategic level.

The results of the SEM analysis show AI adoption has a significant impact on decision-making in terms of operational processes ($\beta = 0.249$, $t = 3.532$, $p < 0.001$). The impact is also evident at the strategic level ($\beta = 0.244$, $t = 4.050$, $p < 0.001$), directly impacting the organization's performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Fredrickson & Mitchell, 1984) and not mediated through BPP. Fredrickson and Mitchell (1984) theorize that in an unstable environment, there is a negative relationship between DMP and performance, but this is a positive relationship in a stable environment. The results show a positive relationship between DMP and organizational performance. Therefore, we can presume organizations operate in a stable business environment. Indeed, the *Environmental*

Uncertainty variable, measured on a 5-point Likert scale, has a mean of 3,208 with a standard deviation of 0.654, indicating a reasonably stable business environment and confirming Aydiner, Tatoglu, Bayraktar, and Zaim (2019) and Fredrickson and Mitchell (1984).

The structural model results confirm that DMP plays a critical mediating role in the impact of AI adoption on BPP. Specifically, DMP fully mediates the effects of CBPA and BPII, with additional partial mediation of OL. DMP exhibits a positive correlation with BPP indicators, with the most substantial influence on process efficiency ($r = 0.534$, $p < 0.001$) and the least on process flexibility. These findings underscore DMP's pivotal role as a determinant of process efficiency, directly affecting the smoothness and effectiveness of operations, including speed, coordination, and resource allocation (Majumdar, 2014).

DMP has a mean value of 3.348 with a standard deviation of 0.840, indicating a moderate level of decision-making performance. The correlation of organizational context with *DMP* is similar to that with *BPP*, indicating the factors are interrelated and mutually reinforcing. *DMP* is positively correlated with *BPMM* ($r = 0.589$, $p < 0.001$), indicating that efforts to manage processes improve decision-making. *DDC* ($r = 0.515$, $p < 0.001$) and *DM* ($r = 0.349$, $p < 0.001$) are also positively correlated with *DMP*, implying an organizational approach that emphasizes the use of data to make informed decisions. A positive correlation between *DMP* and *Adhocracy Culture* ($r = 0.247$, $p < 0.001$) indicates that a culture focused on innovation and creativity will have better decision-making. A negative correlation with *Hierarchy Culture* ($r = -0.180$, $p < 0.001$), which is focused on structure and stability, implies that decision-making performance is lower in these cultures. Also, *DMP* is negatively correlated with the *Firm Size* ($r = -0.176$, $p < 0.001$) and *Firm Age* ($r = -0.178$, $p < 0.001$), indicating larger and older organizations will have lower DMP. Larger and older organizations may have more complex organizational structures and decision-making processes, making effective and efficient decision-making challenging, as indicated by Interview 1 in the exploratory research phase.

We conclude that *DMP* positively influences operational processes and organizational performance. Thus, enhanced decision-making through the use of AI technologies is an important performance indicator of AI business value operationally and strategically.

7.1.4 The Mediating Role of Cognitive Business Process Automation

Does CBPA mediate the positive impact of AI adoption on DMP and BPP?

As part of our automation–augmentation perspective, we position CBPA as an operational capability, that is, “an organization’s ability to perform functional activities using purposefully chosen groups of resources.” *CBPA* measured the impact of AI adoption on cognitive business process automation, which goes beyond rule-based automation by integrating AI and cognitive computing capabilities. This approach distinguishes AI's impact from other automation technologies. It emphasizes the cognitive approach that facilitates human-machine collaboration, thereby contributing to a perspective of AI adoption focused on automation and augmentation.

The measurement centers on processes that require substantial knowledge and decision-making, qualities that align closely with AI's capabilities and are particularly suitable for automation. There is a significant overlap between knowledge-intensive and decision-making business processes (see Section 4.1.3). These processes are more complex and less automatable than purely structured processes. The objective was to determine if cognitive technologies create business value through their ability to automate these processes.

Although no universally accepted classification system neatly separates all business processes, we incorporated two common approaches that combine knowledge-intensive and decision-making processes. 1) Process complexity categorizes processes based on their level of complexity, with knowledge-intensive and decision-making processes typically falling under more complex categories. Measurement of process complexity involved assessing how cognitive technologies enable automation across structured and unstructured business processes. 2) Process automation suitability classifies processes based on their potential level for automation. Knowledge-intensive and decision-making processes often require human intervention and are less easily automated. The assessment of process automation suitability involved evaluating the spectrum of automation enabled by cognitive technologies, spanning from manual to fully automated processes.

Process complexity is more helpful in analyzing process efficiency, while automation suitability is better for identifying opportunities for technology adoption (Di Ciccio et al., 2015; Szelagowski & Lupeikiene, 2020; Vagia et al., 2016; Zhou, Zhang, Chen, & Liu, 2023). In this context, the results show that *CBPA* has a mean value of 2.385 with a standard deviation of 0.889, which indicates a moderate level and extent of cognitive business process automation. As regards the sub-dimensions, the *Level* variable has a mean value of 2.499 with a standard deviation of 0.994, meaning responses are more spread out and diverse. The result indicates a moderate level of automation, specifically, with respect to decision selection, the automation agent selects one decision and executes it with human approval. The *Extent* variable has a mean value of 2.271 with a standard deviation of 0.979, meaning responses are spread out and diverse. The result indicates the extent of automation is low and is centered on structured business processes with ad hoc exceptions and unstructured business processes with predefined fragments (i.e., structured and semi-structured). The finding of a moderate level of automation is in line with Raisch and Krakowski (2021), Daugherty and Wilson (2018), and Karan et al. (2021).

The structural model analysis shows that AI adoption significantly and strongly affects *CBPA* ($\beta = 0.697$, $t = 11.306$, $p < 0.001$). However, *CBPA* has no significant direct effect on *BPP* in terms of the efficiency of execution or scalability to full automation, where an agent acts autonomously. In contrast, it has an (expected) significant and direct effect on *DMP* ($\beta = 0.146$, $t = 2.313$, $p = 0.021$). Thus, automation efforts aim to improve decision-making efficiency and effectiveness at the augmentation end of the human–machine collaboration spectrum, corresponding to a moderate level of automation. The human-in-the-loop system supports a wide extent of augmented processes ranging from structured to semi-structured processes when execution relies entirely or partially on human judgment.

These results support the arguments by Brynjolfsson and McAfee (2014), Daugherty and Wilson (2018), Davenport and Kirby (2016), and Raisch and Krakowski (2021) that organizations should prioritize augmentation. Raisch and Krakowski (2021) explain that automation instills a logic of formal or procedural rationality, and they emphasize the importance of following formal procedures and rules in decision-making. This conflicts with the logic of substantive rationality, and it is thus important to consider the broader context and implications of decisions to achieve results consistent with organizational goals and values. While procedural rationality can help to ensure consistency and fairness in decision-making, it concerns only the efficiency or effectiveness of decision-making and not the implications of the decisions made. Therefore, it should be bound by human judgment as a real digital cognitive mediator does not yet exist (Rouse & Spohrer, 2018). This explanation is consistent with the results obtained.

Regarding the role of mediation, the direct effect of AI adoption on *BPP* and *DMP* is insignificant. Thus, we conclude that *CBPA* indeed mediates the impact of AI adoption on *DMP*, albeit partially. The proportion of variance in the latent variable ($R^2 = 0.486$) is above moderate, indicating that a large proportion of the variation in the CBPA variable is explained by the independent variable of AI adoption, suggesting a strong relationship.

Automating routine tasks and reducing errors and variability can contribute to BPM maturity (*BPMM*) by freeing human resources for more complex and value-added activities (van der Aalst, La Rosa, & Santoro, 2016) and we thus expect the correlation between *CBPA* and *BPMM* ($r = 0.396$, $p < 0.001$); *DDC* ($r = 0.354$, $p < 0.001$) and *DM* ($r = 0.277$, $p < 0.001$) also positively correlate with *CBPA*. This finding implies an organizational approach (via BPM, data-driven culture, and digital transformation) to automation that emphasizes the use of data to make informed decisions. A positive correlation between *CBPA* and *Adhocracy Culture* ($r = 0.170$, $p < 0.001$) indicates that a culture focused on innovation and creativity is likely to engage in more automation. The negative correlation between *CBPA* and *Hierarchy Culture* ($r = -0.113$, $p = 0.017$) shows that such a culture, which is focused on structure and stability, hinders automation. Also, *CBPA* is negatively correlated with *Firm Age* ($r = -0.118$, $p < 0.012$), indicating older organizations are unwilling or have difficulty implementing automation systems. We identify two reasons for this in the exploratory interviews: organizations may have legacy systems that are not easily compatible with new technologies (Interview 1) or are resistant to change in a cultural sense (Interviews 1 and 3). The positive correlation with *Environmental Uncertainty* ($r = 0.200$, $p < 0.001$), organizations in more competitive and unstable business environments are more willing to automate.

Overall, *CBPA* does not have a significant direct effect on *BPP* but has a significant direct impact on *DMP*, indicating that organizations lean more toward augmenting than automating business processes.

7.1.5 The Mediating Role of Organizational Learning

Does OL mediate the positive impact of AI adoption on DMP and BPP?

Organizational learning (*OL*) is positioned as an essential mediator of AI adoption and represents the augmentation potential of AI (in our automation–augmentation perspective). AI can explicate the organizational knowledge base, provided that it is represented in Big Data, by developing new, incremental knowledge or updating existing knowledge. Consistent with the dynamic capabilities view, AI integrates, builds, or reconfigures competencies to address rapidly changing environments (Eisenhardt & Martin, 2000). Organizational competencies can remain dynamic, allowing the organization to become more efficient by developing new knowledge through organizational learning (Senge, 1998).

OL is rated at a moderate to high level (mode value is 4.0) on the 5-point Likert scale, with a mean value of 3.650 and a standard deviation of 0.982. These results confirm that organizational learning has an important role in organizations adopting AI.

The structural model analysis shows that AI adoption significantly and strongly affects *OL* ($\beta = 0.488$, $t = 8.910$, $p < 0.001$). Next, *OL* has a significant direct effect on *DMP* ($\beta = 0.371$, $t = 6.905$, $p < 0.001$) and *BPP* ($\beta = 0.341$, $t = 5.541$, $p < 0.001$). These findings confirm the impact of AI adoption that takes place by increasing the organization's capabilities in acquiring, creating, integrating, and distributing information and knowledge. As already established, AI does not directly impact DMP and BPP (the direct relationships are insignificant), and organizations prefer augmentation, leaving humans in the loop of decision-making. In this manner, AI indirectly affects human decisions through complex learning processes that are difficult to predict (Schmidt, 2017). This interaction can result in incremental single-loop improvements or more radical double-loop learning (Wijnhoven, 2022) innovations. A positive correlation between *OL* and the efficiency of process performance indicates that it can directly impact *BPP* ($r = 0.537$, $p < 0.001$). Also, by learning new processes and techniques, employees can produce higher quality ($r = 0.553$, $p < 0.001$) and more flexible ($r = 0.519$, $p < 0.001$) processes; organizational learning can promote a culture of innovation and creativity, leading to new ideas and processes that improve process performance. These results highlight OL's significant impact on process quality. From theory, OL promotes knowledge sharing and disseminating best practices. Successful methods proven effective in one area can be applied across the organization, enhancing overall process quality (Armistead, 1999). Analyzing both past failures and successes in process execution enables organizations to manage process risks proactively. OL also deepens understanding of customer needs and preferences, facilitating continuous process improvement aligned with market demands and enhancing competitiveness, thus increasing overall quality (Migdadi, 2022).

Regarding the mediating role of organizational learning, the direct effect of AI adoption on BPP and DMP is insignificant, and we conclude that *OL* partially mediates this impact. Despite not indicating a good fit (R^2 is 0.286), *OL* is confirmed as one of four mediators of AI adoption.

OL positively correlates with *BPMM* ($r = 0.519$, $p < 0.001$). Organization learning and BPM maturity are closely related concepts (Jamali, 2006); they both involve continuous improvement and adaptation. *DDC* ($r = 0.505$, $p < 0.001$) and *DM* ($r = 0.302$, $p < 0.001$) also positively correlate with *OL* due to digital technologies being essential for the capture and analysis of data, communication and collaboration, and remaining agile and adaptable. Organizational learning is important in various models of digital maturity (Ruel, Rowlands, & Njoku, 2020; Teichert, 2019). A positive correlation between *OL* and *Adhocracy Culture* ($r = 0.255$, $p < 0.001$) indicates that a culture focused on innovation and creativity is recommended for successful AI adoption. A negative correlation between *OL* and *Hierarchy Culture* ($r = -0.242$, $p < 0.001$), focused on structure and stability, presents a hindrance.

In addition, *OL* is negatively correlated with *Firm Size* ($r = -0.158$, $p < 0.001$) and *Firm Age* ($r = -0.200$, $p < 0.001$), indicating larger and older organizations are less successful at organizational learning. Some evidence suggests that learning may be negatively correlated with the size and age of the organization. This is because more extensive and older organizations tend to have more established routines, processes, and procedures that can impede learning and innovation. There is also some qualitative evidence (Interviews 1, 2, 3, and 9) to suggest that *OL* may be negatively correlated with *Firm Size* and *Firm Age*. Again, we observe a positive correlation with *Environmental Uncertainty* ($r = 0.200$, $p < 0.001$) since organizations in more competitive and unstable business environments are more inclined to focus on organizational learning for the purposes of innovation (Chang, Tang, Cheng, & Chen, 2022). The results regarding the control variables confirm that *Firm Size* negatively impacts *OL* ($\beta = -0.224$, $t = -5.034$, $p < 0.001$); this confirms the findings from Jiménez-Jiménez and Sanz-Valle (2011) and Jansen, Van Den Bosch, and Volberda (2005).

The SEM moderation analysis shows that *BPMM* negatively moderates the relationship between AI adoption and *OL* ($\beta = -0.148$, $t = -3.579$, $p < 0.001$). A higher *BPMM* implies more strictly defined processes, which negatively influence the organization's learning potential. Several studies show that higher BPM maturity may make organizations inflexible and bureaucratic (Adler et al., 2005; Antoniol et al., 2004; Nawrocki et al., 2002). This view suggests that higher BPM maturity has a negative impact on organizational learning and innovation, as noted by (Herbsleb et al., 1997). During exploratory interviews (Interviews 1, 2, 3, and 9), several potential explanations were offered. These include resistance to change and a lack of experimentation, where a focus on efficiency and standardization may discourage experimentation and risk-taking, which are important for learning and innovation. Organizations may have a limited scope, as BPM practices optimize existing processes. They may fail to explore new possibilities or alternatives or have a narrow focus, as BPM maturity can emphasize process improvement rather than broader organizational goals and objectives. Organizations may have a myopic view of their performance, limiting their ability to learn and grow.

In conclusion, organizational learning mediates the positive impact of AI adoption on DMP and BPP. According to the results, such learning is one of the most effective ways to extract business value from AI, improving the performance of knowledge-intensive processes and enhancing the efficiency of decision making, preventing unnecessary trial-and-error, and increasing the effectiveness and speed of decision-making.

7.1.6 The Mediating Role of Incremental Business Process Innovation

Does BPII mediate the positive impact of AI adoption on DMP and BPP?

From the automation–augmentation perspective *BPII* is employed to examine the incremental transformational effects of AI adoption. We incorporate an ambidextrous approach, recognizing the importance of organizations exploring new domains and simultaneously exploiting those already in place to survive and grow (March, 1991; O'Reilly III & Tushman, 2011). Thus, we distinguish between incremental and radical transformation effects. Adopting the knowledge-based perspective, we see innovation as a way for organizations to leverage their knowledge assets to create new products or services, improve processes, and find new ways to deliver value. As regards improvement, organizations are using embedded AI technology or an AI-enabled innovation process to search for solutions in knowledge domains related to their existing knowledge base. This generates comparatively incremental solutions in innovation since they rely very closely on existing knowledge.

Considering that *BPII* is normally distributed, the mean is a good indicator of central tendency. On the 5-point Likert scale, *BPII* is rated at a moderate to high level (mode = 4.0), with a mean value of 3.565 and a standard deviation of 0.886. Among the respondents, 41.5% claimed that their organizations pursue continuous process improvements.

The structural model analysis shows that AI adoption significantly and positively affects BPII ($\beta = 0.282$, $t = 5.285$, $p < 0.001$). Next, *BPII* directly affects *DMP* ($\beta = 0.369$, $t = 6.474$, $p < 0.001$). However, the relationship with *BPP* is insignificant. This suggests incremental improvements are primarily related to AI-assisted decision-making that has less of a direct impact on process performance. Based on the result for *CBPA*, that organizations are leaning toward augmentation rather than automation, augmentation primarily impacts the decision-making processes of a human-in-the-loop system. This would explain why most AI-enabled incremental process improvements manifest in improved DMP. Therefore, *DMP* fully mediates the impact of *BPII* on *BPP*.

As established above, the direct effect of AI adoption on *DMP* is insignificant. Indicating a moderate fit (the proportion of variance R^2 is 0.396), *BPII* is confirmed to be one of four mediators of AI adoption. Thus, we conclude that *BPII* partially mediates the impact of AI adoption on *DMP*. *BPII* positively correlates with *BPMM* ($r = 0.545$, $p < 0.001$).

BPM consolidates several objectives and methodologies, one being process innovation (Rosemann et al., 2004). The concepts of process innovation and BPM maturity are inherently related. Dijkman et al. (2016) demonstrate that a higher level of innovation is associated with greater BPM maturity. Having a data-driven culture has a significant impact on an organization's data-driven-innovation capabilities that are enhanced by applying advanced information and communication technology (Chatterjee, Chaudhuri, et al., 2021).

The positive correlation between *DDC* ($r = 0.514$, $p < 0.001$) and *DM* ($r = 0.307$, $p < 0.001$) is therefore expected. The SEM moderation analysis shows that *DDC* moderates the relationship between *BPII* and *BPP* ($\beta = 0.078$, $t = 2.422$, $p = 0.015$). Although the moderation is significant and positive, the resulting relationship between *BPII* and *BPP* remains insignificant. A positive correlation between *BPII* and *Clan Culture* ($r = 0.103$, $p = 0.030$), which is a culture characterized by a high degree of flexibility and a high degree of internal focus, is probably the result of the view that incremental improvements draw from the existing knowledge base, focusing on the internal environment. A positive correlation between *BPII* and *Adhocracy Culture* ($r = 0.122$, $p < 0.010$) is expected; this entrepreneurial culture emphasizes creativity, innovation, and risk-taking. A negative correlation with *Hierarchy Culture* ($r = -0.145$, $p < 0.001$) shows that this culture, which is focused on structure and stability, is incompatible with innovation (Cameron & Quinn, 2011).

BPII negatively correlates with *Firm Age* ($r = -0.106$, $p < 0.025$), indicating older organizations are less innovative. Coad, Segarra, and Teruel (2016) explain that older organizations undertake incremental innovation along established, less risky trajectories. Again, we observe a positive correlation with *Environmental Uncertainty* ($r = 0.200$, $p < 0.001$) because organizations in more competitive and unstable business environments are more likely to focus on innovation (Chang et al., 2022).

Accordingly, incremental innovations do not have a significant direct impact on BPP but do have a significant direct effect on DMP, indicating that they are primarily focused on decision-making.

7.1.7 The Mediating Role of Radical Business Process Innovation

Does BPIR mediate the positive impact of AI adoption on DMP and BPP?

The ambidextrous approach to innovation includes radical improvements (*BPIR*) as the counterpart to the incremental improvements just considered. This involves exploring new domains as sources of innovation (March, 1991; O'Reilly III & Tushman, 2011). To generate more creative and innovative ideas or opportunities, organizations must be more exploratory and reach beyond existing knowledge domains to new fields and external data sources and. AI systems can generate, identify, and evaluate more creative and experimental ideas. Analyzing large datasets of existing ideas, patterns, and trends can generate new ideas using algorithms and ML techniques. Automatically identifying and classifying existing ideas and concepts makes analyzing and comparing them easier. Potential ideas can be evaluated based on various criteria such as novelty, feasibility, and market demand. In addition, new and more innovative concepts can be generated by combining and refining existing ideas. As such, these radical improvements in business processes, also known as business process redesign or reengineering, complements incremental improvement in our automation–augmentation framework and allows us to examine the radical, more substantial transformational effects of AI adoption.

The mean value of *BPIR* indicates the central tendency, given that *BPIR* (like *BPII*) has a normal distribution. On the 5-point Likert scale, *BPIR* is rated at a moderate level (mode = 4.0), with a mean value of 2.792 and a standard deviation of 0.957. Only 6.5% of respondents reported that their organizations implement new and radical processes to improve.

According to the analysis of the structural model, the adoption of AI has a significant and positive impact on *BPIR* ($\beta = 0.276$, $t = 4.644$, $p < 0.001$), which is comparable in strength to its effect on *BPII*. Unlike *BPII*, *BPIR* significantly and directly affects *BPP* ($\beta = 0.316$, $t = 5.042$, $p < 0.001$) but not *DMP*. The relationship between *BPIR* and *DMP* is insignificant. This suggests radical improvements are primarily because the use of AI to design new processes or redesign existing process has the most impact on the efficiency, effectiveness, and flexibility of business processes (Al-Anqoudi, Al-Hamdani, Al-Badawi, & Hedjam, 2021; Cao & Jiang, 2022; Jurksiene & Pundziene, 2016). The correlation results with the indicators of process performance demonstrate these radical improvements significantly impact process quality ($r = 0.485$, $p < 0.001$), closely followed by efficiency ($r = 0.477$, $p < 0.001$), and with a lesser impact on flexibility ($r = 0.397$, $p < 0.001$). These radical improvements elevate process quality by eliminating inefficiencies and incorporating advanced technologies to enhance accuracy and compliance. Section 7.1.2 examines AI's influence on quality, currently identified as a primary driver for adopting AI. Arguably, this is an effect of AI adoption being on an automation–augmentation spectrum, where augmentation results in incremental improvements related to decision-making and automation implies a redesign of processes, thus having a more comprehensive impact on process performance, as suggested by Al-Anqoudi et al. (2021).

The direct impact of AI adoption on *BPP* is insignificant. The proportion of variance R^2 for *BPIR* is 0.377. According to the results, it is one of four important mediators of AI adoption. Thus, we conclude that *BPIR* partially mediates the impact of AI adoption on *BPP*.

BPIR is positively correlated with *BPMM* ($r = 0.458$, $p < 0.001$). As established, the concepts of process innovation, process redesign, and BPM maturity are interrelated and mutually reinforcing. The positive correlation with *DDC* ($r = 0.514$, $p < 0.001$) and *DM* ($r = 0.307$, $p < 0.001$) is also expected, as having a data-driven culture highly influences an organization's data-driven innovation (Chatterjee, Chaudhuri, et al., 2021). Like *BPII*, *BPIR* is positively correlated with *Adhocracy Culture* ($r = 0.218$, $p < 0.001$) is expected as this type of culture emphasizes creativity, innovation, and risk-taking. A negative correlation with *Hierarchy Culture* ($r = -0.145$, $p < 0.001$), a culture focused on structure and stability, is incompatible with innovation (Cameron & Quinn, 2011).

BPIR negatively correlates with *Firm Size* ($r = -0.098$, $p < 0.037$) and *Firm Age* ($r = -0.195$, $p < 0.001$), indicating larger and older organizations are less successful at radical innovation. Despite some studies indicating that firm size and age do not significantly affect innovation (Cheng & Huizingh, 2014; Ritala, Olander, Michailova, & Husted, 2015; Stam, 2009). Chandy and Tellis (2000) suggest that larger organizations may not be as likely to engage in radical innovation because of inertia. In this context, the theory of inertia posits that established systems and organizations tend to resist change and prefer to maintain their current state. Ritala et al. (2015) emphasize that age affects innovation novelty; younger organizations produce more novel outcomes, as Henderson and Clark (1990) suggest. Again, we observe a positive correlation between *BPII* and *Environmental Uncertainty* ($r = 0.146$, $p < 0.001$) because organizations in more competitive and unstable business environments are more likely to focus on innovation (Chang et al., 2022).

In summary, radical innovations do not significantly impact the process of decision-making but significantly impact process performance. The results confirm that AI facilitates radical innovations through process redesign, significantly affecting business process efficiency, effectiveness, and flexibility.

7.1.8 Organizational Learning Impact on Business Process Innovation

Does OL positively influence BPII and BPIR?

Organizational learning (*OL*) can help an organization identify areas for improvement in existing processes and develop ideas for incremental improvements, drawing from their existing knowledge base. Over time, a company can refine and optimize its processes by continuously learning from experience and feedback. Organizational learning can also lead to radical process innovations as other knowledge domains are explored and new knowledge generated, encouraging experimentation and risk-taking (Sheng & Chien, 2016). Organizations with a culture that supports continuous learning and improvement are more likely to explore innovative approaches to problem solving and process optimization. This can produce radical process innovations that fundamentally transform business operations (Zhao, Li, & Liu, 2016). The impact of organizational learning on innovation is well established (Aragón-Correa et al., 2007; García-Morales et al., 2012; Hung et al., 2011; Jiménez-Jiménez & Sanz-Valle, 2011; Weerawardena et al., 2006). However, there is limited empirical research on whether AI-enabled knowledge acquisition, sharing, and utilization (i.e., organizational learning) influence process performance by facilitating innovation. In order to investigate the ambidexterity of innovation, incremental and radical process innovations are examined separately.

The structural model analysis shows that *OL* significantly impacts *BPII* ($\beta = 0.446$, $t = 8.442$, $p < 0.001$) and *BPIR* ($\beta = 0.434$, $t = 7.001$, $p < 0.001$). These results validate the impact of OL via increased AI-enabled knowledge capabilities on process innovation.

We confirm OL's mediating role (Table 84) between AI adoption and *BPP*. The results confirm *OL* is a partial mediator (AI also impacts *BPII* and *BPIR* directly) between AI adoption and *BPII* and *BPIR* (Table 86). Thus, *OL* is positioned as the primary mediator in a series of mediations that connect AI adoption and organizational performance. In conclusion, OL is an essential facilitator in generating AI business value.

The SEM moderation analysis shows that *BPMM* negatively moderates the relationship between *OL* and *BPII* ($\beta = -0.164$, $t = -3.628$, $p < 0.001$). A mature BPM environment may focus on maintaining stability and efficiency at the expense of innovation and learning (Dijkman et al., 2016). This explains the negative moderating effect of the relationship between *OL* and *BPII*. However, *BPMM* does not impact the relationship between *OL* and *BPIR*. It is worth noting that radical process innovation often requires the organization to make significant changes and depart from existing processes and practices. Radical process improvement is a set of activities often decoupled from existing processes (i.e., R&D activities). In contrast, incremental process innovation focuses on minor improvements to existing processes. Therefore, it is conceivable that *BPMM* may not affect *BPIR*. Additionally, Dijkman et al. (2016) point out that there is a possible negative relationship between innovativeness and BPM maturity, with more innovative organizations having lower BPM maturity levels, indicative of smaller organizations. This is consistent with our finding of a negative correlation between *BPMM* and *Firm Size* ($r = -0.145$, $p = 0.002$).

These findings confirm *OL* has a positive impact on incremental and radical BPI. Organizational learning promotes continuous improvement of processes, products, and services, leading to increased competitiveness. Organizations that foster a culture of learning and innovation can stay ahead of the curve and adapt to environmental uncertainty.

7.2 Additional Findings

The study's empirical findings affirm that cognitive business process automation–augmentation, organizational learning, and incremental process improvements are vital mediators in enhancing DMP through AI adoption. Furthermore, organizational learning and radical process improvements significantly boost BPP. AI-enabled capabilities should positively leverage decision-making processes and ambidextrous process transformation to yield business value. Critical management activities involved in pursuing business goals include improving decision-making, overcoming inertia, and implementing innovation and change. Next, we discuss automation–augmentation in the context of paradox theory and ambidextrous innovation.

7.2.1 Automation–augmentation

As theorized by Raisch and Krakowski (2021), there is no empirical evidence that fully AI-enabled automation directly impacts process performance, demonstrating that AI adoption augments and improves decision-making processes. Notably, decision-making is fully mediated by *CBPA* ($\beta = 0.23$, $t = 2.313$, $p = 0.021$), *BPII* ($\beta = 0.23$, $t = 6.474$, $p < 0.001$), and *OL* ($\beta = 0.23$, $t = 6.905$, $p < 0.001$), based on two inherent characteristics of AI, decision-making and knowledge engineering. Automating business processes using AI does not necessarily produce immediate performance improvements.

AI can thus enhance and complement rather than replace human capabilities and skills. According to Raisch and Krakowski (2021), the augmentation approach can lead to superior performance. However, they acknowledge that augmentation cannot be easily separated from automation, as both concepts involve trade-offs and tensions. Therefore, they suggest using a paradox perspective to understand and manage the complex dynamics of AI adoption. Paradox theory suggests that the concepts of automation and augmentation are interdependent and paradoxical; they can coexist and change over time (Waldman, Putnam, Miron-Spektor, & Siegel, 2019).

Based on the results (Section 7.1.4), we agree organizations must adopt a broader perspective that balances automation and augmentation to leverage the potential of AI while mitigating its challenges (Raisch & Krakowski, 2021). Paradox theory prescribes the use of management strategies such as acceptance (acknowledging and embracing the existence of paradoxical tensions), differentiation (creating clear boundaries and distinctions between paradoxical poles such as automation and augmentation), integration (making connections and synergies between the paradoxical poles, such as automation and augmentation), or transcendence (moving beyond the paradoxical poles, by creating a new perspective or reality that transcends their contradictions; Schad, Lewis, Raisch, & Smith, 2016; Smith & Lewis, 2011).

The main difference between the paradox theory perspective and ambidextrous design (Section 2.8) is that the former treats the exploration-exploitation conflict as a paradoxical tension that needs to be embraced and balanced, while ambidextrous design views these as a trade-off (structural and temporal) that needs to be separated and coordinated. The paradox perspective offers a more comprehensive and dynamic way to manage multiple demands, while ambidextrous design provides a more pragmatic and static view of how to achieve organizational performance (Papachroni, Heracleous, & Paroutis, 2015).

We conclude that viewing automation–augmentation from the lens of paradox theory enables us to move beyond separation-oriented prescriptions toward synthesis and track how the concepts dynamically relate over time. After all, automation–augmentation is a spectrum (Section 2.7.1) and empirical research in this area can more closely and pragmatically track practice using this approach.

7.2.2 Ambidextrous Innovation

March (1991) presents the concept of ambidexterity in the context of organizational learning. An organization must possess exploratory and exploitative capabilities to achieve sustainable competitive advantage (March, 1991). Ambidextrous innovation theory has been widely used to explain the mechanisms of managerial capability, organizational performance, and competitive advantage (Chen & Yu, 2022).

Cao, Gedajlovic, and Zhang (2009) present two dimensions of ambidexterity: balanced and combined. The first prioritizes a balance between exploration and exploitation as these compete for scarce resources and are incompatible (March, 1991). They represent different competencies and processes and require distinct systems and cultures (Heirati, O'Cass, & Sok, 2017; Wei, Yi, & Yuan, 2011). The second dimension conceptualizes exploitation and exploration as distinct and separable modes of activity, and organizations can engage in both concurrently (Gibson & Birkinshaw, 2004; Soto-Acosta, Popa, & Martinez-Conesa, 2018), with results depending on their combination and interaction.

Another approach to organizational design presents sequential, structural, contextual, and hybrid ambidexterity. These were developed to resolve the tensions and contradictions associated with executing exploitation and exploration and achieve combined effects (Martin, Keller, & Fortwengel, 2019; O'Reilly III & Tushman, 2013; Raisch, Birkinshaw, Probst, & Tushman, 2009). Sequential ambidexterity shifts the organization's strategic focus from exploitation and exploration and back again over time (Boumgarden, Nickerson, & Zenger, 2012). Structural ambidexterity assigns separate departments in an organization as responsible for either exploitation or exploration (O'Reilly III & Tushman, 2008). Contextual ambidexterity establishes a specific context to enable all organizational members to oscillate between exploitation and exploration situationally (Martin et al., 2019). Hybrid ambidexterity is an approach that combines units engaged in explorative and exploitative ambidexterity with units engaged in contextual ambidexterity (Niewöhner et al., 2021).

He and Wong (2004) propose a mix of ambidextrous innovation strategies. First, organizations prioritize developing exploratory or exploitative innovation according to their situation. However, the effect is dominated by the balance or gap. Second, organizations simultaneously implement exploratory and exploitative innovation, making them orthogonal, interactive, and complementary (Soto-Acosta et al., 2018). Both are independent but can also be substitutes or complements.

According to O Reilly and Tushman (2004), organizations with ambidextrous structures are much more likely to develop breakthrough processes than those with other organizational structures while sustaining or improving their business models. Their innovation strategies balance the rapidly changing market environment by effectively balancing incremental and radical innovations (Teece, 2014). Consequently, such organizations proactively implement continuous innovation strategies (Lee & Trimi, 2018). Ma, Jia, and Wang (2022) demonstrate that digital transformation (i.e., the adoption of IT) positively impacts ambidextrous innovation, a mediator between technological adaptation and organizational performance. Applying this to AI adoption, we ask the following question: *Does AI facilitate ambidextrous innovation?*

Grover, Purvis, and Segars (2007) present empirical evidence that IT can enable ambidextrous innovation. Their findings show that the configuration of organizational components appropriate for radical innovation is diametrically opposed to the configuration appropriate for incremental innovation; these configurations can successfully be bound within the same organization to exploit efficiencies and explore opportunities. Consistent with these findings, we present evidence (Sections 7.1.6, 7.1.7, and 7.1.8) that AI adoption similarly impacts incremental and radical innovation – presenting itself as a suitable technology to build a proper ambidextrous set-up and drive and balance exploration and exploitation of knowledge and technology. The impact of AI adoption on *BPII* ($\beta = 0.282$, $t = 5.285$, $p < 0.001$) and *BPIR* ($\beta = 0.276$, $t = 4.644$, $p < 0.001$) is direct and positive. Next, the following results confirm incremental improvements impact *DMP* ($\beta = 0.369$, $t = 6.474$, $p < 0.001$), while radical improvements offer significant *BPP* improvements ($\beta = 0.316$, $t = 5.042$, $p < 0.001$).

According to the knowledge-based view, reusing existing knowledge is a key part of exploitative innovation, while exploratory innovation requires that existing and new knowledge is recombined (Li, Li, & Zhou, 2022). Organizations expand their knowledge base by acquiring external knowledge (Liao & Tsai, 2019) that will complement additional knowledge and may not come from internal knowledge heterogeneity and facilitate organizations' participation in ambidextrous innovation (Rosenkopf & Almeida, 2003). The ability to effectively use external knowledge largely depends on the prior level of knowledge, as it increases absorptive capacity (Jansen, Van Den Bosch, & Volberda, 2006). However, not all knowledge supports ambidextrous innovation. Excessive external knowledge heterogeneity leads to information overload, and excessive internal knowledge heterogeneity increases complexity, hinders coordination, and raises R&D costs, weakening the organization's innovation capability (Cohen & Levinthal, 1990; Grant, 1996a). For ambidextrous innovation, organizations must be able to combine, process, and apply the knowledge and technology acquired to better utilize their technological knowledge base (Li, Li, et al., 2022). The knowledge-based impact is tested with the organizational variable. Results show *OL* has a direct and positive impact on *BPII* ($\beta = 0.446$, $t = 8.442$, $p < 0.001$) and *BPIR* ($\beta = 0.434$, $t = 7.001$, $p < 0.001$). This is consistent with the knowledge perspective, in terms of which AI facilitates the acquisition, creation, integration, and distribution of information and knowledge.

Chen and Yu (2022) present empirical evidence that exploratory and exploitative innovations significantly restrain organizational obsolescence (i.e., organizational performance declines with age). Environmental turbulence negatively moderates the relationship between exploratory innovation and organizational obsolescence. Similarly, Buccieri, Javalgi, and Cavusgil (2020) explain how environmental dynamism positively moderates the relationship between international entrepreneurial culture and ambidextrous innovation. In applying these findings to our research model, we expect that *Environmental Uncertainty* will impact AI adoption, *BPII*, *BPIR*, and *OL*. The results show that AI adoption, *OL*, *BPII* and *BPIR* do correlate positively with *Environmental Uncertainty* ($r = 0.146$ - 0.264, $p < 0.001$). However, when we test for the moderation effect of *Environmental Uncertainty* in the proposed model, we cannot confirm any significant impact. Examining the box and whiskers plot of the mean values for *Environmental Uncertainty* separated by *Country* (Appendix 6), we observe that the ratings are consistently between 3.0 and 4.0 (mean between 2.804 and 3.812, with a standard deviation between 0.088 and 1.149), indicating moderate levels of environmental uncertainty across all countries. A causal moderation effect is also unlikely to be significant since there is too little variance.

The literature identifies organizational culture as an essential determinant of ambidextrous innovation. Niewöhner et al. (2021) state that an ambidextrous innovation culture should include norms such as openness, autonomy, initiative, and willingness to take risks. It should be loose because the design of these values can be varied according to the type of innovation desired. Grover et al. (2007) argue that entrepreneurial culture is needed where there is risk-taking and experimentation that could not exist in a centralized organization (Tushman & O'Reilly III, 1996). However, simultaneous exploitation requires a delicate balance between size, autonomy, teamwork, speed, exploitation, and experimentation (Grover et al., 2007).

Examining the proposed organizational context, the results are consistent with the ambidextrous innovation culture. Incremental process improvement is more likely in a culture that combines the characteristics of clan and adhocracy culture (Section 7.1.6)); that is, it is characterized by a high degree of flexibility, internal focus, teamwork, collaboration, creativity, innovation, and risk-taking. Having an internal focus is a characteristic of exploitation and incremental improvement, focusing on the internal environment and building on existing knowledge. In contrast, radical process improvements primarily require creativity, innovation, and risk-taking (Section 7.1.7). Incremental and radical improvements are not possible with rigid structures and stability, characteristics incompatible with innovation (Cameron & Quinn, 2011). These findings make a significant contribution to the emerging literature on AI-enabled innovation.

7.3 Distinguishing AI from IT – Unique Contributions and Business Value

In Section 2.2, we established that AI resources represent a subset of IT resources (Deng, Zhang, He, et al., 2023; Deng, Zhang, & Xu, 2023; Mikalef & Gupta, 2021; Wamba-

Taguimdje et al., 2020b). Authors in the context of the academic research fields distinguish and separate IT and AI; however, in the context of business value research, AI is usually considered a subset of IT (Engel et al., 2022; Jakšič & Marinč, 2019; Koo & Le, 2024; Mikalef et al., 2019; Mikalef & Gupta, 2021; Perifanis & Kitsios, 2023; Spring, Faulconbridge, & Sarwar, 2022). AI relies on and extends the capabilities provided by IT infrastructure and services. While IT covers a broad range of technologies (i.e., hardware, software, databases, networks, and various information systems) and practices for managing and processing information, AI focuses on developing systems that can perform intelligent tasks (i.e., machine learning, natural language processing, computer vision, and robotics), making it a specialized but integral part of the IT landscape. Comparing AI with the dimensions of IT business value (Mooney et al., 1996), it aligns very well, as automational, informational, and transformational effects are key AI impacts at the process level (Wamba-Taguimdje et al., 2020b). Accordingly, we developed the proposed AI business value model by contextualizing the integrative IT business value model (Melville et al., 2004). Therefore, we expect similar relationships between constructs and their impact on organizational performance.

Recent studies on IT business value have shown that the productivity paradox was only a temporary problem pertaining to time and measurement (Kohli & Grover, 2008). Furthermore, the complementary relationship between IT and value is now well-established. IT technology and software tools must be integrated into a business value-creation process, working synergistically with various organizational and information systems factors (Melville et al., 2004; Wade & Hulland, 2004) to create value for an organization. Comparable to IT (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Kohli & Grover, 2008), AI does not directly impact organizational performance but is part of a business value-creating process. The direct impact of AI adoption on organizational performance, with a standardized total effect of 0.418 and organizational performance explaining a relatively small proportion of variance ($R^2 = 0.194$), suggests that AI's influence is moderated.

Similar to other forms of capital, IT creates value through productivity. Value can manifest itself in process improvements, profitability, or consumer benefits (Kohli & Grover, 2008) and at different levels (e.g., individual, process, or organization). It has been recognized that more significant IT usage at a lower level (e.g., individual) could be aggregated to the organizational level and serve as a mediator between IT investment and organizational value (Devaraj & Kohli, 2003). A single organization executes numerous business processes to achieve its business goals, providing opportunities for applying IT to improve processes and organizational performance (Melville et al., 2004). The impact of IT capabilities on business-process performance has been studied extensively in the literature. Many IT studies have indicated that successful IT infrastructure investments generate substantial changes within business processes, leading to superior performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019). Hence, the impact of AI adoption was expected to be mediated by process-related capabilities and other organizational factors. Our empirically validated AI business value research model is process-oriented (Melville et al., 2004; Mooney et al., 1996) and operates under the same premise as IT, where AI business value is generated at the process level (Elbashir et al., 2008). Simultaneously, a significant and direct relationship ($\beta = 0.174$, $t = 3.382$, $p < 0.01$) exists between business processes and AI adoption, influencing both tangible and intangible organizational performance, aligning with findings in IT business value research (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019; Sun, Strang, & Firmin, 2017).

Despite these claims about the direct effect of IT and AI capabilities on business-process performance, these effects may not be realized without a solid and effective decision-making process. IT decision support systems and business intelligence tools have provided organizations with the information to make informed decisions. These tools aggregate and analyze data to present actionable insights (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Ghasemaghaei et al., 2018). AI takes this a step further with advanced predictive analytics and prescriptive analytics. AI can predict future trends based on past data and suggest optimal actions to achieve desired outcomes, providing a more dynamic and proactive decision-making support system (Phillips-Wren, 2012; Sachan, Yang, Xu, Benavides, & Li, 2020). IT business value research has positioned decision-making as a process-level effect, demonstrating it significantly impacts business process performance and organizational performance (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Cao et al., 2019; Sidorova, 2019). Comparing the decision-making impact of our AI business value research model and the results in IT business value research (Alzghoul, Khaddam, Abousweilem, Irtaimeh, & Alshaar, 2024; Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Cao et al., 2019; Djalic, Nikolic, Bakator, & Erceg, 2021; Khaddam, Alzghoul, Abusweilem, & Abousweilem, 2023), we can see the results are similar with two exceptions. First, in IT business value research, the impact on BPP is direct; however, when introducing the DMP variable, the impact is fully mediated (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019). This suggests that technologies like big data analytics explicitly influence decision-making. Conversely, AI affects both process performance and decision-making, indicating the presence of additional mediators between AI and BPP. In this context, we present BPIR and OL. Second, several IT business value authors confirm the direct impact of DMP on organizational performance (Alzghoul et al., 2024; Cao et al., 2019; Djalic et al., 2021; Khaddam et al., 2023), however when presenting *BPP* in the research model, *DMP* is fully mediated (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019), despite the positive impact been previously theorized by Fredrickson and Mitchell (1984). Conversely, AI impacts organizational performance through *DMP* ($\beta = 0.241$, $t = 4.097$, $p < 0.001$) and *BPP* ($\beta = 0.562$, $t = 9.382$, $p < 0.001$) simultaneously. The high and positive impact of *DMP* on *BPP* is very similar in IT and our (AI business value) research model *BPP* ($\beta = 0.560$, $t = 10.192$, $p < 0.001$). We can conclude that *AI* impacts *DMP*, which impacts performance at the process level and strategic decision-making at the organizational level. Nonetheless, it must be noted that we found only one IT business value research article referencing decision-making and process performance in the research model (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019) and one for AI business value, where *DPM* is the only mediator (Chen, Esperança, et al., 2022).

While prior research has extensively theorized on process automation and IT (Mooney et al., 1996), automation of business processes is somewhat under-researched (Aysolmaz et al., 2023; Engel et al., 2022). IT can improve the efficiency of operational processes through automation or enhance their effectiveness and reliability by linking them (Mooney et al., 1996), affecting productivity and profitability (Kromann & Sørensen, 2019). Even though few empirical studies support this hypothesis, we can infer that it is valid by examining research focusing on barriers and success factors where digitalization and alignment with IT are identified as key factors (Moreira, Mamede, & Santos, 2024). Automation is often highlighted as a key characteristic of AI, facilitating higher levels and greater scope of business process optimization. We examine *CBPA* results and find that *AI* impacts automation the most ($\beta = 0.697$, $t = 11.306$, $p < 0.001$). However, there is no significant impact of *CBPA* on *BPP*, but there is on *DMP* ($\beta = 0.146$, $t = 2.313$, $p = 0.021$). These results suggest an augmentation level of automation focused on decision-making. Automation, therefore, does not directly impact BPP in terms of efficiency, quality, and flexibility via decision-making performance. Research on IT business value highlights that high exploitative business process IT capabilities indicate significant support for business processes through task automation and data integration. Companies that overemphasize exploitative business process IT capabilities, i.e., investing heavily in task automation and data integration, may become overly dependent on existing business process implementations (Heckmann, 2015). The study's results indicate that the same applies to AI-enabled automation; no significant impact on BPP suggests that AI-enabled automation is viewed as an exploitation toolset.

Research on IT business value has shown that organizational learning is essential in moderating how IT (such as big data analytics, industry 4.0 technologies, and IT capability) influences organizational performance (Al-Omoush et al., 2024; Bahrami et al., 2016; Khan et al., 2020; Lai et al., 2009; Real et al., 2006; Tippins & Sohi, 2003; Tortorella et al., 2020) and innovation (Husain et al., 2016; Obeso et al., 2020; Saide & Sheng, 2020). Moreover, by showing that the knowledge acquired through organizational learning can mediate the effect of IT competency on organizational performance, the authors provide evidence that the usefulness of an organization's resources varies with changes in organizational knowledge (Real et al., 2006; Tippins & Sohi, 2003). Next, IT-enabled organizational learning has been acknowledged as a vital enabler of knowledge creation and innovation adoption (Al-Omoush et al., 2024; Ma, Peng, & Shi, 2008; Migdadi, 2022). Organizations with higher organizational learning intensity seem to be more efficient in balancing exploitative (incremental) and exploratory (radical) innovations in an ambidextrous manner (Nguyen, Shen, & Le, 2022). Research also indicates that knowledge drives innovation in organizations with high absorptive capacity and learning capabilities (Costa & Monteiro, 2016). In the context of IT business value, the positive impact of knowledge on the performance of knowledge-intensive processes has been studied extensively (Armistead, 1999; Yoshikuni & Albertin, 2020). Also, research established IT-enabled organizational learning's impact on decision-making processes, where most of the effect is expected at the selection decision-making phase (i.e., in which the best solution is chosen) (Nicolas, 2004) and knowledge sharing (Gui, Lei, & Le, 2022; Mohammed & Jalal, 2011; Shahmoradi, Safadari, & Jimma, 2017).

Comparing the study results to IT business value research shows that AI's relationships and impacts on organizational learning are similar to those of conventional IT. There is a significant impact of *AI adoption* on *OL* ($\beta = 0.488$, $t = 8.910$, $p < 0.001$) and *OL* impacts *BPII* ($\beta = 0.446$, $t = 8.442$, $p < 0.001$), *BPIR* ($\beta = 0.434$, $t = 7.001$, $p < 0.001$), *DMP* ($\beta = 0.371$, $t = 6.905$, $p < 0.001$) and *BPP* ($\beta = 0.341$, $t = 5.541$, $p < 0.001$). However, the intensity of AI's impact on OL is higher than that of conventional IT (Ma et al., 2008). Accordingly, the impact of OL on BPII and BPIR is higher with AI (Gui et al., 2022; Migdadi, 2022; Nguyen et al., 2022). Interestingly, the OL's impact on BPP is lower (Ma et al., 2008; Yoshikuni & Albertin, 2020). However, when removing DMP as the mediating variable, the impact intensity on *BPP* ($\beta = 0.440$, $t = 7.747$, $p < 0.001$) is very similar to that of conventional IT. We conclude that DMP partially mediates the impact of OL on DMP. In the context of IT business value, it is theorized that the impact on DMP comes at the selection decision-making phase (Nicolas, 2004). We observe similar results for AI, where the level of cognitive process automation is at the level of decision selection (see Section 7.1.4). These findings confirm that organizational learning affects business process performance and decision-making processes through knowledge-intensive processes, and this is true for both AI and conventional IT.

Overall, AI has a greater impact on knowledge management than other forms of information technology due to its distinctive capabilities and advantages (Jarrahi, Askay, et al., 2022). AI, especially natural language processing (e.g., large language models), automates knowledge extraction and organization from diverse sources like documents, emails, and social media, aiding rapid identification and structuring of relevant knowledge assets. AI-powered search engines enhance retrieval accuracy by understanding query context, surpassing conventional keyword-based methods. AI fosters knowledge sharing by identifying experts, facilitating connections, and enabling seamless collaboration, which is necessary for breaking down departmental barriers and promoting a culture of knowledge exchange. AI systems continuously learn from interactions and feedback, adapting knowledge management processes to ensure ongoing relevance and improvement.

The impact of information technology on innovation has been well established in the literature on IT business value (Chen, Wang, Nevo, Benitez-Amado, & Kou, 2015; Koo & Le, 2024; Shehzad, Zhang, Alam, & Cao, 2022; van de Wetering & Besuyen, 2021; Van de Wetering, Mikalef, & Helms, 2017). Several studies have shown that IT can impact incremental and radical innovation activities separately (Mikalef, 2016; van de Wetering & Besuyen, 2021; Van de Wetering et al., 2017), as well as facilitate ambidextrous innovation

(Lee, Dwivedi, Tan, Ooi, & Wong, 2023; Liao, Hu, & Wei, 2023; Yoshikuni, Dwivedi, & Dwivedi, 2024). The SEM analysis shows that *adopting AI*, like IT, significantly and positively impacts both *BPII* ($\beta = 0.282$, $t = 5.285$, $p < 0.001$) and *BPIR* ($\beta = 0.276$, $t = 4.644$, $p < 0.001$) process innovation. These impacts are similar in magnitude and, as with IT, slightly more pronounced for incremental than radical innovation (Shehzad et al., 2022; van de Wetering & Besuyen, 2021). Additionally, research on IT business value indicates that IT-enabled capabilities are more crucial for young organizations to develop innovative capabilities than established ones. The analysis confirms a similar negative correlation between organizational age and both incremental and radical business process innovation (Section 6.5.2). IT business value studies show that combining incremental and radical process innovation (ambidexterity) leads to better business process performance (Arif & Hasan, 2021; Heckmann & Maedche, 2018). This is especially true when BPM practices are also implemented (Ferraris, Monge, & Mueller, 2018). Like IT, AI-enabled incremental and radical process innovations significantly impact business performance. Interestingly, while AI-driven incremental process innovations do not directly impact business process performance, they are mediated through *DMP* ($\beta = 0.369$, $t = 6.474$, $p < 0.001$). In contrast, AI-driven *BPIR* have a direct impact on *BPP* ($\beta = 0.276$, $t = 4.644$, $p < 0.001$) and are not mediated by DMP. This indicates that incremental improvements are mainly related to AI-assisted decision-making with a lesser direct impact on process performance, whereas radical improvements, driven by AI to design or redesign processes, significantly enhance the efficiency, effectiveness, and flexibility of business processes.

In summary, IT and AI contribute to business value through similar relationships, although they exhibit some differences. IT excels at streamlining current processes and infrastructure, while AI unlocks transformative change through data analysis, automation, and groundbreaking innovation. AI's impact on learning, knowledge management, and process innovation surpasses conventional IT, fostering incremental improvements and radical breakthroughs in decision-making and business processes.

7.4 The Impact of Large Language Models and Generative Pre-trained Transformer Technology

Large Language Models (LLM) are at the forefront of AI advancement. They refer to a family of highly complex neural network models with numerous parameters specialized in natural language processing (i.e., the development of algorithms and models that enable computers to understand, interpret, and generate human language).

LLMs are considered a subset of AI designed to understand and generate human language (Naveed et al., 2023). The OECD (2024) definition of AI systems used in the study (presented in Section 2.1) is inclusive and was updated to include “explicit and implicit objective,” which refers to advancements in AI capabilities, specifically GPT-enabled LLMs.

LLMs were first brought to public attention with ChatGPT and GPT-4, two LLMs developed based on Generative Pre-trained Transformer (GPT), a compelling LLM architecture by OpenAI (Radford, Narasimhan, Salimans, & Sutskever, 2018). GPT is based on the Transformer architecture described in the seminal article Wasvami (Vaswani et al., 2017). This architecture utilizes self-attention mechanisms to process and generate text sequences, making it highly efficient and effective for natural language processing tasks.

GPT-based LLMs have quickly gained widespread interest and surprised almost every industry sector with their superior performance in analysis and communication. This superior performance refers to their exceptional abilities in understanding, processing, and generating human language. They excel in text comprehension, data insights, and problem-solving, as well as in natural language generation, conversational abilities, and multilingual capabilities. Moreover, these models are now expanding their reach from text to audio and video, demonstrating their versatility and broadening their impact across different media formats (Han, Hou, & Sun, 2023).

Data collection for this study concluded in June 2022, prior to the introduction of ChatGPT in November 2022. We argue that the measurement scale remains valid and effectively captures the adoption of LLM and GPT; however, we would anticipate higher levels of adoption due to ChatGPT's introduction. Next, we discuss managerial perspectives today when LLM and GPT are gaining traction in business.

7.4.1 Managerial Perspectives Today

Artificial Intelligence is a broad field that encompasses various technologies and applications, including machine learning, robotics, computer vision, natural language processing, and more. When asked about AI, managers may have a broader range of associations and understandings. Discussions around AI might evoke broader technological trends and strategic implications, including automation, ethical considerations, workforce impact, and innovation potential.

LLMs are AI models used in various applications (e.g., chatbots, virtual assistants, automated content generation, contextual search functions) focused on understanding and generating human-like text. Managers may have a narrower and more focused understanding of LLMs, mainly if they are familiar with their applications in tasks like text generation, and natural language understanding.

The term GPT specifically refers to a series of well-known models developed by OpenAI[21] (e.g., GPT-3, GPT-4). Managers familiar with AI might be more likely to recognize GPT than LLM if they have followed AI advancements (Aggarwal, 2023).

[21] OpenAI, https://www.openai.com

Regarding business implications, managers might consider AI's impact on their business operations, including process automation, data analysis, decision-making, and strategic planning. While LLMs can specifically enhance communication, customer interactions, marketing, content creation, and internal knowledge management (Arman & Lamiyar, 2023; George & George, 2023; Reinkemeyer, 2024).

Overall, the differences in results depend on the manager's understanding of AI and LLMs. While there is expected to be an overlap in the responses due to the intrinsic relationship between AI and LLMs, the specificity of LLMs as a subset of AI technologies will likely lead to different emphases in managers' perspectives. They might provide more focused and nuanced insights related to LLM and GPT applications when asked about LLMs compared to the broader topic of AI needed for this study. Hence, the narrower scope of LLMs would make the results far more specific, excluding several other AI applications for business operations, and the findings would be much less generalizable.

7.4.2 Shifting Focus of AI Applications

Hypothesizing LLMs and GPT as AI subsets included in the measurement scale of AI adoption, we argue repeating the measurements today would yield different results. Public perception of LLMs, GPT, generative AI, and AI underwent a significant transformation. The focus of AI applications is shifting.

Over time, after the research data was collected, advancements and understanding of AI grew significantly. OpenAI's ChatGPT[22] is, first and foremost, a productivity tool widely accessible to individuals. For many people, including managers, this has been the first use case for AI technology. The capabilities demonstrated with ChatGPT expanded the understanding and potential of AI technologies and applications. As witnessed by startup investments (Burtsev, Reeves, & Job, 2024) and many more published use cases, public interest in the technology reduced the AI knowledge gap. It positively affected AI investment, deployment, and use (TechCrunch, 2021). The amount of AI-related research has increased (Movva et al., 2024; Ruiz-Real, Uribe-Toril, Torres, & De Pablo, 2021). Numerous LLM implementations are cloud-based or open-source, simplifying and accelerating implementation and deployment while also increasing accessibility for developers (Noyan, 2023).

Managers might have a limited understanding of AI in general. However, the term LLM, being more specific, might prompt them to recall related AI concepts they know, resulting in a somewhat different response. Note that GPT is a prominent LLM but it's not the only one. Other LLMs from various companies have varying capabilities (Ruiz-Real et al., 2021).

[22] ChatGPT, https://openai.com/chatgpt/

So, if a manager is asked explicitly about LLM, they might focus on the text-centric capabilities offered by this type of AI.

The hype cycle[23] suggests that new technologies undergo a cycle of inflated expectations followed by disillusionment before reaching a plateau of productivity (Dedehayir & Steinert, 2016). AI might be further along this cycle (Khandabattu & Jaffri, 2024), leading to less specific or enthusiastic responses from managers than the newer terms of LLM and GPT.

As AI matures, applications are moving beyond basic automation towards tasks requiring language understanding and generation. Managers might be considering a new phase or evolution in technology beyond AI, represented by LLM. This could indicate a shift in industry trends where LLM technologies are becoming more prominent or gaining traction, influencing strategic decisions and investments by companies. Managers who understand the capabilities and limitations of LLMs will be better positioned to discuss AI (Burtsev et al., 2024).

There is a growing concern about some AI systems' "black box" nature (e.g., fully automated loan approval process that must be highly transparent). LLMs, with their focus on language processing, offer a potential path toward more transparent and explainable AI, which could be a crucial aspect of higher acceptance by managers and, ultimately, AI adoption (Singh, Inala, Galley, Caruana, & Gao, 2024).

With LLMs, AI's ethical and societal implications became more tangible (Movva et al., 2024; Pankajakshan, Biswal, Govindarajulu, & Gressel, 2024). AI models like GPT raise ethical concerns about bias, misinformation, and manipulation (Jiao, Afroogh, Xu, & Phillips, 2024; Zhang, Sharma, Du, & Liu, 2024). The societal impact of deploying such powerful language models could presumably negatively impact the managers' responses. During the data-gathering phase of this study, several potential participants informally reached out to voice their concerns about ethical AI and refused to participate. Conversely, LLMs could signify a focus on ensuring AI systems strictly comply with legal standards and ethical guidelines.

Managers might be interested in practical applications and case studies where LLM technologies have demonstrated superior performance in addressing critical business challenges compared to conventional AI approaches. However, LLMs currently do not surpass the performance of conventional AI tools in specialized domains (e.g., financial modeling and analysis, supply chain optimization, time-series forecasting, expert systems, and rule-based reasoning). This suggests that the capabilities and limitations of LLMs compared to conventional AI tools would be an important consideration for managers (Burtsev et al., 2024).

[23] The Gartner Hype Cycle is a graphical representation developed by the research and advisory firm Gartner, which showcases the maturity, adoption, and social application of specific technologies over time.

Efficient LLM inference also presents challenges, as LLM deployments often use complex and power-hungry AI accelerators (like GPUs, TPUs, IPUs; Stojkovic, Choukse, Zhang, Goiri, & Torrellas, 2024). This suggests that managers could consider the efficiency and cost-effectiveness of LLM deployment.

Limited practical applications and adoption highlight that while LLMs have remarkable capabilities, their direct use in practical applications and their ability to replace conventional AI tools requires further experimental validation (Cheung, 2024; Fahland, Fournier, Limonad, Skarbovsky, & Swevels, 2024). Therefore, managers could consider LLMs' practical applicability and adoption in specific business domains.

With AI tools currently emphasizing augmentation (see Section 7.1.4) and a human in the loop, prompt engineering and human-AI interaction considerations indicate that the quality of the mutual learning between the human and the generative AI improves with well-structured prompts and constructive feedback. This suggests that the skills and techniques required for effectively leveraging LLMs, such as prompt engineering, would be relevant for managers to consider (Pitkäranta & Pitkäranta, 2024).

As LLM-based generative AI products become more prevalent, managers have started testing and planning to incorporate these technologies into their businesses' ongoing management to enhance their development as learning organizations (Earley, 2023). This implies that the organizational and strategic implications of adopting LLMs are important for managers.

Essentially, the hypothetical transition from AI to LLM would produce different outcomes. This could involve various theoretical discussions about the scope of AI and LLM and considerations regarding perception, awareness, familiarity, business implications, and the evolving focus of AI applications.

7.4.3 Measuring Deployment Across Technologies and Paradigms

The broad scope of AI was considered when conceptualizing and operationalizing the AI adoption construct. We assessed AI adoption level as an exogenous, component-based variable (unlike antecedents or determinants) related to the deployment and actual use of particular AI applications and technologies (Chapter 3). The construct encompasses a wide space of AI applications. Although it does not reference LLMs explicitly, it includes natural language processing technology and several LLM applications in application domains (see use cases in Table 16, Cognitive Engagement and Technologies). This approach made measuring AI deployment and use more applicable to business environments. We did not discriminate between symbolic and connectionist approaches to AI (Babbar, Yadav, Singhal, & Sharma, 2018). We included applications of both symbolic AI (based on rules and logic) and connectionist AI (based on neural networks and statistical learning). LLMs and GPTs fall under the connectionist paradigm.

8 CONCLUSION

Big Data and AI technology are at the forefront of IT investment, although the mechanisms and conditions producing business value remain largely unexplored in empirical research. Recent studies highlight the need to employ relevant mediating variables to understand the relationship between AI resources, capabilities, and organizational performance. This study adds to the discussion on AI business value. The study's novelty is that it considers the combined mediating effects of *CBPA*, *OL*, *BPI*, *DMP*, and *BPP* in the relationship between AI adoption and organizational performance. The results confirm the proposed serial multiple-mediation research model and establish a full serial mediation effect. Additionally, we confirm the theorized central mechanism of business value generation through AI-enabled automation, augmentation, and innovation capabilities. The results have several theoretical and managerial implications.

8.1 Theoretical Contributions

In line with the existing literature on AI and performance, this study builds on the theoretical framework of the resource-based and dynamic capabilities approaches. We consider the ability of AI to extend the knowledge base and draw on the knowledge-based perspective, which treats knowledge as an important source of competitive advantage (Grant, 1996b). Although there is a rich theoretical discussion about AI's potential to generate business value, few large-scale empirical studies back up this assertion. This study addresses this issue and considers if and through what mechanisms AI adoption can result in any measurable business value. Aiming for a structured approach, we study the adoption of AI in the setting of BPM, focusing on operational and dynamic capabilities developed to manage and improve business processes. Thus, we adapt the integrative model of IT business value (Melville et al., 2004) to analyze the impact of AI adoption at the process and organizational levels. Several aspects of this study contribute to the literature on AI business value.

First, we present an alternative concept of AI adoption to capture a more accurate and generalizable view of AI's impact on organizational performance. We introduce an exogenous, component-based variable related to the level of deployment, actual use, or utilization of specific AI applications and technologies. We thus do not consider the antecedents and determinants of readiness for adoption, the process of adoption, and adoption intention. We followed a systematic approach and executed a component-based conceptualization, as recommended by Podsakoff et al. (2016). The procedure included examining definitions and antonyms from dictionaries, a comprehensive literature review, and in-depth semi-structured interviews with subject-matter experts and practitioners. We further investigated AI types, features, technologies, and application domains to identify more specific characteristics and uncover conceptual themes of AI adoption.

We used the lens of business capabilities or application domains rather than technological capabilities to organize the extracted characteristics. Based on the example of Sonenshein et al. (2014), we impose a higher level of business capabilities by aggregating the key characteristics into five distinct dimensions. We rely on the resource-based and dynamic capabilities views to identify AI resources for the AI-related elements that must be brought together to ensure the successful deployment and use of AI technology. These resources are the organization's ability to develop a set of distinct AI-enabled capabilities (the ability to mobilize AI resources to exploit strategic assets and achieve innovative changes) through implementing AI applications, tools, or technology. We refined the conceptual definition of the construct by discussing it with subject-matter experts and peers.

Second, we applied the methodical approach of MacKenzie et al. (2011) to operationalize the concept of AI adoption. We generated items from the literature review, the theoretical definition of the construct, interviews with experts, and a review of 1,860 AI-related projects from business and academia. We combine these based on their similarity into five distinct groups representing the five dimensions of the focal construct: Data acquisition and preprocessing, cognitive insights, cognitive engagement, cognitive decision assistance, and cognitive technologies. A four-member expert panel made an assessment of content validity. Scale purification and refinement were conducted based on the results of a pilot study. Reliability and validity were assessed in the main empirical study, producing a robust AI adoption measure.

Third, this study extends the emerging literature on AI by providing a nomological network that links AI adoption to organizational performance. While previous research has assumed a direct impact of AI adoption on performance (Kim et al., 2022; Mikalef & Gupta, 2021; Mishra et al., 2022; Wamba, 2022), our results confirm that the effect on organizational performance is indirect and contingent upon dynamic, operational capabilities, decision-making, and process performance. It is among the first studies to draw on the automation and augmentation perspective to assess the impact of AI adoption on organizational performance through the mediation effects of cognitive business process automation, innovation, and organizational learning. A further point about the capabilities built on automation and augmentation aspects of AI technology is that they should impact decision-making and business processes to improve the performance of these and the overall organizational performance. The serial multiple-mediation model developed in this study contributes to resource-based, dynamic capabilities and knowledge perspectives by examining the relevant mediating variables in the relationship between AI technology and organizational performance. We recognize this as a notable contribution to the emerging literature on AI business value.

Fourth, positioning automation as an important mediator, we conceptualized and operationalized the CBPA concept. In measuring the level and extent of automation in the BPM context, we recognize CBPA as the organization's ability to automate knowledge-intensive (unpredictable, non-repeatable, highly flexible, and complex) business processes using cognitive technologies. This is a notable addition to the AI literature (Berente, Gu, Recker, & Santhanam, 2021; Rai, Constantinides, & Sarker, 2019; Raisch & Krakowski, 2021), and scholars have called for an exploration of how the emergence of automation and augmentation in management leads to action and change.

Fifth, in a large-scale EU study, we empirically demonstrate the positive impact of AI adoption on performance. The study's empirical results validate the proposed serial multiple-mediation model, and we can conclude that BPM capabilities, that is, cognitive business process automation–augmentation, organizational learning, and incremental and radical process improvements, are important predictors for boosting DMP and BPP. The findings show organizations can generate and capture business value by implementing AI in end-to-end organizational processes. We demonstrate that automation and augmentation (dual AI applications or use) are interdependent. Resulting from the operational capabilities of automation and incremental improvements of business processes, as well as the dynamic capabilities of organizational learning and radical process improvements, AI extends the existing knowledge base and demonstrates an inherent innovation effect. The results confirm that AI technology exhibits characteristics of exploitation and exploration stemming from an expanded knowledge base and the technology itself. This allows organizations to pursue ambidextrous strategies and sustain competitive performance gains.

Lastly, we include the organizational context to establish how AI business value is generated. Organizations can achieve significant performance improvements by aligning IT resources with additional organizational factors (Mooney et al., 1996; Wiengarten et al., 2013). In this study, we represent the organizational context via digital transformation factors as moderation variables for *BPMM*, *DDC*, *DM*, and *OC*. In addition, we include factors that may influence the relationship between the independent and dependent variables. In addition to firm age, size, industry, and country, we introduce environmental uncertainty to account for the increasing frequency of environmental dynamism and complexity in business.

Summarizing, we have adapted the established IT business value model using context-specific theorizing to the context of AI technology. Pursuing a complex nomological framework, we include several perspectives on realizing business value from AI investments, thus enriching the emerging literature on AI. We follow several avenues, identifying AI-related resources and operational and dynamic capabilities that mediate the impact of AI and support our perspective on the automation–augmentation spectrum. Knowledge-related and transformational characteristics of AI enable the exploitation and exploration of information and knowledge more efficiently, allowing organizations to compete in mature markets and develop new products and services for emerging markets simultaneously; this is also referred to as organizational ambidexterity. In light of the ongoing digital transformation of organizations, AI is a wide-reaching and promising capability that needs constant exploration by the information systems community.

8.2 Managerial Implications

Organizations have difficulties leveraging AI technologies and extracting business value. Furthermore, AI is highly dependent on data and domain knowledge, making it hard to integrate and align with existing business processes (Chui, 2017). From a management perspective, the findings provide essential insights for organizations planning to invest in AI-enabled business value projects. The results outline the five distinct AI-related business application capabilities or application domains that organizations should develop to impact organizational performance.

1) A highly developed data acquisition and preprocessing capability is the foundation for successful AI projects. The capability is crucial for extracting data (from business operations, SCADA/the Internet of Things, documents, and external sources) for exploitation and exploration (data warehousing and data lakes). Organizations must understand their data to extract value and trust its quality. These factors are tied to a higher level of DDC.
2) The extraction and interpretation of insights is most linked to AI-enabled predictive modeling, anomaly detection in marketing, customer relationships, and customer experiences.
3) The capability to support AI-enhanced human–computer interaction and collaboration with customers and employees via chatbots, virtual assistants, computer vision applications (e.g., Virtual try-on, Interior home designer), and recommendation systems with higher levels of AI-enabled personalization (e.g., sentiment analysis, intent classification, content curation, discovery, sensors, and targeting).
4) The capability to augment or automate decision-making processes via AI-enabled decision automation systems (e.g., next best action, next best offer, automated scheduling, automated routing), knowledge engineering and expert systems (e.g., generative design, drug development, product innovation, protein engineering, material discovery, genomics, marketing strategy engineering), and decision support systems (e.g., actionable analytics and recommendations, clinical decision support, decision intelligence, and modeling).
5) The capability to integrate AI technologies with existing IT resources, services, and devices (e.g., predictive modeling and analytics, anomaly and deviant behavior detection, machine learning, and deep learning).

The research is framed in a BPM setting so managers can easily align the findings with the BPM structures in their organization. The results confirm the proposed full serial multiple-mediation model, meaning AI adoption impacts OP indirectly. Managers should thus adopt AI in end-to-end organizational processes to generate and capture AI technology’s full business value potential.

The findings show managers can expect the greatest impact in the form of enhanced process efficiency and quality and slightly less in the flexibility of processes. At the operational level, value is seen in increased speed, scale, granularity, and accuracy of information processing (e.g., error and problem detection, full or partial automation, improved information flow, predicting the opportunities for economies of scale, finding alternative uses of resources, saving costs, achieving higher labor productivity, and determining new distribution channels). We considered DMP a separate construct with an essential role in linking AI adoption to BPP. Our findings show a substantial impact of AI adoption on decision-making, enhancing quality, speed, and effectiveness (e.g., faster knowledge extraction and propagation) at the operational process and strategic level, thus directly impacting organization performance. Fredrickson and Mitchell (1984) note that there is a negative relationship between DMP and performance in an unstable environment, but a positive relationship is expected in a stable environment. The results confirm that DMP mediates the link between AI capabilities and performance. However, the results cannot confirm the direction of the relationship as the control variable, *Environmental Uncertainty*, had no significant effect.

The results pertaining to automation and augmentation show that for overall, automation takes place at the level of supervision and decision support for structured and unstructured processes. Consequently, CBPA does not directly affect BPP in terms of execution efficiency or scalability. In contrast, it is expected to have a significant direct effect on DMP. The impact of AI adoption can be observed at the augmentation end of the human–machine collaboration spectrum in the form of more efficient and effective decision-making. The preference for human-in-the-loop systems explains the support for a wide extent of augmented processes ranging from structured to unstructured processes when execution relies on full or partial human judgment. The findings corroborate the combined advice of Brynjolfsson and McAfee (2014), Daugherty and Wilson (2018), Davenport and Kirby (2016), and Raisch and Krakowski (2021) that managers should prioritize augmentation, which they relate to superior performance.

We verified the knowledge perspective using organizational learning as a mediator. The results confirm the impact of AI adoption via the increased knowledge capabilities involved in acquiring, creating, integrating, and distributing information and knowledge. It significantly impacts DMP, BPP (via knowledge-intensive processes), and process innovation. We find this learning partially mediates the direct impact of AI adoption on innovation. Interestingly, the effects are the same for incremental and radical process innovation. This suggests AI is a technology that can simultaneously enable and drive the exploitation and exploration of process innovation. These findings could help managers achieve the otherwise elusive ambidextrous organization (through the process of AI adoption) that outperforms other organizational types (Benner & Tushman, 2001; O'Reilly III & Tushman, 2011; Tushman & O'Reilly III, 1996).

The transformational effects of AI adoption were confirmed using incremental and radical process improvement as mediators. Our findings indicate that AI adoption mediated by incremental process improvements significantly impacts DMP, not BPP. In contrast, AI adoption is mediated by radical process improvements (new or redesigned processes), directly affecting BPP, not DMP. These findings are in line with existing research on process innovation (Cao & Jiang, 2022; Jurksiene & Pundziene, 2016). This suggests incremental improvements are mostly related to AI-assisted decision-making, which has a lower impact on performance than radical improvements; in the latter, AI is used to design new or redesign an existing process, having the most impact on efficiency, effectiveness, and flexibility of business processes. Organizations should thus prioritize AI knowledge and skill development so that employees can effectively drive incremental and radical improvements using AI tools.

In our examination of the organizational context, only *BPMM* and *DDC* have a limited moderating effect. As previously theorized (Section 2.10.3), a higher *BPMM* implies more strictly defined processes, negatively influencing an organization's potential for finding innovative solutions. Findings confirm that *BPMM* significantly dampens the relationship between AI and OL and OL and BPII. In contrast, *DDC* positively influences the relationship between BPII and BPP. However, the mediation relationship between BPII and BPP remains insignificant. According to several empirical studies (Table 3), *DDC* should have a positive effect. Despite this, we find that the level of *DDC* is very high in all cases; thus, we cannot detect a significant moderating effect.

The same applies to *DM*. Interestingly, the clan, adhocracy, market, and hierarchy cultures had no moderating effect. A scenario where OC may not affect AI adoption is when the organization has a culture of innovation and adoption of technology. In such cases, the organization may already be open to adopting new technologies, and the culture may support experimentation and risk-taking. Indeed, most most organizations in the study have clan (37.92%) or adhocracy (23.45%) cultures. An adhocracy culture is closely related to innovation and is characterized by a flexible and dynamic work environment that values innovation, experimentation, and risk-taking. In a clan culture, collaboration, teamwork, and employee empowerment are emphasized, which can create an environment conducive to innovation (Quinn & Cameron, 1999). Organizations with this culture may be more likely to adopt AI technologies without significant resistance or barriers.

We examine control variables to exclude potential influencing factors and find that only firm size significantly impacts organizational performance and learning variables. As expected, larger organizations (De Mel, McKenzie, & Woodruff, 2009; Hall & Jones, 1999; Pervan & Višić, 2012) had better performance than smaller organizations. However, larger organizations had a lower level of organizational learning than smaller organizations. These results are consistent with findings from Jiménez-Jiménez and Sanz-Valle (2011) and Jansen et al. (2005). The age, industry, and country in which firms are based had no impact.

Finally, the findings invite managers to recognize the need for a structured approach to AI deployment in end-to-end organizational processes. This underscores the importance of prioritizing AI knowledge and employee skill development. Managers should consider the five proposed AI application domains and consider cognitive business process automation, innovation, and organizational learning as central BPM capabilities for AI business value generation before expecting any measurable gains in organizational performance.

8.3 Limitations and Recommendations for Future Research

This research offers valuable insights and important empirical findings, although caution should be exercised when interpreting the results. First, we use a cross-sectional survey to validate the proposed research model. Self-reporting bias and endogeneity issues are typical limitations of this research design (Jordan & Troth, 2020). Future studies could employ a longitudinal approach to ascertain the differences before and after AI adoption. The case study research design would resolve endogeneity issues but would not contribute to the generalizability of the findings. As the study relies on perceptual performance measures only, some objective measures should be used in future studies to improve the accuracy of the results. Although, objective measures for wide-scale empirical research are hard to obtain.

Second, the study relies on a single respondent from each organization. Future studies could consider more than one respondent or different data sources from a specific organization to triangulate a more reliable measure. Employees from other organizational units exhibit distinct behaviors and understanding of AI-related capabilities. This would also help to overcome common method bias problems of relationship inflation between constructs.

Third, using the EU for the survey setting hinders the generalizability of the findings. The policies, strategy, and funding of AI initiatives in the EU differ from those in the US or China, which are key players in AI technology development (Dixon, 2022). Future research in different settings may provide interesting observations by allowing comparison. Research collaboration with the US and other countries highly involved in the researched topics may also provide greater access to data.

Fourth, because of the already complex research model and the length of the related questionnaire, the scope and level of detail regarding measuring the constructs were limited. Several topics were identified that could be explored further. Analyzing the impact on specific loops in the triple loop learning concept will uncover if AI is indeed an organization transforming (i.e., context and assumptions changing) technology. The impact of AI on knowledge visualization (e.g., summarization capability of large language models), creating, searching, and distribution—and the effect of AI productivity tools on an individual level.

Fifth, the study employed methods to establish the validity of the findings (see Sections 3.8 and 4.6). The study's credibility depends on the accuracy and reliability of the collected data. However, the complex nature of AI adoption and subjective interpretations of AI applications, such as participants' struggles with technical terminology, might have influenced the conclusions. To address this, we provided illustrative use cases and inline or tooltip descriptions in the online questionnaire to clarify the scale items. Despite efforts to ensure the credibility of sample cases (see Sections 5.5.2, 6.1.2, 6.4.5, and 6.4.6), potential biases or errors may have impacted the results.

Sixth, several validation steps were executed during the AI adoption construct development to optimize the measurement scale and make it most generalizable. Despite efforts to ensure the study's reproducibility, the unique qualitative context and conditions (e.g., the current state of technology) in which the research was conducted may impede replicating the findings in different settings, timespans, or populations. The following paragraph discusses a specific applicable example.

Seventh, large language models (LLM) and Generative Pre-Trained Transformers (GPT) emerged. Technological advances may produce different results over time in the rapidly changing field of AI and business value studies. While LLM and GPT broadly refer to AI, both could offer a more focused and practical perspective in discussions related to AI adoption, mainly when the context involves language processing and textual analysis applications. Different terminology choices could influence how participants perceive the relevance, applicability, and potential benefits of adopting such technologies in their organizations. However, as indicated by the interviews, managers may have varying degrees of familiarity with AI depending on their industry, role, and exposure to technological advancements. Many might have a general understanding of AI and its implications but may not be as familiar with the specifics of LLM and GPT. Participants specifically interested in or responsible for tasks involving text analysis, content generation, or customer interaction through written communication may find LLM and GPT more relevant and understandable (dependent on the industry). As a result, AI responses are likely to be more informed and broader than LLM or GPT responses, which might be narrower or less detailed. AI is a broad term that encompasses a wide range of technologies and applications. Therefore, it must be noted that LLM, GPT, and Generative AI (i.e., computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data; Feuerriegel, Hartmann, Janiesch, & Zschech, 2024) are AI technologies and used in various AI applications (e.g., chatbots and virtual assistants, content creation, drug creation, language translation, summarization tools, coding assistance, legal assistance, customer Interaction, etc.). As indicated by the interviews, the majority of participants from business are more familiar with AI applications than specific technologies. The operationalization of the AI adoption construct took this into account. Generated scale items were generated around AI application domains and included use cases to better illustrate the applications referenced. Although this mitigates the emergence of new AI technologies, it must be acknowledged that ChatGPT, developed by OpenAI, popularized and increased the adoption of AI. Data collection for this study was finished in June 2022, and ChatGPT was introduced in November 2022. We are confident the measurement scale would still be valid and capture the adoption of LLM and GPT; however, we expect the adoption levels to be higher.

Lastly, organizations may use AI algorithms for particular roles, implying new design requirements like transparency and predictability. AI algorithms may no longer execute in predictable contexts, which requires new safety assurances and the engineering of artificial ethical considerations. Therefore, future research should examine the social implications and the ethical and moral issues surrounding AI and its use.

8.4 Reproducibility and Transparency of Research

Accuracy, reproducibility, and transparency are essential for robust, credible, and ethical research (Christensen & Soderberg, 2016). We have addressed several related issues, including publication bias, motivated reasoning, data sharing, workflow management, formal policies, open research access, and reporting of research contributions.

Publication bias is pervasive in scientific research, and studies with positive results are more likely to be published than those with null or negative results (Christensen & Soderberg, 2016). We mitigate these risks by including a pre-analysis plan in the form of a dissertation proposal. Hence, we can confirm prediction integrity (i.e., the successful prediction may be granted a special status in elevating confidence in the theory on which the prediction is based) and all negative results are included.

The unintentional bias we considered was primarily related to motivated reasoning, which can occur without intention because we are more likely to believe that our hypothesis is true, accepting it uncritically when it is confirmed and scrutinizing it when it is not. We reduced the impact of motivated reasoning by acknowledging its impact and consciously countering biased information processing (Christensen & Soderberg, 2016). We employed various strategies to reduce motivated reasoning, including the use of various sources of information, particularly articles that value evidence-based reasoning, peer review, and extensive discussion.

All code and workflows (i.e., data, code, organization, and documentation) have been included for reproducibility (Chapters 3, 4, 6, and Appendix 2). All complex decisions regarding the research project are argued to avoid ambiguous and possibly arbitrary decisions (Christensen & Soderberg, 2016; Freese, Rauf, & Voelkel, 2022).

In addition to code, the data are made available to make replication theoretically possible (Christensen & Miguel, 2020). As concerns about privacy and confidentiality have grown in recent years (Freese et al., 2022), we have ensured that the research complies with formal policies, that is, the university's code of ethics (Ljubljana, 2009) and the European Union General Data Protection Regulation regarding privacy and confidentiality when conducting interviews and collecting data (Section 5.5.8).

New software and computational improvements have made it possible to replicate and share data more easily (Christensen & Miguel, 2020). To reduce computational issues, we have included a detailed description (i.e., version, suite, libraries) of tools, software packages, and programming code (Appendix 2).

Research accessibility was prioritized, ensuring broad dissemination. The thesis will be publicly available via COBISS (Institute of Information Science, 2024), and the journal article will be published under an open-access license. All persons involved were credited based on the Project CRediT-developed taxonomy (The Niso CRediT Standing Committee, 2012).

We considered transparency in qualitative research, specifically interviews. In terms of data verification, we separated first- and second-order information, establishing the reliability of the participants (Section 3.4.2), and we based the categorization scheme on the established framework (Section 3.4.1.6) to ensure it accurately reflects the patterns or themes present in the raw data (Freese et al., 2022).

When working within a null hypothesis testing framework, the power of a study and the probability of rejecting the null hypothesis when it is false is extremely important (Christensen & Miguel, 2020). We analyzed the SEM results using the post-hoc SEM power analysis, ensuring the value exceeded the 90% threshold (Section 6.5.3). For greater detail of the decisions made in the analysis (Christensen & Miguel, 2020), a statistical model uncertainty is presented. Each model in the space of plausible models (Section 6.5) was assigned a probability of being true based on researcher priors and goodness of fit criteria.

The degrees of freedom refer to fishing for statistical significance within a study. This issue is known as data mining: the manipulation or repeated searching through statistical or regression models unknowingly (or deliberately) until significance is obtained (Christensen & Soderberg, 2016). This risk was mitigated with a pre-analysis plan (i.e., dissertation proposal) that included or assumed the main outcome measures (identifying which are primary and which are secondary), the precise composition of any groups used for mean effects analysis, the subgroups analyzed, the direction of expected impact, the primary specification for the analysis, a description of the sample to be used, key data sources, a description of hypotheses to be tested and multiple hypothesis tests, details of how variables will be constructed, a preliminary structural model, the rules for terminating data collection before data collection begins (related to predefined sample size), a report on eliminated observations (Section 6.1), statistical specification and the timestamp for verification (Christensen & Miguel, 2020).

Since there are no formal social science reporting standards in economics (Christensen & Miguel, 2020; Christensen & Soderberg, 2016), our results were presented in full in a format commonly used in related research.

This thesis includes a repository containing an electronic copy of this thesis and all of the supplementary files described in Appendix 2.

REFERENCE LIST

1. Abbad, M., Jaber, F., AlQeisi, K., & Eletter, S. (2021). Artificial Intelligence, Big Data, and Value Co-creation: A Conceptual Model. In *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success* (pp. 475-483): Springer.
2. Abdi, K., Mardani, A., Senin, A. A., Tupėnaitė, L., Naimavičienė, J., Kanapeckienė, L., & Kutut, V. (2018). The effect of knowledge management, organizational culture and organizational learning on innovation in automotive industry.
3. Abubakar, A. M., Elrehail, H., Alatailat, M. A., & Elçi, A. (2019). Knowledge management, decision-making style and organizational performance. *Journal of Innovation & Knowledge, 4*(2), 104-114.
4. Adler, P. S., McGarry, F. E., Irion-Talbot, W. B., & Binney, D. J. (2005). Enabling process discipline: lessons from the journey to CMM Level 5. *MIS Quarterly Executive, 4*(1), 215-227.
5. Aggarwal, S. (2023). A review of ChatGPT and its impact in different domains. *International Journal of Applied Engineering Research, 18*(2), 119-123.
6. Agrawal, A., Gans, J., & Goldfarb, A. (2017). *What to expect from artificial intelligence*. MA, USA: MIT Sloan Management Review Cambridge.
7. Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction, judgment, and complexity: a theory of decision-making and artificial intelligence. In *The economics of artificial intelligence: An agenda* (pp. 89-110): University of Chicago Press.
8. Agrawal, A., Gans, J., & Goldfarb, A. (2019a). Economic policy for artificial intelligence. *Innovation Policy and the Economy, 19*(1), 139-159.
9. Agrawal, A., Gans, J. S., & Goldfarb, A. (2019b). Exploring the impact of artificial intelligence: Prediction versus judgment. *Information Economics and Policy, 47*, 1-6.
10. Aguirre, S., & Rodriguez, A. (2017). *Automation of a Business Process Using Robotic Process Automation (RPA): A Case Study*, Cham.
11. Agyei-Owusu, B., Amedofu, M. K., Asamoah, D., & Kumi, C. A. (2021). *The effect of data driven culture on customer development and firm performance: the role of supply chain information sharing and supply chain information quality.* Paper presented at the Responsible AI and Analytics for an Ethical and Inclusive Digitized Society: 20th IFIP WG 6.11 Conference on e-Business, e-Services and e-Society, I3E 2021, Galway, Ireland, September 1–3, 2021, Proceedings 20.
12. Ahmad, T., & Van Looy, A. (2020). Business process management and digital innovations: A systematic literature review. *Sustainability, 12*(17), 6827.
13. Aiken, L. R. (1985). Three coefficients for analyzing the reliability and validity of ratings. *Educational and psychological measurement, 45*(1), 131-142.
14. Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2022). Transforming business using digital innovations: The application of AI, blockchain, cloud and data analytics. *Annals of Operations Research*, 1-33.
15. Al-Anqoudi, Y., Al-Hamdani, A., Al-Badawi, M., & Hedjam, R. (2021). Using machine learning in business process re-engineering. *Big Data and Cognitive Computing, 5*(4), 61.
16. Al-Omoush, K. S., Garcia-Monleon, F., & Iglesias, J. M. M. (2024). Exploring the interaction between big data analytics, frugal innovation, and competitive agility: The mediating role of organizational learning. *Technological Forecasting and Social Change, 200*, 123188.

17. Al Mansoori, S., Salloum, S. A., & Shaalan, K. (2020). The impact of artificial intelligence and information technologies on the efficiency of knowledge management at modern organizations: a systematic review. *Recent advances in intelligent systems and smart applications*, 163-182.
18. Alekseeva, L., Gine, M., Samila, S., & Taska, B. (2020). AI Adoption and Firm Performance: Management versus IT. *Available at SSRN 3677237*.
19. Alghamdi, N. A., & Al-Baity, H. H. (2022). Augmented Analytics Driven by AI: A Digital Transformation beyond Business Intelligence. *Sensors, 22*(20), 8071.
20. Ali Taha, V., Sirkova, M., & Ferencova, M. (2016). The impact of organizational culture on creativity and innovation. *Polish journal of management studies, 14*.
21. Aljumah, A. I., Nuseir, M. T., & Alam, M. M. (2021). Organizational performance and capabilities to analyze big data: do the ambidexterity and business value of big data analytics matter? *Business Process Management Journal, 27*(4), 1088-1107.
22. Almazmomi, N., Ilmudeen, A., & Qaffas, A. A. (2021). The impact of business analytics capability on data-driven culture and exploration: achieving a competitive advantage. *Benchmarking: An International Journal*.
23. Almuslamani, H. A. I. (2022). *Developing Artificial Intelligence via Organizational Learning Capability to Improve Innovation Performance: A Case Study of Aluminium Bahrain (Alba).* Paper presented at the 2022 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS).
24. Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *Artificial Intelligence, 6*, 26-2018.
25. Alsheibani, S., Messom, C., & Cheung, Y. (2019). Towards an Artificial Intelligence Maturity Model: From Science Fiction to Business Facts.
26. Alsyouf, I. (2007). The role of maintenance in improving companies’ productivity and profitability. *International Journal of Production Economics, 105*(1), 70-78.
27. Alzghoul, A., Khaddam, A. A., Abousweilem, F., Irtaimeh, H. J., & Alshaar, Q. (2024). How business intelligence capability impacts decision-making speed, comprehensiveness, and firm performance. *Information Development, 40*(2), 220-233.
28. Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic Management Journal, 14*(1), 33-46.
29. Amoako, G., Omari, P., Kumi, D. K., Agbemabiase, G. C., & Asamoah, G. (2021). Conceptual framework—artificial intelligence and better entrepreneurial decision-making: the influence of customer preference, industry benchmark, and employee involvement in an emerging market. *Journal of Risk and Financial Management, 14*(12), 604.
30. An, J. (2024). AI-assisted Stakeholder Management and Organizational Learning: Evidence from the US Intelligent Service Community.
31. Anagnoste, S. (2018). Robotic Automation Process - The operating system for the digital enterprise. *Proceedings of the International Conference on Business Excellence, 12*(1), 54-69. doi:10.2478/picbe-2018-0007
32. Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin, 103*(3), 411.
33. Angermann, H., & Hänisch, T. (2020). *KIM-RPA: An on background knowledge based framework for the agile implementation of smart RPA use-cases in business applications context.* Paper presented at the 24th World Multi-Conference on Systemics, Cybernetics and Informatics, WMSCI 2020.

34. Ansari, W. A., Diya, P., Patil, S., & Patil, S. (2019). A Review on Robotic Process Automation-The Future of Business Organizations. *Available at SSRN 3372171*.
35. Antoniol, G., Gradara, S., & Venturi, G. (2004). Methodological issues in a CMM Level 4 implementation. *Software Process: Improvement and Practice, 9*(1), 33-50.
36. Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems, 25*, 29-44.
37. Aragón-Correa, J. A., García-Morales, V. J., & Cordón-Pozo, E. (2007). Leadership and organizational learning's role on innovation and performance: Lessons from Spain. *Industrial Marketing Management, 36*(3), 349-359.
38. Aral, S., & Weill, P. (2007). IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation. *Organization science, 18*(5), 763-780.
39. Argyris, C., & Schön, D. A. (1997). Organizational Learning: A Theory of Action Perspective. *Reis*(77/78), 345-348. doi:10.2307/40183951
40. Arif, M. R., & Hasan, D. (2021). Relationship between innovation activities and business performance: A case study in Indonesia. *The Journal of Asian Finance, Economics and Business, 8*(4), 307-315.
41. Arman, M., & Lamiyar, U. R. (2023). Exploring the implication of ChatGPT AI for business: Efficiency and challenges. *International Journal of Marketing and Digital Creative, 1*(2), 64-84.
42. Armistead, C. (1999). Knowledge management and process performance. *Journal of Knowledge Management, 3*(2), 143-157.
43. Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of marketing research, 14*(3), 396-402.
44. Asawo, S. P., & Ogbonda, E. (2022). Triple-Loop Organizational Learning and Workers' Innovative Behaviour: A Response Mechanism for Pandemic Induced Work Disruptions. *Nigerian Academy of Management Journal, 17*(2), 1-12.
45. Ashaari, M. A., Singh, K. S. D., Abbasi, G. A., Amran, A., & Liebana-Cabanillas, F. J. (2021). Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective. *Technological Forecasting and Social Change, 173*, 121119.
46. Aydiner, A. S., Tatoglu, E., Bayraktar, E., & Zaim, S. (2019). Information system capabilities and firm performance: Opening the black box through decision-making performance and business-process performance. *International Journal of Information Management, 47*, 168-182.
47. Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research, 96*, 228-237. doi:10.1016/j.jbusres.2018.11.028
48. Aysolmaz, B., Joshi, A., & Stubhan, M. (2023). Examining and comparing the critical success factors between business process management and business process automation. *Journal of global information management (JGIM), 31*(1), 1-27.
49. Babbar, P., Yadav, K., Singhal, A., & Sharma, V. (2018). Connectionist model in artificial intelligence. *International Journal of Applied Engineering Research, 13*(7), 5154-5159.
50. Babina, T., Fedyk, A., He, A. X., & Hodson, J. (2021). Artificial Intelligence, Firm Growth, and Product Innovation. *Firm Growth, and Product Innovation (November 9, 2021)*.
51. Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2021). An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision

making for improving firm performance. *Industrial Marketing Management, 92*, 178-189.

52. Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change, 163*, 120420.
53. Bagozzi, R. P., & Phillips, L. W. (1982). Representing and testing organizational theories: A holistic construal. *Administrative science quarterly*, 459-489.
54. Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*(1), 74-94.
55. Bahrami, M. A., Kiani, M. M., Montazeralfaraj, R., Zadeh, H. F., & Zadeh, M. M. (2016). The mediating role of organizational learning in the relationship of organizational intelligence and organizational agility. *Osong public health and research perspectives, 7*(3), 190-196.
56. Baier, M.-S., Lockl, J., Röglinger, M., & Weidlich, R. (2022). Success factors of process digitalization projects–insights from an exploratory study. *Business Process Management Journal, 28*(2), 325-347.
57. Balasundaram, S., & Venkatagiri, S. (2020). *A structured approach to implementing Robotic Process Automation in HR.* Paper presented at the Journal of Physics: Conference Series.
58. Banasiewicz, A. (2021). *Organizational Learning in the Age of Data* (1 ed.). Cham, Switzerland: Springer Nature.
59. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management, 17*(1), 99-120.
60. Baron, R. A. (2004). The cognitive perspective: a valuable tool for answering entrepreneurship's basic "why" questions. *Journal of business venturing, 19*(2), 221-239.
61. Barua, A., Kriebel, C. H., & Mukhopadhyay, T. (1995). Information technologies and business value: An analytic and empirical investigation. *Information Systems Research, 6*(1), 3-23.
62. Baskerville, R., & Dulipovici, A. (2006). The theoretical foundations of knowledge management. *Knowledge management research & practice, 4*(2), 83-105.
63. Basri, W. (2020). Examining the impact of artificial intelligence (AI)-assisted social media marketing on the performance of small and medium enterprises: toward effective business management in the Saudi Arabian context. *International Journal of Computational Intelligence Systems, 13*(1), 142.
64. Basten, D., & Haamann, T. (2018). Approaches for organizational learning: A literature review. *Sage Open, 8*(3), 2158244018794224.
65. Baum, J. A., Li, S. X., & Usher, J. M. (2000). Making the next move: How experiential and vicarious learning shape the locations of chains' acquisitions. *Administrative science quarterly, 45*(4), 766-801.
66. Baumgartner, H., & Homburg, C. (1996). Applications of structural equation modeling in marketing and consumer research: A review. *International journal of Research in Marketing, 13*(2), 139-161.
67. Bawack, R. E., Fosso Wamba, S., & Carillo, K. (2019). *Artificial Intelligence in Practice: Implications for IS Research.* Paper presented at the Americas Conference on Information Systems (AMCIS) 2019 Cancun, Mexico.
68. Bawack, R. E., & Wamba, S. F. (2019). Where Information Systems Research Meets Artificial Intelligence Practice: Towards the Development of an AI Capability Framework.

69. Beck, C. T., & Gable, R. K. (2001). Ensuring content validity: An illustration of the process. *Journal of nursing measurement, 9*(2), 201-215.
70. Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research, 333*(2), 627-652.
71. Benner, M., & Tushman, M. (2001). Exploitation, Exploration, and Process Management: The Productivity Dilemma Revisited. *The Academy of Management Review, 28*. doi:10.5465/AMR.2003.9416096
72. Benner, M. J., & Tushman, M. L. (2015). Reflections on the 2013 Decade Award—"Exploitation, exploration, and process management: The productivity dilemma revisited" ten years later. *Academy of management review, 40*(4), 497-514.
73. Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological bulletin, 88*(3), 588.
74. Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly, 45*(3), 1433-1450.
75. Berndtsson, M., Forsberg, D., Stein, D., & Svahn, T. (2018). *Becoming a data-driven organisation.* Paper presented at the 26th European Conference on Information Systems (ECIS2018), Portsmouth, United Kingdom, June 23-28, 2018.
76. Bernolak, I. (1997). Effective measurement and successful elements of company productivity: the basis of competitiveness and world prosperity. *International Journal of Production Economics, 52*(1-2), 203-213.
77. Berruti, F., Nixon, G., Taglioni, G., & Whiteman, R. (2017). Intelligent process automation: The engine at the core of the next-generation operating model. *Digital McKinsey*, 9.
78. Berthoin Antal, A., & Krebsbach-Gnath, C. (1998). Consultants as agents of organizational learning: The importance of marginality.
79. Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS Quarterly*, 169-196.
80. Bhatnagar, N. (2020) Role of Robotic Process Automation in Pharmaceutical Industries. In*: Vol. 921. 4th International Conference on Advanced Machine Learning Technologies and Applications, AMLTA 2019* (pp. 497-504): Springer Verlag.
81. Bhatt, G. D., & Grover, V. (2005). Types of information technology capabilities and their role in competitive advantage: An empirical study. *Journal of management information systems, 22*(2), 253-277.
82. Bhatti, S. H., Santoro, G., Khan, J., & Rizzato, F. (2021). Antecedents and consequences of business model innovation in the IT industry. *Journal of Business Research, 123*, 389-400.
83. Birasnav, M., Chaudhary, R., & Scillitoe, J. (2019). Integration of social capital and organizational learning theories to improve operational performance. *Global Journal of Flexible Systems Management, 20*(2), 141-155.
84. Bisogno, S., Calabrese, A., Gastaldi, M., & Levialdi Ghiron, N. (2016). Combining modelling and simulation approaches: How to measure performance of business processes. *Business Process Management Journal, 22*(1), 56-74.
85. Boardman, B., Harden, T., & Martínez, S. (2018). Limited range spatial load balancing in non-convex environments using sampling-based motion planners. *Autonomous Robots, 42*(8), 1731-1748. doi:10.1007/s10514-018-9713-x

86. Bohanec, M., Robnik-Šikonja, M., & Borštnar, M. K. (2017). Organizational learning supported by machine learning models coupled with general explanation methods: A Case of B2B sales forecasting. *Organizacija, 50*(3), 217-233.
87. Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological bulletin, 110*(2), 305.
88. Bosilj Vukšić, V., Pejić Bach, M., Grublješič, T., Jaklič, J., & Stjepić, A.-M. (2017). *The role of alignment for the impact of business intelligence maturity on business process performance in Croatian and Slovenian companies.* Paper presented at the 2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO).
89. Boumgarden, P., Nickerson, J., & Zenger, T. R. (2012). Sailing into the wind: Exploring the relationships among ambidexterity, vacillation, and organizational performance. *Strategic Management Journal, 33*(6), 587-610.
90. Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. *Journal of product innovation management, 40*(2), 139-153.
91. Brace, I. (2018). *Questionnaire design: How to plan, structure and write survey material for effective market research* (4 ed.). London, England: Kogan Page Publishers.
92. Brás, J., Pereira, R., & Moro, S. (2023). Intelligent process automation and business continuity: Areas for future research. *Information, 14*(2), 122.
93. Bratnicka, K., & Bratnicki, M. (2013). Linking two dimensions of organizational creativity to firm performance: the mediating role of corporate entrepreneurship and the moderating role of environment. *Advances in Business-Related Scientific Research Journal, 4*(2), 153-163.
94. Brem, A., Giones, F., & Werle, M. (2021a). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. *IEEE Transactions on Engineering Management*.
95. Brem, A., Giones, F., & Werle, M. (2021b). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. *IEEE Transactions on Engineering Management, 70*(2), 770-776.
96. Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of econometrics, 65*(1), 83-108.
97. Breznik, L., & D. Hisrich, R. (2014). Dynamic capabilities vs. innovation capability: are they related? *Journal of Small Business and Enterprise Development, 21*(3), 368-384.
98. Bright, J. R. (1958). *Automation and management*: Division of Research, Graduate School of Business Administration, Harvard ….
99. Brock, J. K.-U., & Von Wangenheim, F. (2019). Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. *California management review, 61*(4), 110-134.
100. Brown, T. A. (2015). *Confirmatory factor analysis for applied research*: Guilford publications.
101. Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*: WW Norton & Company.
102. Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science, 358*(6370), 1530-1534.
103. Brynjolfsson, E., Rock, D., & Syverson, C. (2017). *Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics* (0898-2937). Retrieved from https://www.nber.org/papers/w24001

104. Buccieri, D., Javalgi, R. G., & Cavusgil, E. (2020). International new venture performance: Role of international entrepreneurial culture, ambidextrous innovation, and dynamic marketing capabilities. *International business review, 29*(2), 101639.
105. Bulusu, L., & Abellera, R. (2020). *AI meets BI: Artificial intelligence and business intelligence*. London, England: CRC Press.
106. Burgess, A. (2018). AI Capabilities Framework. In *The Executive Guide to Artificial Intelligence* (pp. 29-54): Springer.
107. Burke, B., Cearley, D., Jones, N., Smith, D., Chandrasekaran, A., Lu, C., & Panetta, K. (2019). Gartner top 10 strategic technology trends for 2020-Smarter with Gartner. In: Gartner.
108. Burtsev, M., Reeves, M., & Job, A. (2024). The working limitations of large language models. *MIT Sloan Management Review*, *65*(2), 8-10.
109. Büschgens, T., Bausch, A., & Balkin, D. B. (2013). Organizational culture and innovation: A meta-analytic review. *Journal of product innovation management, 30*(4), 763-781.
110. Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming, third edition* (3 ed.). London, England: Routledge.
111. Calantone, R. J., Cavusgil, S. T., & Zhao, Y. (2002). Learning orientation, firm innovation capability, and firm performance. *Industrial Marketing Management, 31*(6), 515-524.
112. Çallı, B. A., & Çallı, L. (2021). Relationships between digital maturity, organizational agility, and firm performance: an empirical investigation on SMEs. *Business & Management Studies: An International Journal*, *9*(2), 486-502.
113. Cameron, K. S., & Quinn, R. E. (2011). *Diagnosing and changing organizational culture: Based on the competing values framework* (3 ed.). Chichester, England: Jossey Bass Wiley.
114. Cao, G., Duan, Y., & Cadden, T. (2019). The link between information processing capability and competitive advantage mediated through decision-making effectiveness. *International Journal of Information Management, 44*, 121-131.
115. Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation, 106*, 102312.
116. Cao, Q., Gedajlovic, E., & Zhang, H. (2009). Unpacking organizational ambidexterity: Dimensions, contingencies, and synergistic effects. *Organization science, 20*(4), 781-796.
117. Cao, R., & Jiang, R. (2022). Resolving strategic dilemmas in ambidextrous organizations: An integrated second-order factor model perspective. *Frontiers in Psychology*, 655.
118. Capon, N., Farley, J. U., Lehmann, D. R., & Hulbert, J. M. (1992). Profiles of product innovators among large US manufacturers. *Management Science, 38*(2), 157-169.
119. Carlile, B., Marti, A., & Delamarter, G. (2017). Columnar Database Techniques for Creating AI Features. *arXiv preprint arXiv:1712.02882*.
120. Castaneda, D. I., Manrique, L. F., & Cuellar, S. (2018). Is organizational learning being absorbed by knowledge management? A systematic review. *Journal of Knowledge Management, 22*(2), 299-325.
121. CB Insights. (2021). AI 100: The Artificial Intelligence Startups Redefining Industries In 2021. Retrieved from https://www.cbinsights.com/research/artificial-intelligence-top-startups/
122. Cepeda, G., & Vera, D. (2007). Dynamic capabilities and operational capabilities: A knowledge management perspective. *Journal of Business Research, 60*(5), 426-437.

123. Chakraborti, T., Isahagian, V., Khalaf, R., Khazaeni, Y., Muthusamy, V., Rizk, Y., & Unuvar, M. (2020) From Robotic Process Automation to Intelligent Process Automation: – Emerging Trends –. In*: Vol. 393 LNBIP. Blockchain Forum and Robotic Process Automation, RPA Forum, held as part of the 18th International Conference on Business Process Management, BPM 2020* (pp. 215-228): Springer Science and Business Media Deutschland GmbH.
124. Chalmers, E. (2018). *Machine Learning With Certainty: A Requirement For Intelligent Process Automation*.
125. Chan, P. Y., & Mills, A. M. (2002). Motivators and inhibitors of e-commerce technology adoption: online stock trading by small brokerage firms in New Zealand. *Journal of Information Technology Case and Application Research, 4*(3), 38-56.
126. Chandy, R. K., & Tellis, G. J. (2000). The incumbent's curse? Incumbency, size, and radical product innovation. *Journal of Marketing, 64*(3), 1-17.
127. Chang, D. R., & Cho, H. (2008). Organizational memory influences new product success. *Journal of Business Research, 61*(1), 13-23.
128. Chang, M.-L., Tang, A. D., Cheng, C.-F., & Chen, W.-K. (2022). The bright side of environmental uncertainty for organizational learning: the moderating role of political skill. *Asian Business & Management*, 1-30.
129. Chang, Y.-C. EXAMINING THE FACTORS THAT AFFECT ERP ASSIMILATION.
130. Chatterjee, S., Chaudhuri, R., Kamble, S., Gupta, S., & Sivarajah, U. (2022). Adoption of Artificial Intelligence and Cutting-Edge Technologies for Production System Sustainability: A Moderator-Mediation Analysis. *Information Systems Frontiers*, 1-16.
131. Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Does data-driven culture impact innovation and performance of a firm? An empirical examination. *Annals of Operations Research*, 1-26.
132. Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2021). The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context. *Industrial Marketing Management*, *97*, 205-219.
133. Chaudhuri, R., Chatterjee, S., Vrontis, D., & Thrassou, A. (2021). Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture. *Annals of Operations Research*, 1-35.
134. Chen, D., Esperança, J. P., & Wang, S. (2022). The impact of artificial intelligence on firm performance: an application of the resource-based view to e-commerce firms. *Frontiers in Psychology, 13*.
135. Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of management information systems, 32*(4), 4-39.
136. Chen, H. (2019). Success Factors Impacting Artificial Intelligence Adoption---Perspective From the Telecom Industry in China.
137. Chen, J., Wang, X., Shen, W., Tan, Y., Matac, L. M., & Samad, S. (2022). Environmental uncertainty, environmental regulation and enterprises' green technological innovation. *International Journal of Environmental Research and Public Health, 19*(16), 9781.
138. Chen, M., Herrera, F., & Hwang, K. (2018). Cognitive computing: architecture, technologies and intelligent applications. *Ieee Access, 6*, 19774-19783.

139. Chen, S., & Yu, D. (2022). The impacts of ambidextrous innovation on organizational obsolescence in turbulent environments. *Kybernetes, 51*(3), 1009-1037.
140. Chen, Y., Li, C., & Wang, H. (2022). Big Data and Predictive Analytics for Business Intelligence: A Bibliographic Study (2000–2021). *Forecasting, 4*(4), 767-786.
141. Chen, Y., & Lin, Z. (2021). Business intelligence capabilities and firm performance: A study in China. *International Journal of Information Management, 57*, 102232.
142. Chen, Y., Wang, Y., Nevo, S., Benitez-Amado, J., & Kou, G. (2015). IT capabilities and product innovation performance: The roles of corporate entrepreneurship and competitive intensity. *Information & Management, 52*(6), 643-657.
143. Chen, Z., Huang, S., Liu, C., Min, M., & Zhou, L. (2018). Fit between organizational culture and innovation strategy: Implications for innovation performance. *Sustainability, 10*(10), 3378.
144. Cheng, C. C., & Huizingh, E. K. (2014). When is open innovation beneficial? The role of strategic orientation. *Journal of product innovation management, 31*(6), 1235-1253.
145. Chetty, T. (2019). *Big data: toward the influence of organisation culture and artificial intelligence on firm performance.* University of Pretoria,
146. Cheung, M. (2024). A Reality check of the benefits of LLM in business. *arXiv preprint arXiv:2406.10249*.
147. Chong, D., & Shi, H. (2015). Big data analytics: a literature review. *Journal of Management Analytics, 2*(3), 175-201.
148. Choon-Ling, S., Hock-Hai, T., Tan, B. C. Y., & Kwok-Kee, W. (2004). Effects of environmental uncertainty on organizational intention to adopt distributed work arrangements. *IEEE Transactions on Engineering Management, 51*(3), 253-267. doi:10.1109/TEM.2004.830859
149. Christensen, G., & Miguel, E. (2020). Transparency and reproducibility: Potential solutions. *The production of knowledge: Enhancing progress in social science*, 165-196.
150. Christensen, G., & Soderberg, C. (2016). Manual of best practices in transparent social science research. *Retrieved April, 2*, 2017.
151. Chui, M. (2017). Artificial intelligence the next digital frontier? *McKinsey and Company Global Institute, 47*.
152. Coad, A., Holm, J. R., Krafft, J., & Quatraro, F. (2018). Firm age and performance. *Journal of Evolutionary Economics, 28*(1), 1-11.
153. Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: does firm age play a role? *Research Policy, 45*(2), 387-400.
154. Coccoli, M., Maresca, P., & Stanganelli, L. (2016). Cognitive computing in education. *Journal of E-learning and Knowledge Society, 12*(2).
155. Cockburn, I. M., Henderson, R., & Stern, S. (2018). *The impact of artificial intelligence on innovation*. Retrieved from https://www.nber.org/papers/w24449
156. Code of ethics of the Faculty of Economics of the University of Ljubljana, (University of Ljubljana, School of Economics and Business 2012).
157. Cohen, J. (1988). edition 2. Statistical power analysis for the behavioral sciences. In: Hillsdale. Erlbaum.
158. Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative science quarterly, 35*(1), 128-152.
159. Collier, J. E. (2020). *Applied structural equation modeling using AMOS: Basic to advanced techniques*. NY, USA: Routledge Taylor & Francis Group.

160. Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management, 60*, 102383.
161. Coombs, C., Hislop, D., Taneva, S. K., & Barnard, S. (2020). The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review. *The Journal of Strategic Information Systems, 29*(4), 101600.
162. Cortez, P., & Santos, M. F. (2013). Knowledge discovery and business intelligence.
163. Costa, V., & Monteiro, S. (2016). Key knowledge management processes for innovation: a systematic literature review. *VINE Journal of Information and Knowledge Management Systems, 46*(3), 386-410.
164. Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical assessment, research, and evaluation, 10*(1), 7.
165. Coughlan, M., Cronin, P., & Ryan, F. (2009). Survey research: Process and limitations. *International Journal of Therapy and Rehabilitation, 16*(1), 9-15.
166. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *psychometrika, 16*(3), 297-334.
167. Crossan, M. M., Lane, H. W., & White, R. E. (1999). An organizational learning framework: From intuition to institution. *Academy of management review, 24*(3), 522-537.
168. Cruz, C. J. X. (2024). Transforming Competition into Collaboration: The Revolutionary Role of Multi-Agent Systems and Language Models in Modern Organizations. *arXiv preprint arXiv:2403.07769*.
169. Culnan, M. J., McHugh, P. J., & Zubillaga, J. I. (2010). How large US companies can use Twitter and other social media to gain business value. *MIS Quarterly Executive, 9*(4).
170. Curado, C., & Bontis, N. (2006). The knowledge-based view of the firm and its theoretical precursor. *International Journal of Learning and Intellectual Capital, 3*(4), 367-381.
171. D'Silva, V., & Lawler, B. (2022). What makes a company successful at using AI. *Harvard business review*(28).
172. Dabbous, A., Aoun Barakat, K., & Merhej Sayegh, M. (2022). Enabling organizational use of artificial intelligence: an employee perspective. *Journal of Asia Business Studies, 16*(2), 245-266.
173. Damanpour, F. (1991). Organizational innovation: A meta-analysis of effects of determinants and moderators. *Academy of Management Journal, 34*(3), 555-590.
174. Damanpour, F., & Schneider, M. (2009). Characteristics of innovation and innovation adoption in public organizations: Assessing the role of managers. *Journal of public administration research and theory, 19*(3), 495-522.
175. Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability, 14*(3), 43-53.
176. Daugherty, P. R., & Wilson, H. J. (2018). *Human+ machine: Reimagining work in the age of AI*. Boston, MA, USA: Harvard Business Press.
177. Davenport, T., & Harris, J. (2017). *Competing on analytics: Updated, with a new introduction: The new science of winning*. Boston, MA: Harvard Business Press.
178. Davenport, T. H. (1999). Knowledge management and the broader firm: strategy, advantage, and performance. *Knowledge management handbook, 2*, 1-2.

179. Davenport, T. H., Harris, J. G., De Long, D. W., & Jacobson, A. L. (2001). Data to knowledge to results: building an analytic capability. *California management review, 43*(2), 117-138.
180. Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*: Harper Business New York.
181. Davenport, T. H., & Mahidhar, V. (2018). What's your cognitive strategy. *MIT Sloan Management Review, 59*(4), 19-23.
182. Davenport, T. H., & Prusak, L. (1998). *Working knowledge: How organizations manage what they know*: Harvard Business Press.
183. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard business review, 96*(1), 108-116.
184. Davern, M. J., & Kauffman, R. J. (2000). Discovering potential and realizing value from information technology investments. *Journal of management information systems, 16*(4), 121-143.
185. de Almeida Rodrigues Gonçalves, J. C., Baiao, F. A., Santoro, F. M., & Guizzardi, G. (2023). A cognitive BPM theory for knowledge-intensive processes. *Business Process Management Journal, 29*(2), 465-488.
186. de Camargo Fiorini, P., Seles, B. M. R. P., Jabbour, C. J. C., Mariano, E. B., & de Sousa Jabbour, A. B. L. (2018). Management theory and big data literature: From a review to a research agenda. *International Journal of Information Management, 43*, 112-129.
187. De Haes, S., Van Grembergen, W., Joshi, A., & Huygh, T. (2020). COBIT as a Framework for Enterprise Governance of IT. In *Enterprise governance of information technology* (pp. 125-162): Springer.
188. De Mauro, A., Greco, M., & Grimaldi, M. (2016). A formal definition of Big Data based on its essential features. *Library review*.
189. De Mel, S., McKenzie, D. J., & Woodruff, C. M. (2009). Innovative firms or innovative owners? Determinants of innovation in micro, small, and medium enterprises. *Determinants of Innovation in Micro, Small, and Medium Enterprises (May 1, 2009). World Bank Policy Research Working Paper*(4934).
190. Deal, T. E., & Kennedy, A. A. (1982). *Corporate cultures: The rites and rituals of corporate life*. La Vergne, TN: Basic Books.
191. Dedehayir, O., & Steinert, M. (2016). The hype cycle model: A review and future directions. *Technological Forecasting and Social Change, 108*, 28-41.
192. Dedić, N., & Stanier, C. (2017). *Towards differentiating business intelligence, big data, data analytics and knowledge discovery.* Paper presented at the Innovations in Enterprise Information Systems Management and Engineering: 5th International Conference, ERP Future 2016-Research, Hagenberg, Austria, November 14, 2016, Revised Papers 5.
193. Dehning, B., & Richardson, V. J. (2002). Returns on investments in information technology: A research synthesis. *Journal of information systems, 16*(1), 7-30.
194. Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering, 61*(5), 637-643.
195. Demirkan, H., Earley, S., & Harmon, R. R. (2017). Cognitive computing. *IT professional, 19*(4), 16-20.
196. Deng, G., Zhang, J., He, L., & Xu, Y. (2023). Research on the impact of e-commerce platform's AI resources on seller opportunism: a cultivational governance mechanism. *Nankai Business Review International*(ahead-of-print).

197. Deng, G., Zhang, J., & Xu, Y. (2023). How e-commerce platforms build channel power: the role of AI resources and market-based assets. *Journal of Business & Industrial Marketing*.
198. Deng, M., Fang, X., Tian, Z., & Luo, W. (2022). The Impact of environmental uncertainty on corporate innovation: evidence from Chinese listed companies. *Sustainability, 14*(9), 4902.
199. Devaraj, S., & Kohli, R. (2003). Performance impacts of information technology: Is actual usage the missing link? *Management Science, 49*(3), 273-289.
200. Dewar, R. D., & Dutton, J. E. (1986). The adoption of radical and incremental innovations: An empirical analysis. *Management Science, 32*(11), 1422-1433.
201. Dhar, V. (2013). Data science and prediction. *Communications of the ACM, 56*(12), 64-73.
202. Di Ciccio, C., Marrella, A., & Russo, A. (2015). Knowledge-Intensive Processes: Characteristics, Requirements and Analysis of Contemporary Approaches. *Journal on Data Semantics, 4*(1), 29-57. doi:10.1007/s13740-014-0038-4
203. DiBella, A. J., Nevis, E. C., & Gould, J. M. (1996). Understanding organizational learning capability. *Journal of management studies, 33*(3), 361-379.
204. Diebold, J. (1955). Automation. *Textile Research Journal, 25*(7), 635-640.
205. Diewert, W. E. (2014). Decompositions of profitability change using cost functions. *Journal of econometrics, 183*(1), 58-66.
206. Dijkman, R., Lammers, S. V., & De Jong, A. (2016). Properties that influence business process management maturity and its effect on organizational performance. *Information Systems Frontiers, 18*(4), 717-734.
207. Dixon, R. B. L. (2022). A principled governance for emerging AI regimes: lessons from China, the European Union, and the United States. *AI and Ethics*, 1-18.
208. Dixon, S. E., Meyer, K. E., & Day, M. (2007). Exploitation and exploration learning and the development of organizational capabilities: A cross-case analysis of the Russian oil industry. *Human relations, 60*(10), 1493-1523.
209. Djalic, N., Nikolic, M., Bakator, M., & Erceg, Z. (2021). Modeling the influence of information systems on sustainable business performance and competitiveness. *Sustainability, 13*(17), 9619.
210. Doll, W. J., Xia, W., & Torkzadeh, G. (1994). A confirmatory factor analysis of the end-user computing satisfaction instrument. *MIS Quarterly*, 453-461.
211. Drucker, P. F. (2011). *Technology, management, and society*: Harvard Business Press.
212. Drydakis, N. (2022). Artificial Intelligence and reduced SMEs' business risks. A dynamic capabilities analysis during the COVID-19 pandemic. *Information Systems Frontiers, 24*(4), 1223-1247.
213. Duan, Y., Cao, G., & Edwards, J. S. (2020). Understanding the impact of business analytics on innovation. *European Journal of Operational Research, 281*(3), 673-686.
214. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63-71.
215. Dube, T., Van Eck, R., & Zuva, T. (2020). Review of technology adoption models and theories to measure readiness and acceptable use of technology in a business organization. *Journal of Information Technology and Digital World, 2*(4), 207-212.
216. Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in

humanitarian supply chain: A practice-based view. *International Journal of Production Economics*, *250*, 108618.

217. Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2018). *Fundamentals of business process management* (2 ed. Vol. 1). Berlin, Germany: Springer.

218. Dunston, P. S., & Wang, X. (2005). Mixed reality-based visualization interfaces for architecture, engineering, and construction industry. *Journal of construction engineering and management, 131*(12), 1301-1309.

219. Dwarkanhalli, H., Ananthanarayanan, M., & Mazumder, A. (2018). How Cognitive Computing Unlocks Business Process Management’s Performance-Enhancing Virtues In. London, England: Cognizant.

220. Earley, S. (2023). What executives need to know about knowledge management, large language models and generative AI. *Applied Marketing Analytics, 9*(3), 215-229.

221. Easterby-Smith, M., & Lyles, M. A. (2011). *Handbook of organizational learning and knowledge management*: John Wiley & Sons.

222. Eberhardt, J., Bilchik, A., & Stojadinovic, A. (2012). Clinical decision support systems: potential with pitfalls. *Journal of Surgical Oncology, 105*(5), 502-510.

223. Edwards, J. S., Duan, Y., & Robins, P. C. (2000). An analysis of expert systems for business decision making at different levels and in different roles. *European Journal of Information Systems, 9*(1), 36-46.

224. Eichhorn, B. R. (2014). Common method variance techniques. *Cleveland State University, Department of Operations & Supply Chain Management. Cleveland, OH: SAS Institute Inc, 1*(11).

225. Eikebrokk, T. R., & Olsen, D. H. (2020). *Robotic Process Automation and Consequences for Knowledge Workers; a Mixed-Method Study*, Cham.

226. Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal, 21*(10-11), 1105-1121.

227. Elbashir, M. Z., Collier, P. A., & Davern, M. J. (2008). Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *International Journal of Accounting Information Systems*, *9*(3), 135-153.

228. Elia, G., & Margherita, A. (2022). A conceptual framework for the cognitive enterprise: pillars, maturity, value drivers. *Technology Analysis & Strategic Management, 34*(4), 377-389.

229. Engel, C., Ebel, P., & Leimeister, J. M. (2022). Cognitive automation. *Electronic Markets, 32*(1), 339-350.

230. Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2021). Artificial intelligence and business value: a literature review. *Information Systems Frontiers*, 1-26.

231. Eremina, Y., Lace, N., & Bistrova, J. (2019). Digital maturity and corporate performance: The case of the Baltic states. *Journal of open innovation: technology, market, and complexity, 5*(3), 54.

232. Ertemel, A. V. (2015). Consumer insight as competitive advantage using big data and analytics. *International Journal of Commerce and Finance, 1*(1), 45-51.

233. Eskildsen, J. K., Dahlgaard, J. J., & Norgaard, A. (1999). The impact of creativity and learning on business excellence. *Total Quality Management, 10*(4-5), 523-530.

234. Etscheid, J. (2019) Artificial Intelligence in Public Administration: A Possible Framework for Partial and Full Automation. In*: Vol. 11685 LNCS. 18th IFIP WG 8.5 International Conference on Electronic Government, EGOV 2019* (pp. 248-261): Springer.

235. ETSI. (2021). Accessibility requirements for ICT products and services EN 301 549 V3.2.1. In.
236. Ettlie, J. E. (1983). Organizational policy and innovation among suppliers to the food processing sector. *Academy of Management Journal, 26*(1), 27-44.
237. Eurostat. (2020). Business demography by legal form (from 2004 onwards, NACE Rev. 2). Population of active enterprises. Retrieved from https://ec.europa.eu/eurostat/databrowser/view/BD_9AC_L_FORM_R2__custom_3540433/default/table?lang=en
238. Eurostat. (2022). *Artificial intelligence by NACE Rev.2 activity [dataset]*. Retrieved from: https://ec.europa.eu/eurostat/databrowser/view/isoc_eb_ain2/default/table?lang=en&category=isoc.isoc_e.isoc_eb
239. Eurostat, N. (2008). Rev. 2–statistical classification of economic activities in the european community. *Office for Official Publications of the European Communities, Luxemburg*.
240. Ezirim, C. B., Nwibere, B., & Emecheta, B. (2010). Organizational culture and performance: The Nigerian experience. *International Journal of Business and Public Administration, 7*(1), 40-57.
241. Fahland, D., Fournier, F., Limonad, L., Skarbovsky, I., & Swevels, A. J. (2024). How well can large language models explain business processes? *arXiv preprint arXiv:2401.12846*.
242. Farshid, M., Paschen, J., Eriksson, T., & Kietzmann, J. (2018). Go boldly!: Explore augmented reality (AR), virtual reality (VR), and mixed reality (MR) for business. *Business Horizons, 61*(5), 657-663.
243. Fayyad, U. M., Piatetsky-Shapiro, G., & Smyth, P. (1996). *Knowledge Discovery and Data Mining: Towards a Unifying Framework.* Paper presented at the KDD.
244. Feng, D., Dai, Y., Huang, J., Zhang, Y., Xie, Q., Han, W., . . . Wang, H. (2023). Empowering many, biasing a few: Generalist credit scoring through large language models. *arXiv preprint arXiv:2310.00566*.
245. Fernández, A., del Río, S., López, V., Bawakid, A., del Jesus, M. J., Benítez, J. M., & Herrera, F. (2014). Big Data with Cloud Computing: an insight on the computing environment, MapReduce, and programming frameworks. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 4*(5), 380-409.
246. Ferraris, A., Monge, F., & Mueller, J. (2018). Ambidextrous IT capabilities and business process performance: an empirical analysis. *Business Process Management Journal, 24*(5), 1077-1090.
247. Ferreira, A., & Otley, D. (2009). The design and use of performance management systems: An extended framework for analysis. *Management accounting research, 20*(4), 263-282.
248. Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative ai. *Business & Information Systems Engineering, 66*(1), 111-126.
249. Fichman, R. G. (2000). The diffusion and assimilation of information technology innovations. *Framing the domains of IT management: Projecting the future through the past, 105127*, 105-128.
250. Finch, G., Goehring, B., & Marshall, A. (2017). The enticing promise of cognitive computing: high-value functional efficiencies and innovative enterprise capabilities. *Strategy & Leadership, 45*(6), 26-33.
251. Flechsig, C., Lohmer, J., Voß, R., & Lasch, R. (2022). Business process maturity model for digital transformation: an action design research study on the integration

of information technology. *International Journal of Innovation Management, 26*(03), 2240012.
252. Flood, R. L., & Romm, N. R. (2018). A systemic approach to processes of power in learning organizations: part I–literature, theory, and methodology of triple loop learning. *The learning organization, 25*(4), 260-272.
253. Forbes Insights. (2019). *Accelerating Business Value With Intelligent Automation. The 2019 Kofax Intelligent Automation Benchmark Study.* Retrieved from
254. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39-50.
255. Forrester, R. H. (2000). Capturing learning and applying knowledge: an investigation of the use of innovation teams in Japanese and American automotive firms. *Journal of Business Research, 47*(1), 35-45.
256. Fotheringham, D., & Wiles, M. A. (2022). The effect of implementing chatbot customer service on stock returns: an event study analysis. *Journal of the Academy of Marketing Science*, 1-21.
257. Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard business review*, 63-73.
258. Fredrickson, J. W., & Mitchell, T. R. (1984). Strategic decision processes: Comprehensiveness and performance in an industry with an unstable environment. *Academy of Management Journal, 27*(2), 399-423.
259. Freese, J., Rauf, T., & Voelkel, J. G. (2022). Advances in transparency and reproducibility in the social sciences. *Social Science Research, 107*, 102770.
260. Frohm, J. (2008). *Levels of Automation in production systems*: Chalmers University of Technology Göteborg.
261. Gable, G. G., Sedera, D., & Chan, T. (2008). Re-conceptualizing information system success: The IS-impact measurement model. *Journal of the association for information systems, 9*(7), 18.
262. Gallego-Gomez, C., & De-Pablos-Heredero, C. (2020). Artificial intelligence as an enabling tool for the development of dynamic capabilities in the banking industry. *International Journal of Enterprise Information Systems (IJEIS), 16*(3), 20-33.
263. Gama, F., & Magistretti, S. (2023). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. *Journal of product innovation management*.
264. Ganji, D. S., & Karandikar, S. (2019). Artificial Intelligence: A Risk Factor. *Artificial Intelligence, 6*(04).
265. Garbuio, M., & Lin, N. (2021). Innovative idea generation in problem finding: Abductive reasoning, cognitive impediments, and the promise of artificial intelligence. *Journal of product innovation management, 38*(6), 701-725.
266. García-Morales, V. J., Jiménez-Barrionuevo, M. M., & Gutiérrez-Gutiérrez, L. (2012). Transformational leadership influence on organizational performance through organizational learning and innovation. *Journal of Business Research, 65*(7), 1040-1050.
267. Garmaki, M., Boughzala, I., & Wamba, S. F. (2016). *The effect of Big Data Analytics Capability on Firm Performance.* Paper presented at the PACIS.
268. Gaskin, J. (2021a). Confirmatory Factor Analysis. Retrieved from http://statwiki.gaskination.com/index.php?title=CFA
269. Gaskin, J. (2021b). Exploratory factor analysis. Retrieved from http://statwiki.gaskination.com/index.php?title=EFA

270. Gefen, D., Ben-Assuli, O., Stehr, M., Rosen, B., & Denekamp, Y. (2019). Governmental intervention in Hospital Information Exchange (HIE) diffusion: a quasi-experimental ARIMA interrupted time series analysis of monthly HIE patient penetration rates. *European Journal of Information Systems, 28*(6), 627-645.
271. George, A. S., & George, A. H. (2023). A review of ChatGPT AI's impact on several business sectors. *Partners universal international innovation journal, 1*(1), 9-23.
272. Geyer-Klingeberg, J., Nakladal, J., Baldauf, F., & Veit, F. (2018). *Process Mining and Robotic Process Automation: A Perfect Match.* Paper presented at the BPM (Dissertation/Demos/Industry).
273. Ghafoori, A., Gupta, M., Merhi, M. I., Gupta, S., & Shore, A. P. (2024). Toward the role of organizational culture in data-driven digital transformation. *International Journal of Production Economics*, *271*, 109205.
274. Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems, 27*(1), 101-113.
275. Ghattas, J., Soffer, P., & Peleg, M. (2014). Improving business process decision making based on past experience. *Decision support systems, 59*, 93-107.
276. Ghavami, P. (2019). *Big data analytics methods: Analytics techniques in data mining, deep learning and natural language processing* (2 ed.). New York, NY: De Gruyter.
277. Gibson, C. B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. *Academy of Management Journal, 47*(2), 209-226.
278. *GoDigital 2019 - Data and Artificial Intelligence conference*. (2019). Paper presented at the GoDigital 2019.
279. Grant, R. M. (1996a). Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. *Organization science, 7*(4), 375-387.
280. Grant, R. M. (1996b). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(S2), 109-122.
281. Grifell-Tatjé, E., & Lovell, C. K. (2018). Productivity and financial performance. In *The Oxford Handbook of Productivity Analysis* (pp. 329-358): Oxford University Press NY.
282. Gronau, N., & Weber, E. (2004). *Management of knowledge intensive business processes.* Paper presented at the International Conference on Business Process Management.
283. Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *The Journal of Strategic Information Systems, 29*(2), 101614.
284. Grooss, O. F., Presser, M., & Tambo, T. (2022). Balancing Digital Maturity and Operational Performance-Progressing in a Low-digital SME Manufacturing Setting. *Procedia Computer Science, 200*, 495-504.
285. Grosskopf, S. (1993). Efficiency and productivity. *The measurement of productive efficiency: Techniques and applications*, 160-194.
286. Grover, V., Purvis, R. L., & Segars, A. H. (2007). Exploring ambidextrous innovation tendencies in the adoption of telecommunications technologies. *IEEE Transactions on Engineering Management, 54*(2), 268-285.
287. Gruetzemacher, R., & Whittlestone, J. (2022). The transformative potential of artificial intelligence. *Futures, 135*, 102884.

288. Grünberg, T. (2004). Performance improvement: Towards a method for finding and prioritising potential performance improvement areas in manufacturing operations. *International Journal of Productivity and Performance Management, 53*(1), 52-71.
289. Gu, J.-W., & Jung, H.-W. (2013). The effects of IS resources, capabilities, and qualities on organizational performance: An integrated approach. *Information & Management, 50*(2-3), 87-97.
290. Gui, L., Lei, H., & Le, P. B. (2022). Determinants of radical and incremental innovation: the influence of transformational leadership, knowledge sharing and knowledge-centered culture. *European Journal of Innovation Management, 25*(5), 1221-1241.
291. Günther, W. A., Mehrizi, M. H. R., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems, 26*(3), 191-209.
292. Guo, L., & Xu, L. (2021). The effects of digital transformation on firm performance: Evidence from China's manufacturing sector. *Sustainability, 13*(22), 12844.
293. Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management, 53*(8), 1049-1064.
294. Gupta, S., Kar, A. K., Baabdullah, A., & Al-Khowaiter, W. A. (2018). Big data with cognitive computing: A review for the future. *International Journal of Information Management, 42*, 78-89.
295. Gupta, S., Modgil, S., Choi, T.-M., Kumar, A., & Antony, J. (2023). Influences of artificial intelligence and blockchain technology on financial resilience of supply chains. *International Journal of Production Economics, 261*, 108868.
296. Gurumurthy, R., & Schatsky, D. (2019). Pivoting to digital maturity: Seven capabilities central to digital transformation. *Deloitte Insights. Retrieved July, 17*, 2019.
297. Hadjielias, E., Christofi, M., Christou, P., & Drotarova, M. H. (2022). Digitalization, agility, and customer value in tourism. *Technological Forecasting and Social Change, 175*, 121334.
298. Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda☆. *Technological Forecasting and Social Change, 162*, 120392.
299. Haftor, D. M., Climent, R. C., & Lundström, J. E. (2021). How machine learning activates data network effects in business models: Theory advancement through an industrial case of promoting ecological sustainability. *Journal of Business Research, 131*, 196-205.
300. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2013). *Multivariate data analysis: Pearson new international edition* (7 ed.). London, England: Pearson Education.
301. Hair Jr, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced issues in partial least squares structural equation modeling*: saGe publications.
302. Hall, R. E., & Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *The Quarterly journal of economics, 114*(1), 83-116.
303. Han, Y., Hou, J., & Sun, Y. (2023). *Research and Application of GPT-Based Large Language Models in Business and Economics: A Systematic Literature Review in Progress.* Paper presented at the 2023 IEEE International Conference on Computing (ICOCO).
304. Hancock, G. R., & Mueller, R. O. (2001). Rethinking construct reliability within latent variable systems. *Structural equation modeling: Present and future, 195*, 216.

305. Hänel, L. (2017). A list of artificial intelligence tools you can use today. Retrieved from https://www.liamiscool.com
306. Hansen, E. B., & Bøgh, S. (2021). Artificial intelligence and internet of things in small and medium-sized enterprises: A survey. *Journal of Manufacturing Systems, 58*, 362-372.
307. Harmon, P., & Trends, B. P. (2010). *Business process change: A guide for business managers and BPM and Six Sigma professionals*: Elsevier.
308. Hartmann, A. (2006). The role of organizational culture in motivating innovative behaviour in construction firms. *Construction innovation*.
309. Hartmann, P. M., Zaki, M., Feldmann, N., & Neely, A. (2016). Capturing value from big data–a taxonomy of data-driven business models used by start-up firms. *International Journal of Operations & Production Management*.
310. Hassan, N. R. (2019). The origins of business analytics and implications for the information systems field. *Journal of Business Analytics, 2*(2), 118-133.
311. Hau, K. T., & Marsh, H. W. (2004). The use of item parcels in structural equation modelling: Non-normal data and small sample sizes. *British Journal of Mathematical and Statistical Psychology, 57*(2), 327-351.
312. Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: a regression-based approach* (Second edition ed.). New York: Guilford Press.
313. He, Z.-L., & Wong, P.-K. (2004). Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. *Organization science, 15*(4), 481-494.
314. Heckmann, C. S. (2015). *The Impact of Business Process IT Ambidexterity on Business Process Performance.* Paper presented at the ECIS.
315. Heckmann, C. S., & Maedche, A. (2018). IT ambidexterity for business processes: The importance of balance. *Business Process Management Journal, 24*(4), 862-881.
316. Hegazy, M., Hegazy, K., & Eldeeb, M. (2022). The balanced scorecard: Measures that drive performance evaluation in auditing firms. *Journal of Accounting, Auditing & Finance, 37*(4), 902-927.
317. Heimbach, I., Kostyra, D. S., & Hinz, O. (2015). Marketing automation. *Business & Information Systems Engineering*, *57*(2), 129-133.
318. Heirati, N., O'Cass, A., & Sok, P. (2017). Identifying the resource conditions that maximize the relationship between ambidexterity and new product performance. *Journal of Business & Industrial Marketing*.
319. Helbin, T. (2019). *Investigating how Business Process Ambidexterity facilitates business-IT alignment in public sector organizations.* Paper presented at the 2019 13th International Conference on Research Challenges in Information Science (RCIS).
320. Helbin, T., & Van Looy, A. (2021). Is business process management (BPM) ready for ambidexterity? Conceptualization, implementation guidelines and research agenda. *Sustainability*, *13*(4), 1906.
321. Hellsten, L. (2008). *Accumulating content validity evidence: Assessing expert panel ratings of item relevance and representativeness.* Paper presented at the National Council on Measurement in Education Annual Conference, New York.
322. Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly*, 9-30.
323. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135.

324. Herbsleb, J., Zubrow, D., Goldenson, D., Hayes, W., & Paulk, M. (1997). Software quality and the capability maturity model. *Communications of the ACM, 40*(6), 30-40.
325. Herm, L.-V., Janiesch, C., Helm, A., Imgrund, F., Fuchs, K., Hofmann, A., & Winkelmann, A. (2020). *A Consolidated Framework for Implementing Robotic Process Automation Projects*, Cham.
326. Hernaus, T. (2012). Influence of strategic approach to BPM on financial and non-financial performance. *Baltic Journal of Management, 7*(4), 376-396. doi:10.1108/17465261211272148
327. Hernaus, T. (2016). How to go from strategy to results? Institutionalising BPM governance within organisations. *Business Process Management Journal, 22*(1), 173-195. doi:10.1108/BPMJ-03-2015-0031
328. Hernaus, T., Škerlavaj, M., & Dimovski, V. (2008). Relationship between organisational learning and organisational performance: The case of Croatia. *Transformations in business & economics, 7*(2), 32-48.
329. Hildebrand, D., Rösl, S., Auer, T., & Schieder, C. Next-Generation Business Process Management (BPM): A Systematic Literature Review of Cognitive Computing and Improvements in BPM.
330. Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. *Organizational Research Methods, 1*(1), 104-121.
331. Hitomi, K. (1994). Automation—its concept and a short history. *Technovation, 14*(2), 121-128.
332. Ho, L. T., Gan, C., Jin, S., & Le, B. (2022). Artificial Intelligence and Firm Performance: Does Machine Intelligence Shield Firms from Risks? *Journal of Risk and Financial Management, 15*(7), 302.
333. Hoe, S. L. (2008). Issues and procedures in adopting structural equation modelling technique. *Journal of Quantitative Methods, 3*(1), 76.
334. Hofmann, E., Brunner, J. H., & Holschbach, E. (2020). Research in business service purchasing: current status and directions for the future. *Management Review Quarterly, 70*(3), 421-460. doi:10.1007/s11301-019-00172-7
335. Hogan, S. J., & Coote, L. V. (2014). Organizational culture, innovation, and performance: A test of Schein's model. *Journal of Business Research, 67*(8), 1609-1621.
336. Holsapple, C., Lee-Post, A., & Pakath, R. (2014). A unified foundation for business analytics. *Decision support systems, 64*, 130-141.
337. Hong, W., Chan, F. K., Thong, J. Y., Chasalow, L. C., & Dhillon, G. (2014). A framework and guidelines for context-specific theorizing in information systems research. *Information Systems Research, 25*(1), 111-136.
338. Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic journal of business research methods, 6*(1), pp53-60-pp53-60.
339. Hossain, M. A., Agnihotri, R., Rushan, M. R. I., Rahman, M. S., & Sumi, S. F. (2022). Marketing analytics capability, artificial intelligence adoption, and firms' competitive advantage: evidence from the manufacturing industry. *Industrial Marketing Management, 106*, 240-255.
340. Hosseini, S. H., Hajipour, E., Kaffashpoor, A., & Darikandeh, A. (2020). The mediating effect of organizational culture in the relationship of leadership style with organizational learning. *Journal of human Behavior in the social environment, 30*(3), 279-288.

341. Hribar, B., & Mendling, J. (2014). The correlation of organizational culture and success of BPM adoption.
342. Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.
343. Huber, G. P. (1990). A theory of the effects of advanced information technologies on organizational design, intelligence, and decision making. *Academy of management review*, *15*(1), 47-71.
344. Huber, G. P. (1991). Organizational learning: The contributing processes and the literatures. *Organization science, 2*(1), 88-115.
345. Hull, R., & Motahari-Nezhad, H. R. (2016). *Rethinking BPM in a Cognitive World: Transforming How We Learn and Perform Business Processes*, Cham.
346. Hull, R., & Motahari Nezhad, H. R. (2016). *Rethinking BPM in a Cognitive World: Transforming How We Learn and Perform Business Processes*, Cham.
347. Hung, R. Y. Y., Lien, B. Y.-H., Yang, B., Wu, C.-M., & Kuo, Y.-M. (2011). Impact of TQM and organizational learning on innovation performance in the high-tech industry. *International business review, 20*(2), 213-225.
348. Hurwitz, J., Kaufman, M., Bowles, A., Nugent, A., Kobielus, J. G., & Kowolenko, M. D. (2015). *Cognitive computing and big data analytics*: Wiley Online Library.
349. Husain, Z., Dayan, M., & Di Benedetto, C. A. (2016). The impact of networking on competitiveness via organizational learning, employee innovativeness, and innovation process: A mediation model. *Journal of Engineering and Technology Management*, *40*, 15-28.
350. Hutchinson, P. (2020). Reinventing innovation management: The impact of self-innovating artificial intelligence. *IEEE Transactions on Engineering Management, 68*(2), 628-639.
351. Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS Quarterly*, 465-485.
352. IEEE Approved Draft Guide to Terms and Concepts in Intelligent Process Automation. (2017). *IEEE P2755/D1, January 2017*, 1-16.
353. IEEE Guide for Terms and Concepts in Intelligent Process Automation. (2017). *IEEE Std 2755-2017*, 1-16. doi:10.1109/IEEESTD.2017.8070671
354. Institute of Information Science. (2024). COBISS.SI. Retrieved from https://www.cobiss.si/
355. Ivančić, L., Suša Vugec, D., & Bosilj Vukšić, V. (2019). *Robotic Process Automation: Systematic Literature Review*, Cham.
356. Jaaksi, J., Koskinen, J., & Jalava, M. (2018). HOW TO DEFINE AN ORGANIZATION'S MATURITY FOR ADOPTING ARTIFICIAL INTELLIGENCE SOLUTIONS.
357. Jain, V. (2019). An impact of artificial intelligence on business. *International Journal of Research and Analytical Reviews, 6*(2), 302-308.
358. Jakšič, M., & Marinč, M. (2019). Relationship banking and information technology: The role of artificial intelligence and FinTech. *Risk Management, 21*, 1-18.
359. Jamali, D. (2006). Insights into triple bottom line integration from a learning organization perspective. *Business Process Management Journal*.
360. Jansen, J. J., Van Den Bosch, F. A., & Volberda, H. W. (2005). Managing potential and realized absorptive capacity: how do organizational antecedents matter? *Academy of Management Journal*, *48*(6), 999-1015.
361. Jansen, J. J., Van Den Bosch, F. A., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational

antecedents and environmental moderators. *Management Science, 52*(11), 1661-1674.

362. Janssen, K. J., & Revesteyn, P. (2015). Business processes management in the Netherlands and Portugal: The effect of BPM maturity on BPM performance. *Journal of International Technology and Information Management, 24*(1), 3.

363. Janssen, M., Van Der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research, 70*, 338-345.

364. Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2022). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons*.

365. Jarrahi, M. H., Kenyon, S., Brown, A., Donahue, C., & Wicher, C. (2022). Artificial intelligence: a strategy to harness its power through organizational learning. *Journal of Business Strategy*.

366. Jarrahi, M. H., Lutz, C., & Newlands, G. (2022). Artificial intelligence, human intelligence and hybrid intelligence based on mutual augmentation. *Big Data & Society, 9*(2), 20539517221142824.

367. Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of consumer research, 30*(2), 199-218.

368. Jeyaraj, A., Rottman, J. W., & Lacity, M. C. (2006). A review of the predictors, linkages, and biases in IT innovation adoption research. *Journal of Information Technology, 21*(1), 1-23.

369. Jiao, J., Afroogh, S., Xu, Y., & Phillips, C. (2024). Navigating LLM Ethics: Advancements, Challenges, and Future Directions. *arXiv preprint arXiv:2406.18841*.

370. Jiménez-Jiménez, D., & Sanz-Valle, R. (2011). Innovation, organizational learning, and performance. *Journal of Business Research, 64*(4), 408-417.

371. Jobst, L. J., Bader, M., & Moshagen, M. (2021). A tutorial on assessing statistical power and determining sample size for structural equation models. *Psychological methods*.

372. Johnson, P. C., Laurell, C., Ots, M., & Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development–Automation or augmentation, exploration or exploitation? *Technological Forecasting and Social Change, 179*, 121636.

373. Jordan, P. J., & Troth, A. C. (2020). Common method bias in applied settings: The dilemma of researching in organizations. *Australian Journal of Management, 45*(1), 3-14.

374. Joseph, O., & Falana, A. (2021). Artificial Intelligence and Firm Performance: A Robotic Taxation Perspective. In *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success* (pp. 23-56): Springer.

375. Jovanovic, B., & Rousseau, P. L. (2005). General purpose technologies. In *Handbook of economic growth* (Vol. 1, pp. 1181-1224): Elsevier.

376. Jurksiene, L., & Pundziene, A. (2016). The relationship between dynamic capabilities and firm competitive advantage: The mediating role of organizational ambidexterity. *European Business Review*.

377. Kaklauskas, A., & Kanapeckiene, L. (2005). Knowledge management and "BRITA in PuBs" project. *Technological and Economic Development of Economy, 11*(2), 78-86.

378. Kamya, M. T. (2012). Organizational learning and market performance: The interactive effect of market orientation. *Journal of Economics and International Finance, 4*(10), 226.
379. Kane, G. C., Palmer, D., Nguyen-Phillips, A., Kiron, D., & Buckley, N. (2017). Achieving digital maturity. *MIT Sloan Management Review, 59*(1).
380. Kaplan, R. S. (2009). Conceptual foundations of the balanced scorecard. *Handbooks of management accounting research, 3*, 1253-1269.
381. Kaplan, R. S., & Norton, D. P. (1996). *The balanced scorecard: Translating strategy into action*. Boston, MA: Harvard Business School Press.
382. Karaboga, T., Zehir, C., Tatoglu, E., Karaboga, H. A., & Bouguerra, A. (2022). Big data analytics management capability and firm performance: the mediating role of data-driven culture. *Review of Managerial Science*, 1-30.
383. Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, 183-213.
384. Karan, E., Safa, M., & Suh, M. J. (2021) Use of Artificial Intelligence in a Regulated Design Environment – A Beam Design Example. In*: Vol. 98. Lecture Notes in Civil Engineering* (pp. 16-25): Springer.
385. Karimi, J., Somers, T. M., & Gupta, Y. P. (2004). Impact of environmental uncertainty and task characteristics on user satisfaction with data. *Information Systems Research, 15*(2), 175-193.
386. Kassies, H. (2021). *Cultural Factors Influencing the Data Science Challenge in a Municipality.* University of Twente,
387. Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal, 45*(6), 1183-1194.
388. Kazakova, S. S., Dunne, A. A., Bijwaard, D. D., Gossé, J., Hoffreumon, C., & van Zeebroeck, N. (2020). *European enterprise survey on the use of technologies based on artificial intelligence*. Retrieved from
389. Keding, C. (2021). Understanding the interplay of artificial intelligence and strategic management: four decades of research in review. *Management Review Quarterly, 71*(1), 91-134. doi:10.1007/s11301-020-00181-x
390. Keding, C., & Meissner, P. (2021). Managerial overreliance on AI-augmented decision-making processes: How the use of AI-based advisory systems shapes choice behavior in R&D investment decisions. *Technological Forecasting and Social Change, 171*, 120970.
391. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366-410.
392. Kelly, J. E. (2015). Computing, cognition and the future of knowing. *Whitepaper, IBM Reseach, 2*.
393. Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological methods & research, 44*(3), 486-507.
394. Kerpedzhiev, G. D., König, U. M., Röglinger, M., & Rosemann, M. (2020). An Exploration into Future Business Process Management Capabilities in View of Digitalization. *Business & Information Systems Engineering*. doi:10.1007/s12599-020-00637-0
395. Khaddam, A. A., Alzghoul, A., Abusweilem, M. A., & Abousweilem, F. (2023). Business intelligence and firm performance: a moderated-mediated model. *The Service Industries Journal, 43*(13-14), 923-939.

396. Khan, U., Zhang, Y., & Salik, M. (2020). The impact of information technology on organizational performance: The mediating effect of organizational learning. *The Journal of Asian Finance, Economics and Business, 7*(11), 987-998.
397. Khandabattu, H., & Jaffri, A. (2024, 2024/6/17). Hype Cycle for Artificial Intelligence, 2024. Retrieved from https://www.gartner.com/doc/reprints?id=1-2HV4OPON&ct=240618&st=sb
398. Khasawneh, A. M. (2008). Concepts and measurements of innovativeness: The case of information and communication technologies. *International Journal of Arab Culture, Management and Sustainable Development, 1*(1), 23-33.
399. Khine, P. P., & Wang, Z. S. (2018). *Data lake: a new ideology in big data era.* Paper presented at the ITM web of conferences.
400. Kılıç, M., & Uludağ, O. (2021). The Effects of Transformational Leadership on Organizational Performance: Testing the Mediating Effects of Knowledge Management. *Sustainability, 13*(14), 7981.
401. Kim, G., Shin, B., Kim, K. K., & Lee, H. G. (2011). IT capabilities, process-oriented dynamic capabilities, and firm financial performance. *Journal of the association for information systems, 12*(7), 1.
402. Kim, T., & Chang, J. (2018). Organizational culture and performance: a macro-level longitudinal study. *Leadership & Organization Development Journal, 40*(1), 65-84.
403. Kim, T., Park, Y., & Kim, W. (2022). *The Impact of Artificial Intelligence on Firm Performance.* Paper presented at the 2022 Portland International Conference on Management of Engineering and Technology (PICMET).
404. Kirchmer, M., & Franz, P. (2019). *Value-Driven Robotic Process Automation (RPA),* Cham.
405. Kiron, D., Prentice, P. K., & Ferguson, R. B. (2012). Innovating with analytics. *MIT Sloan Management Review, 54*(1), 47.
406. Kiron, D., & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review, 53*(1), 57.
407. Kline, R. B. (2015). *Principles and practice of structural equation modeling, fourth edition* (4 ed.). New York, NY: Guilford Publications.
408. Klumpp, M. (2017). Automation and artificial intelligence in business logistics systems: human reactions and collaboration requirements. *International Journal of Logistics, 21*. doi:10.1080/13675567.2017.1384451
409. Koehler, J. (2018). Business Process Innovation with Artificial Intelligence: Levering Benefits and Controlling Operational Risks. *European Business & Management, 4*(2), 55-66.
410. Kohlbacher, M. (2010). The effects of process orientation: a literature review. *Business Process Management Journal, 16*(1), 135-152. doi:10.1108/14637151011017985
411. Kohli, R., & Grover, V. (2008). Business value of IT: An essay on expanding research directions to keep up with the times. *Journal of the association for information systems, 9*(1), 1.
412. Kokina, J., & Blanchette, S. (2019). Early evidence of digital labor in accounting: Innovation with Robotic Process Automation. *International Journal of Accounting Information Systems, 35*. doi:10.1016/j.accinf.2019.100431
413. König, M., Bein, L., Nikaj, A., & Weske, M. (2020). *Integrating Robotic Process Automation into Business Process Management,* Cham.
414. Koo, K., & Le, L. (2024). IT capability and innovation. *Technological Forecasting and Social Change, 203,* 123359.

415. Korherr, P., Kanbach, D. K., Kraus, S., & Mikalef, P. (2022). From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes. *Digital Business, 2*(2), 100045.
416. Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, *44*(6), 1425-1452.
417. Kress, M., & Seese, D. (2010). *Autonomous Optimization of Business Processes,* Berlin, Heidelberg.
418. Krishnamoorthi, S., & Mathew, S. K. (2018). Business analytics and business value: A comparative case study. *Information & Management, 55*(5), 643-666. doi:https://doi.org/10.1016/j.im.2018.01.005
419. Kromann, L., & Sørensen, A. (2019). Automation, performance and international competition: a firm-level comparison of process innovation. *Economic Policy, 34*(100), 691-722.
420. Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling* (1 ed. Vol. 26). New York, NY: Springer.
421. Kühne, B., & Böhmann, T. (2019). *Data-Driven Business Models-Building the Bridge between Data and Value.* Paper presented at the ECIS.
422. Kullenda, K. (2020). *Enabling firm performance through data driven decision making in maintenance management: a dynamic capabilities view.* University of Pretoria,
423. Kurtmollaiev, S. (2020). Dynamic capabilities and where to find them. *Journal of Management Inquiry*, *29*(1), 3-16.
424. Lacity, M., & Willcocks, L. (2021). Becoming strategic with intelligent automation. *MIS Quarterly Executive*, *20*(2), 1-14.
425. Lacity, M. C., & Willcocks, L. P. (2016). A new approach to automating services. *MIT Sloan Management Review, 58*(1), 41-49.
426. Lai, M.-C., Lin, Y.-T., Lin, L.-H., Wang, W.-K., & Huang, H.-C. (2009). Information behavior and value creation potential of information capital: Mediating role of organizational learning. *Expert systems with Applications*, *36*(1), 542-550.
427. Lambert, D. M., & Harrington, T. C. (1990). Measuring nonresponse bias in customer service mail surveys. *Journal of business Logistics*, *11*(2), 5-25.
428. Landis, R., Edwards, B., & Cortina, J. (2009). On the practice of allowing correlated residuals among indicators in structural equation models. In (pp. 193-214).
429. Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in Human Behavior, 123*, 106878.
430. LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21-32.
431. Lawshe, C. H. (1975). A quantitative approach to content validity. *Personnel Psychology*, *28*(4), 563-575. doi:10.1111/j.1744-6570.1975.tb01393.x
432. Leal-Rodríguez, A. L., Sanchís-Pedregosa, C., Moreno-Moreno, A. M., & Leal-Millán, A. G. (2023). Digitalization beyond technology: Proposing an explanatory and predictive model for digital culture in organizations. *Journal of Innovation & Knowledge*, *8*(3), 100409.
433. Lee, H., & Choi, B. (2003). Knowledge management enablers, processes, and organizational performance: An integrative view and empirical examination. *Journal of management information systems, 20*(1), 179-228.
434. Lee, S. M., & Trimi, S. (2018). Innovation for creating a smart future. *Journal of Innovation & Knowledge, 3*(1), 1-8.

435. Lee, V. H., Dwivedi, Y. K., Tan, G. W. H., Ooi, K. B., & Wong, L. W. (2023). How does information technology capabilities affect business sustainability? The roles of ambidextrous innovation and data-driven culture. *R&D Management*.
436. Leemann, N., & Kanbach, D. K. (2022). Toward a taxonomy of dynamic capabilities–a systematic literature review. *Management Research Review, 45*(4), 486-501.
437. Levine, S., Finn, C., Darrell, T., & Abbeel, P. (2016). End-to-end training of deep visuomotor policies. *The Journal of Machine Learning Research, 17*(1), 1334-1373.
438. Li, J., Ye, Z., & Zhang, C. (2022). Study on the interaction between big data and artificial intelligence. *Systems Research and Behavioral Science, 39*(3), 641-648.
439. Li, X., Li, K., & Zhou, H. (2022). Impact of Inventor's Cooperation Network on Ambidextrous Innovation in Chinese AI Enterprises. *Sustainability, 14*(16), 9996.
440. Liang, H., Wang, N., Xue, Y., & Ge, S. (2017). Unraveling the alignment paradox: how does business—IT alignment shape organizational agility? *Information Systems Research, 28*(4), 863-879.
441. Liang, T.-P., & Liu, Y.-H. (2018). Research landscape of business intelligence and big data analytics: A bibliometrics study. *Expert systems with Applications, 111*, 2-10.
442. Liao, S.-H., Chang, W.-J., Hu, D.-C., & Yueh, Y.-L. (2012). Relationships among organizational culture, knowledge acquisition, organizational learning, and organizational innovation in Taiwan's banking and insurance industries. *The International Journal of Human Resource Management, 23*(1), 52-70.
443. Liao, S.-H., & Wu, C.-c. (2010). System perspective of knowledge management, organizational learning, and organizational innovation. *Expert systems with Applications, 37*(2), 1096-1103.
444. Liao, S., Hu, Q., & Wei, J. (2023). How to leverage big data analytic capabilities for innovation ambidexterity: A mediated moderation model. *Sustainability, 15*(5), 3948.
445. Liao, Y. C., & Tsai, K. H. (2019). Bridging market demand, proactivity, and technology competence with eco-innovations: The moderating role of innovation openness. *Corporate Social Responsibility and Environmental Management, 26*(3), 653-663.
446. Lin, Y.-C. (2014). Construction 3D BIM-based knowledge management system: a case study. *Journal of Civil Engineering and Management, 20*(2), 186-200.
447. Lin, Y., & Wu, L.-Y. (2014). Exploring the role of dynamic capabilities in firm performance under the resource-based view framework. *Journal of Business Research, 67*(3), 407-413.
448. Linton, N. M., Kobayashi, T., Yang, Y., Hayashi, K., Akhmetzhanov, A. R., Jung, S.-m., . . . Nishiura, H. (2020). Incubation period and other epidemiological characteristics of 2019 novel coronavirus infections with right truncation: a statistical analysis of publicly available case data. *Journal of clinical medicine, 9*(2), 538.
449. Little, T. D., Rhemtulla, M., Gibson, K., & Schoemann, A. M. (2013). Why the items versus parcels controversy needn't be one. *Psychological methods, 18*(3), 285.
450. Litvaj, I., Ponisciakova, O., Stancekova, D., Svobodova, J., & Mrazik, J. (2022). Decision-making procedures and their relation to knowledge management and quality management. *Sustainability, 14*(1), 572.
451. Liu, J., Snodgrass, S., Khalifa, A., Risi, S., Yannakakis, G. N., & Togelius, J. (2020). Deep learning for procedural content generation. *Neural Computing and Applications*, 1-19.

452. Liu, S., Chan, F. T., Yang, J., & Niu, B. (2018). Understanding the effect of cloud computing on organizational agility: An empirical examination. *International Journal of Information Management, 43*, 98-111.
453. Liu, W. (2006). Knowledge exploitation, knowledge exploration, and competency trap. *Knowledge and Process Management, 13*(3), 144-161.
454. Code of ethics, University of Ljubljana (2009).
455. Loggen, T., & Ravesteyn, P. (2022). How Does BPM Maturity Affect Process Performance?
456. Lui, A. K., Lee, M., & Ngai, E. W. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research, 308*(1), 373-388.
457. Lynn, M. R. (1986). Determination and quantification of content validity. *Nursing research*.
458. Lyu, W., & Liu, J. (2021). Artificial Intelligence and emerging digital technologies in the energy sector. *Applied Energy, 303*, 117615.
459. Lyytinen, K. (2022). Innovation logics in the digital era: a systemic review of the emerging digital innovation regime. *Innovation, 24*(1), 13-34.
460. Ma, H., Jia, X., & Wang, X. (2022). Digital transformation, ambidextrous innovation and enterprise value: empirical analysis based on listed Chinese manufacturing companies. *Sustainability, 14*(15), 9482.
461. Ma, H., Peng, Y., & Shi, Y. (2008). The effect of information technology and knowledge management capability on R&D process performance. *Journal of Knowledge-based Innovation in China, 1*(1), 43-55.
462. Maalla, A. (2019). *Development Prospect and Application Feasibility Analysis of Robotic Process Automation.* Paper presented at the 4th IEEE Advanced Information Technology, Electronic and Automation Control Conference, IAEAC 2019.
463. MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques. *MIS Quarterly, 35*(2), 293-334. doi:10.2307/23044045
464. Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., . . . Söllner, M. (2019). AI-based digital assistants: Opportunities, threats, and research perspectives. *Business & Information Systems Engineering, 61*, 535-544.
465. Maitland, A., Lin, A., Cantor, D., Jones, M., Moser, R. P., Hesse, B. W., . . . Blake, K. D. (2017). A nonresponse bias analysis of the Health Information National Trends Survey (HINTS). *Journal of health communication, 22*(7), 545-553.
466. Majumdar, R. (2014). Business decision making, production technology and process efficiency. *International Journal of Emerging Markets, 9*(1), 79-97.
467. Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research, 120*, 262-273.
468. Makowski, P. T., & Kajikawa, Y. (2021). Automation-driven innovation management? Toward innovation-automation-strategy cycle. *Technological Forecasting and Social Change, 168*, 120723.
469. Malhotra, N. K., Kim, S. S., & Patil, A. (2006). Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. *Management Science, 52*(12), 1865-1883.
470. Mallinguh, E., Wasike, C., & Zoltan, Z. (2020). The business sector, firm age, and performance: The mediating role of foreign ownership and financial leverage. *International Journal of Financial Studies, 8*(4), 79.

471. Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). *Big data: The next frontier for innovation, competition, and productivity*: McKinsey Global Institute.
472. March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science, 2*(1), 71-87.
473. Marciniak, R., Moricz, P., & Baksa, M. (2020). *Towards Business Services 4.0 - Digital Transformation of Business Services at a Global Technology Company*, Cham.
474. Marie Burvill, S., Jones-Evans, D., & Rowlands, H. (2018). Reconceptualising the principles of Penrose's (1959) theory and the resource based view of the firm: The generation of a new conceptual framework. *Journal of Small Business and Enterprise Development, 25*. doi:10.1108/JSBED-11-2017-0361
475. Marjanovic, O., & Freeze, R. (2011, 4-7 Jan. 2011). *Knowledge Intensive Business Processes: Theoretical Foundations and Research Challenges.* Paper presented at the 2011 44th Hawaii International Conference on System Sciences.
476. Marr, B., Schiuma, G., & Neely, A. (2004). Intellectual capital–defining key performance indicators for organizational knowledge assets. *Business Process Management Journal, 10*(5), 551-569.
477. Martin, A., Keller, A., & Fortwengel, J. (2019). Introducing conflict as the microfoundation of organizational ambidexterity. *Strategic Organization, 17*(1), 38-61.
478. Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management, 42*(4), 489-495.
479. Martínez-Rojas, A., Barba, I., & Enríquez, J. G. (2020) Towards a Taxonomy of Cognitive RPA Components. In*: Vol. 393 LNBIP. Blockchain Forum and Robotic Process Automation, RPA Forum, held as part of the 18th International Conference on Business Process Management, BPM 2020* (pp. 161-175): Springer Science and Business Media Deutschland GmbH.
480. Martins, E.-C., & Terblanche, F. (2003). Building organisational culture that stimulates creativity and innovation. *European Journal of Innovation Management, 6*(1), 64-74.
481. Mashingaidze, K., & Backhouse, J. (2017). The relationships between definitions of big data, business intelligence and business analytics: a literature review. *International Journal of Business Information Systems, 26*(4), 488-505.
482. Matsunaga, M. (2008). Item parceling in structural equation modeling: A primer. *Communication methods and measures, 2*(4), 260-293.
483. McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D., & Barton, D. (2012). Big data: the management revolution. *Harvard business review, 90*(10), 60-68.
484. McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI magazine, 27*(4), 12-12.
485. McCormack, K., Willems, J., Van den Bergh, J., Deschoolmeester, D., Willaert, P., Indihar Štemberger, M., . . . Paulo Valadares de Oliveira, M. (2009). A global investigation of key turning points in business process maturity. *Business Process Management Journal, 15*(5), 792-815.
486. McCormack, K. P., & Johnson, W. C. (2001). *Business process orientation: Gaining the e-business competitive advantage*: Crc Press.

487. McLaren, T. S., Head, M. M., Yuan, Y., & Chan, Y. E. (2011). A multilevel model for measuring fit between a firm's competitive strategies and information systems capabilities. *MIS Quarterly*, 909-929.
488. ME de Waal, B., Maris, A., & Ravesteyn, P. (2017). BPM maturity and performance: The influence of knowledge on BPM. *Communications of the IIMA, 15*(2), 1.
489. Mehandjiev, N. (2019). *The effect of big data analytics capability on firm performance: A pilot study in China.* Paper presented at the European, Mediterranean, and Middle Eastern Conference on Information Systems.
490. Melão, N., & Pidd, M. (2000). A conceptual framework for understanding business processes and business process modelling. *Information systems journal, 10*(2), 105-129.
491. Mele, C., Spena, T. R., & Peschiera, S. (2018). Value creation and cognitive technologies: Opportunities and challenges. *Journal of Creating Value, 4*(2), 182-195.
492. Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value. *MIS Quarterly, 28*(2), 283-322. doi:10.2307/25148636
493. Mendling, J., Pentland, B. T., & Recker, J. (2020). Building a complementary agenda for business process management and digital innovation. In (Vol. 29, pp. 208-219): Taylor & Francis.
494. Mendonça, C. M. C. d., & Andrade, A. M. V. d. (2018). Dynamic capabilities and their relations with elements of digital transformation in Portugal. *Journal of Information Systems Engineering & Management, 3*(3).
495. Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping humans in the loop: pooling knowledge through artificial swarm intelligence to improve business decision making. *California management review, 61*(4), 84-109.
496. Miailhe, N., & Hodes, C. (2017). The third age of artificial intelligence. *Field Actions Science Reports. The journal of field actions*(Special Issue 17), 6-11.
497. Migdadi, M. M. (2022). Knowledge management processes, innovation capability and organizational performance. *International Journal of Productivity and Performance Management, 71*(1), 182-210.
498. Mikalef, P. (2016). Developing IT-enabled innovation capabilities: a dynamic capabilities approach.
499. Mikalef, P., Conboy, K., & Krogstie, J. (2021). Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. *Industrial Marketing Management, 98*, 80-92.
500. Mikalef, P., Fjørtoft, S. O., & Torvatn, H. Y. (2019). *Developing an Artificial Intelligence Capability: A Theoretical Framework for Business Value.* Paper presented at the International Conference on Business Information Systems.
501. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), 103434.
502. Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management, 57*(2), 103169.
503. Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., . . . Niehaves, B. (2023). Examining how AI capabilities can foster organizational

performance in public organizations. *Government Information Quarterly, 40*(2), 101797.
504. Mikalef, P., & Pateli, A. G. (2016). *Developing and Validating a Measurement Instrument of IT-Enabled Dynamic Capabilities.* Paper presented at the ECIS.
505. Miller, D., & Friesen, P. H. (1983). Strategy-making and environment: the third link. *Strategic Management Journal, 4*(3), 221-235.
506. Miller, D. M. (1984). Profitability= productivity+ price recovery. *Harvard business review, 62*(3), 145-153.
507. Miri-Lavassani, K. (2018). Achieving higher supply chain performance via business process orientation. *Business Process Management Journal, 24*(3), 671-694. doi:10.1108/BPMJ-07-2016-0140
508. Miron, E., Erez, M., & Naveh, E. (2004). Do personal characteristics and cultural values that promote innovation, quality, and efficiency compete or complement each other? *Journal of organizational behavior, 25*(2), 175-199.
509. Mishra, A. N., & Pani, A. K. (2020). Business value appropriation roadmap for artificial intelligence. *VINE Journal of Information and Knowledge Management Systems*.
510. Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science*, 1-22.
511. Mishra, S. K., & Pati, S. S. (2020). *A Solar-Hydro Based Frequency Regulation in Two-Area Power System Incorporating Unified Power Flow Control*, Singapore.
512. Mithas, S., Ramasubbu, N., & Sambamurthy, V. (2011). How information management capability influences firm performance. *MIS Quarterly, 35*(1), 237.
513. Modha, D. S., Ananthanarayanan, R., Esser, S. K., Ndirango, A., Sherbondy, A. J., & Singh, R. (2011). Cognitive computing. *Communications of the ACM, 54*(8), 62-71.
514. Mohammed, W., & Jalal, A. (2011). The influence of knowledge management system (KMS) on enhancing decision making process (DMP). *International Journal of Business and Management, 6*(8), 216.
515. Mondal, S., Das, S., & Vrana, V. G. (2023). How to bell the cat? A theoretical review of generative artificial intelligence towards digital disruption in all walks of life. *Technologies, 11*(2), 44.
516. Mooney, J. G., Gurbaxani, V., & Kraemer, K. L. (1996). A process oriented framework for assessing the business value of information technology. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 27*(2), 68-81.
517. Moreira, S., Mamede, H. S., & Santos, A. (2024). Business Process Automation in SMEs: A Systematic Literature Review. *Ieee Access*.
518. Moshagen, M., & Erdfelder, E. (2016). A new strategy for testing structural equation models. *Structural equation modeling: a multidisciplinary journal, 23*(1), 54-60.
519. Movva, R., Balachandar, S., Peng, K., Agostini, G., Garg, N., & Pierson, E. (2024). *Topics, Authors, and Institutions in Large Language Model Research: Trends from 17K arXiv Papers.* Paper presented at the Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers).
520. Mrad, M. (2018). Brand addiction conceptual development. *Qualitative Market Research: An International Journal*.
521. Mukhopadhyay, T., & Kekre, S. (2002). Strategic and operational benefits of electronic integration in B2B procurement processes. *Management Science, 48*(10), 1301-1313.

522. Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological bulletin, 105*(3), 430.
523. Nadal, C., Doherty, G., & Sas, C. (2019). *Technology acceptability, acceptance and adoption-definitions and measurement.* Paper presented at the 2019 CHI Conference on Human Factors in Computing Systems.
524. Naga Lakshmi, M. V. N., Vijayakumar, T., & Sai Sricharan, Y. V. N. (2019). Robotic process automation, an enabler for shared services transformation. *International Journal of Innovative Technology and Exploring Engineering, 8*(6), 1882-1890.
525. Naidu, C. V. A., & Vedavathi, K. (2019). Cognitive modeling: Role of artificial intelligence. *International Journal of Innovative Technology and Exploring Engineering, 8*(6), 1624-1629.
526. Naveed, H., Khan, A. U., Qiu, S., Saqib, M., Anwar, S., Usman, M., . . . Mian, A. (2023). A comprehensive overview of large language models. *arXiv preprint arXiv:2307.06435*.
527. Nawrocki, J. R., Walter, B., & Wojciechowski, A. (2002). *Comparison of CMM level 2 and eXtreme programming.* Paper presented at the Software Quality—ECSQ 2002: Quality Connection—7th European Conference on Software Quality Helsinki, Finland, June 9–13, 2002 Proceedings.
528. Naz, S., Ul Haq, N., & Nasir, S. (2022). Capabilities Pathway To Firm Performance: Moderating Role Of Environmental Dynamism In The Food Manufacturing Firms Of Pakistan. *International Journal of Innovation Management*, 2250030.
529. Newbert, S. L. (2007). Empirical research on the resource-based view of the firm: an assessment and suggestions for future research. *Strategic Management Journal, 28*(2), 121-146.
530. Ng, K. K., Chen, C.-H., Lee, C. K., Jiao, J. R., & Yang, Z.-X. (2021a). A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives. *Advanced Engineering Informatics, 47,* 101246.
531. Ng, K. K. H., Chen, C. H., Lee, C. K. M., Jiao, J. R., & Yang, Z. X. (2021b). A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives. *Advanced Engineering Informatics, 47*. doi:10.1016/j.aei.2021.101246
532. Ng, S. C., Rungtusanatham, J. M., Zhao, X., & Lee, T. (2015). Examining process management via the lens of exploitation and exploration: Reconceptualization and scale development. *International Journal of Production Economics, 163,* 1-15.
533. Nguyen, T. N., Shen, C. H., & Le, P. B. (2022). Influence of transformational leadership and knowledge management on radical and incremental innovation: the moderating role of collaborative culture. *Kybernetes, 51*(7), 2240-2258.
534. Nicolas, R. (2004). Knowledge management impacts on decision making process. *Journal of Knowledge Management, 8*(1), 20-31.
535. Nielsen, B. B., & Raswant, A. (2018). The selection, use, and reporting of control variables in international business research: A review and recommendations. *Journal of World Business, 53*(6), 958-968.
536. Niewöhner, N., Lang, N., Asmar, L., Röltgen, D., Kühn, A., & Dumitrescu, R. (2021). Towards an ambidextrous innovation management maturity model. *Procedia CIRP, 100,* 289-294.
537. Nold III, H. A. (2012). Linking knowledge processes with firm performance: organizational culture. *Journal of Intellectual capital, 13*(1), 16-38.
538. Nonaka, I., & Lewin, A. Y. (1994). Dynamic theory knowledge of organizational creation. *Organization science, 5*(1), 14-37.

539. Noor, A. K. (2014). Potential of cognitive computing and cognitive systems. *Open Engineering, 5*(1).
540. Nordal, H., & El-Thalji, I. (2021). Modeling a predictive maintenance management architecture to meet industry 4.0 requirements: A case study. *Systems Engineering, 24*(1), 34-50.
541. Norman, D. A., & Verganti, R. (2014). Incremental and radical innovation: Design research vs. technology and meaning change. *Design issues, 30*(1), 78-96.
542. Noyan, M. (2023, 2023/7/17). Open-source text generation & LLM ecosystem at hugging face. Retrieved from https://huggingface.co/blog/os-llms
543. Nwankpa, J. K., & Roumani, Y. (2016). IT capability and digital transformation: A firm performance perspective.
544. O'Reilly III, C. A., & Tushman, M. L. (2011). Organizational ambidexterity in action: How managers explore and exploit. *California management review, 53*(4), 5-22.
545. O'Reilly III, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. *Academy of management perspectives, 27*(4), 324-338.
546. O Reilly, C. A., & Tushman, M. L. (2004). The ambidextrous organization. *Harvard business review, 82*(4), 74-83.
547. O'Reilly III, C. A., & Tushman, M. L. (2008). Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. *Research in organizational behavior, 28*, 185-206.
548. Obeso, M., Hernández-Linares, R., López-Fernández, M. C., & Serrano-Bedia, A. M. (2020). Knowledge management processes and organizational performance: the mediating role of organizational learning. *Journal of Knowledge Management, 24*(8), 1859-1880.
549. OECD. (2019). *Artificial Intelligence in Society*. Paris: OECD Publishing.
550. OECD, Recommendation of the Council on Artificial Intelligence, OECD/LEGAL/0449, (2024).
551. Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems, 37*(1), 43.
552. Ongena, G., & Ravesteyn, P. (2020). Business process management maturity and performance: A multi group analysis of sectors and organization sizes. *Business Process Management Journal, 26*(1), 132-149.
553. Othman, R., & Hashim, N. A. (2003). Organizational amnesia: the barrier to organizational learning. *Paper for Academic Track*.
554. Pace, C. R. (1939). Factors influencing questionnaire returns from former university students. *Journal of Applied Psychology, 23*(3), 388.
555. Pallant, J. (2016). Survival manual: A step by step guide to data analysis using SPSS program. In: London: McGraw-Hill Education.
556. Panduro-Ramirez, J., Khurana, S., Othman, B., Lourens, M., Ruiz-Salazar, J. M., & Almashaqbeh, H. A. (2022). *Role of integrated artificial intelligence for knowledge creation and decision making for improving firm performance.* Paper presented at the 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE).
557. Pankajakshan, R., Biswal, S., Govindarajulu, Y., & Gressel, G. (2024). Mapping LLM Security Landscapes: A Comprehensive Stakeholder Risk Assessment Proposal. *arXiv preprint arXiv:2403.13309*.
558. Papachroni, A., Heracleous, L., & Paroutis, S. (2015). Organizational ambidexterity through the lens of paradox theory: Building a novel research agenda. *The Journal of Applied Behavioral Science, 51*(1), 71-93.

559. Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans, 30*(3), 286-297.
560. Patas, J., Bartenschlager, J., & Goeken, M. (2012). *Resource-based view in empirical it business value research--an evidence-based literature review.* Paper presented at the 2012 45th Hawaii International Conference on System Sciences.
561. Pavlou, P. A. (2018). Internet of things–will humans be replaced or augmented? *NIM Marketing Intelligence Review, 10*(2), 42-47.
562. Pejić Bach, M., Bosilj Vukšić, V., Suša Vugec, D., & Stjepić, A.-M. (2019). BPM and BI in SMEs: The role of BPM/BI alignment in organizational performance. *International Journal of Engineering Business Management, 11*, 1847979019874182.
563. Pemberton, J. D., & Stonehouse, G. H. (2000). Organisational learning and knowledge assets–an essential partnership. *The learning organization*.
564. Peppard, J., & Ward, J. (2016). *The strategic management of information systems: Building a digital strategy*: John Wiley & Sons.
565. Pérez López, S., Manuel Montes Peón, J., & José Vázquez Ordás, C. (2004). Managing knowledge: the link between culture and organizational learning. *Journal of Knowledge Management, 8*(6), 93-104.
566. Perifanis, N.-A., & Kitsios, F. (2023). Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information, 14*(2), 85.
567. Pervan, M., & Višić, J. (2012). Influence of firm size on its business success. *Croatian Operational Research Review, 3*(1), 213-223.
568. Peters, T. (2004). *In search of excellence: Lessons from America's best-run companies*. London, England: Profile Books.
569. Peyravi, B., Nekrošienė, J., & Lobanova, L. (2020). Revolutionised technologies for marketing: Theoretical review with focus on artificial intelligence. *Business: Theory and Practice, 21*(2), 827-834.
570. Phillips-Wren, G. (2012). Ai Tools in Decision Making Support Systems: A Review. *International Journal on Artificial Intelligence Tools, 21*(02). doi:10.1142/s0218213012400052
571. Pietronudo, M. C., Croidieu, G., & Schiavone, F. (2022). A solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management. *Technological Forecasting and Social Change, 182*, 121828.
572. Pinochet, L. H. C., Amorim, G. d. C. B., Júnior, D. L., & de Souza, C. A. (2021). Consequential factors of Big Data's Analytics Capability: How firms use data in the competitive scenario. *Journal of Enterprise Information Management*.
573. Pinto, J., & dos Santos, V. D. (2020). *Assessing the Relationship Between BPM Maturity and the Success of Organizations,* Cham.
574. Pitkäranta, T., & Pitkäranta, L. (2024). *Bridging Human and AI Decision-Making with LLMs: The RAGADA Approach.* Paper presented at the Proceedings of the 26th International Conference on Enterprise Information Systems, Query date.
575. Plastino, E., & Purdy, M. (2018). Game changing value from artificial intelligence: eight strategies. *Strategy & Leadership*.
576. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. doi:10.1037/0021-9010.88.5.879

577. Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2016). Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences. *Organizational Research Methods, 19*(2), 159-203.
578. Polit, D. F., Beck, C. T., & Owen, S. V. (2007). Is the CVI an acceptable indicator of content validity? Appraisal and recommendations. *Research in nursing & health, 30*(4), 459-467.
579. Posen, H. E., Keil, T., Kim, S., & Meissner, F. D. (2018). Renewing research on problemistic search—A review and research agenda. *Academy of Management Annals*, *12*(1), 208-251.
580. Power, D., Heavin, C., McDermott, J., & Daly, M. (2018). Defining business analytics: An empirical approach. *Journal of Business Analytics*, *1*(1), 40-53.
581. Prajogo, D. I., & McDermott, C. M. (2011). The relationship between multidimensional organizational culture and performance. *International Journal of Operations & Production Management*.
582. Prieto, B. (2019). Impacts of artificial intelligence on management of large complex projects. *PM World Journal, 8*(5), 1-20.
583. Pringle, T., & Zoller, E. (2018). How to achieve AI maturity and why it matters. *Ovum*.
584. The Process Performance Index. (2022).
585. Protogerou, A., Caloghirou, Y., & Lioukas, S. (2012). Dynamic capabilities and their indirect impact on firm performance. *Industrial and corporate change, 21*(3), 615-647.
586. Prott, D., & Ebner, M. (2020). The Use of Gamification in Gastronomic Questionnaires.
587. Putra, H., & Mahendrawathi, E. (2024). The Role of Business Process Management in Digital Innovation and Digital Transformation: A Systematic Literature Review. *Procedia Computer Science, 234*, 829-836.
588. Quinn, M., & Strauss, E. (2017). *The Routledge Companion to Accounting Information Systems*: Routledge.
589. Quinn, R., & Cameron, K. (1999). Diagnosing and changing organizational culture. *Reading: Addison-Wesley*.
590. Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training.
591. Raghavan, V. V., Gudivada, V. N., Govindaraju, V., & Rao, C. R. (2016). *Cognitive computing: Theory and applications*: Elsevier.
592. Raghu, T., & Vinze, A. (2007). A business process context for Knowledge Management. *Decision support systems, 43*(3), 1062-1079.
593. Rahman, M. S., Hossain, M. A., & Fattah, F. A. M. A. (2021). Does marketing analytics capability boost firms' competitive marketing performance in data-rich business environment? *Journal of Enterprise Information Management, 35*(2), 455-480.
594. Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms:: Toward human-ai hybrids. *MIS Quarterly, 43*(1), iii-ix.
595. Raisch, S., Birkinshaw, J., Probst, G., & Tushman, M. L. (2009). Organizational ambidexterity: Balancing exploitation and exploration for sustained performance. *Organization science, 20*(4), 685-695.
596. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of management review, 46*(1), 192-210.

597. Raj, R., & Srivastava, K. B. (2013). The mediating role of organizational learning on the relationship among organizational culture, HRM practices and innovativeness. *Management and Labour Studies, 38*(3), 201-223.
598. Rammer, C., Fernández, G. P., & Czarnitzki, D. (2022). Artificial intelligence and industrial innovation: Evidence from German firm-level data. *Research Policy, 51*(7), 104555.
599. Ransbotham, S., Khodabandeh, S., Kiron, D., Candelon, F., Chu, M., & LaFountain, B. (2020). Expanding AI's impact with organizational learning.
600. Rao, S. S., Nahm, A., Shi, Z., Deng, X., & Syamil, A. (1999). Artificial intelligence and expert systems applications in new product development—a survey. *Journal of Intelligent Manufacturing, 10*(3), 231-244.
601. Ravichandran, T., Lertwongsatien, C., & Lertwongsatien, C. (2005). Effect of information systems resources and capabilities on firm performance: A resource-based perspective. *Journal of management information systems, 21*(4), 237-276.
602. Real, J. C., Leal, A., & Roldán, J. L. (2006). Information technology as a determinant of organizational learning and technological distinctive competencies. *Industrial Marketing Management, 35*(4), 505-521.
603. Reichert, M. (2011). *What BPM Technology Can Do for Healthcare Process Support*, Berlin, Heidelberg.
604. Reijers, H. A., van Wijk, S., Mutschler, B., & Leurs, M. (2010). *BPM in practice: who is doing what?* Paper presented at the International Conference on Business Process Management.
605. Reinkemeyer, L. (2024). Business Perspective: The Future of Intelligent Business Process Execution. In *Process Intelligence in Action: Taking Process Mining to the Next Level* (pp. 233-245): Springer.
606. Renaud, K., & Van Biljon, J. (2008). *Predicting technology acceptance and adoption by the elderly: a qualitative study*. Paper presented at the Proceedings of the 2008 annual research conference of the South African Institute of Computer Scientists and Information Technologists on IT research in developing countries: riding the wave of technology.
607. Richardson, S. (2020). Cognitive automation: A new era of knowledge work? *Business Information Review, 37*(4), 182-189. doi:10.1177/0266382120974601
608. Ritala, P., Olander, H., Michailova, S., & Husted, K. (2015). Knowledge sharing, knowledge leaking and relative innovation performance: An empirical study. *Technovation, 35*, 22-31.
609. Rizk, Y., Isahagian, V., Boag, S., Khazaeni, Y., Unuvar, M., Muthusamy, V., & Khalaf, R. (2020) A Conversational Digital Assistant for Intelligent Process Automation. In*: Vol. 393 LNBIP. Blockchain Forum and Robotic Process Automation, RPA Forum, held as part of the 18th International Conference on Business Process Management, BPM 2020* (pp. 85-100): Springer Science and Business Media Deutschland GmbH.
610. Robert Baum, J., & Wally, S. (2003). Strategic decision speed and firm performance. *Strategic Management Journal, 24*(11), 1107-1129.
611. Robey, D., Boudreau, M.-C., & Rose, G. M. (2000). Information technology and organizational learning: a review and assessment of research. *Accounting, Management and Information Technologies, 10*(2), 125-155.
612. Rocha, G. S., Lacerda, D. P., Veit, D. R., Rodrigues, L. H., & Dresch, A. (2017). In the process babel: Definitions, concepts, and tools in a disordered field. *Knowledge and Process Management, 24*(3), 196-203. doi:10.1002/kpm.1543

613. Roeglinger, M., Seyfried, J., Stelzl, S., & Muehlen, M. z. (2018). *Cognitive Computing: What's in for Business Process Management? An Exploration of Use Case Ideas,* Cham.
614. Rogers, E. M. (2010). *Diffusion of innovations*: Simon and Schuster.
615. Rogers, M., & Rogers, M. (1998). *The definition and measurement of productivity*: Melbourne Institute of Applied Economic and Social Research Melbourne, Australia.
616. Rohit, D., & Webster Frederick, E. (1989). Organizational culture and marketing: defining the research agenda. *Journal of Marketing, 53*(1), 3-15.
617. Romao, M., Costa, J., Costa, C. J., & Ieee. (2019). Robotic Process Automation: A case study in the Banking Industry. In *2019 14th Iberian Conference on Information Systems and Technologies*.
618. Rosemann, M., De Bruin, T., & Hueffner, T. (2004). A model for business process management maturity. *ACIS 2004 Proceedings*, 6.
619. Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science, 49*(6), 751-766.
620. Rouse, W. B., & Spohrer, J. C. (2018). Automating versus augmenting intelligence. *Journal of Enterprise Transformation, 8*(1-2), 1-21.
621. Rowe, F., Besson, P., & Hemon, A. (2017). *Socio-technical inertia, dynamic capabilities and environmental uncertainty: Senior management views and implications for organizational transformation.* Paper presented at the Proceedings of the 25th European Conference on Information Systems (ECIS), Guimarães, Portugal.
622. Ruel, H., Rowlands, H., & Njoku, E. (2020). Digital business strategizing: the role of leadership and organizational learning. *Competitiveness Review: An International Business Journal, 31*(1), 145-161.
623. Ruiz-Real, J. L., Uribe-Toril, J., Torres, J. A., & De Pablo, J. (2021). Artificial intelligence in business and economics research: Trends and future. *Journal of Business Economics and Management, 22*(1), 98-117.
624. Runkler, T. A. (2020). *Data analytics: Models and algorithms for intelligent data analysis* (3 ed.). Wiesbaden, Germany: Springer Vieweg.
625. Russel, S., & Norvig, P. (2016). *Artificial intelligence: a modern approach* (3 ed.): Pearson Education Limited.
626. Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4 ed.). Upper Saddle River, NJ: Pearson.
627. Russom, P. (2011). Big data analytics. *TDWI best practices report, fourth quarter, 19*(4), 1-34.
628. Sachan, S., Yang, J.-B., Xu, D.-L., Benavides, D. E., & Li, Y. (2020). An explainable AI decision-support-system to automate loan underwriting. *Expert systems with Applications, 144*, 113100.
629. Sadegh Sharifirad, M., & Ataei, V. (2012). Organizational culture and innovation culture: exploring the relationships between constructs. *Leadership & Organization Development Journal, 33*(5), 494-517.
630. Saide, S., & Sheng, M. L. (2020). Toward business process innovation in the big data era: A mediating role of big data knowledge management. *Big data, 8*(6), 464-477.
631. Salavou, H., & Lioukas, S. (2003). Radical product innovations in SMEs: the dominance of entrepreneurial orientation. *Creativity and innovation management, 12*(2), 94-108.

632. Salviotti, G., Gaur, A., & Pennarola, F. (2019). *Strategic Factors Enabling Digital Maturity: An Extended Survey.* Paper presented at the The 13th Mediterranean Conference on Information Systems (MCIS).
633. Samek, W., Wiegand, T., & Müller, K.-R. (2017). Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. *arXiv preprint arXiv:1708.08296*.
634. Sanchez, R., & Mahoney, J. T. (1996). Modularity, flexibility, and knowledge management in product and organization design. *Strategic Management Journal, 17*(S2), 63-76.
635. Santhanam, R., & Hartono, E. (2003). Issues in Linking Information Technology Capability to Firm Performance. *MIS Quarterly, 27*(1), 125-153. doi:10.2307/30036521
636. Santoro, F. M., & Baião, F. A. (2017). *Knowledge-intensive process: A research framework.* Paper presented at the International Conference on Business Process Management.
637. Santos, F., Pereira, R., & Vasconcelos, J. B. (2019). Toward robotic process automation implementation: an end-to-end perspective. *Business Process Management Journal*.
638. Sanz-Valle, R., Naranjo-Valencia, J. C., Jiménez-Jiménez, D., & Perez-Caballero, L. (2011). Linking organizational learning with technical innovation and organizational culture. *Journal of Knowledge Management*, *15*(6), 997-1015.
639. Sanzogni, L., Guzman, G., & Busch, P. (2017). Artificial intelligence and knowledge management: questioning the tacit dimension. *Prometheus, 35*(1), 37-56.
640. Sarker, I. H. (2022). AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart systems. *SN Computer Science, 3*(2), 158.
641. Saunila, M., Ukko, J., Rantala, T., Nasiri, M., & Rantanen, H. (2020). Preceding operational capabilities as antecedents for productivity and innovation performance. *Journal of Business Economics, 90*(4), 537-561.
642. Schacht, S., Keusch, F., Bergmann, N., & Morana, S. (2017). Web survey gamification–increasing data quality in web surveys by using game design elements.
643. Schad, J., Lewis, M. W., Raisch, S., & Smith, W. K. (2016). Paradox research in management science: Looking back to move forward. *Academy of Management Annals, 10*(1), 5-64.
644. Schatsky, D., Muraskin, C., & Gurumurthy, R. (2014). Demystifying artificial intelligence: what business leaders need to know about cognitive technologies. *A Deloitte Series on Cognitive Technologies*.
645. Schmidt, A. (2017). Technologies to amplify the mind. *Computer, 50*(10), 102-106.
646. Schroder, A., Constantiou, I. D., Tuunainen, V., & Austin, R. D. (2022). *Human-AI Collaboration-Coordinating Automation and Augmentation Tasks in a Digital Service Company.* Paper presented at the HICSS.
647. Schryen, G. (2013). Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. *European Journal of Information Systems, 22*(2), 139-169.
648. Seidel, S., Berente, N., Lindberg, A., Lyytinen, K., & Nickerson, J. V. (2018). Autonomous tools and design: a triple-loop approach to human-machine learning. *Communications of the ACM, 62*(1), 50-57.
649. Senge, P. (1998). *The fifth discipline fieldbook: Strategies and tools for building a learning organisation*. New York, NY: Bantam Doubleday Dell Publishing Group.

650. Shahmoradi, L., Safadari, R., & Jimma, W. (2017). Knowledge management implementation and the tools utilized in healthcare for evidence-based decision making: a systematic review. *Ethiopian journal of health sciences, 27*(5), 541-558.
651. Shahzad, F., Xiu, G., & Shahbaz, M. (2017). Organizational culture and innovation performance in Pakistan's software industry. *Technology in Society, 51*, 66-73.
652. Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of management review, 25*(1), 217-226.
653. Shanks, G., & Bekmamedova, N. (2012). Achieving benefits with business analytics systems: an evolutionary process perspective. *Journal of Decision Systems, 21*(3), 231-244.
654. Sharda, R., Delen, D., & Turban, E. (2016). *Business intelligence, analytics, and data science: a managerial perspective*: Pearson.
655. Shehzad, M. U., Zhang, J., Alam, S., & Cao, Z. (2022). Determining the role of sources of knowledge and IT resources for stimulating firm innovation capability: a PLS-SEM approach. *Business Process Management Journal, 28*(4), 905-935.
656. Sheng, M. L., & Chien, I. (2016). Rethinking organizational learning orientation on radical and incremental innovation in high-tech firms. *Journal of Business Research, 69*(6), 2302-2308.
657. Shivers-Blackwell, S. (2006). The influence of perceptions of organizational structure & culture on leadership role requirements: The moderating impact of locus of control & self-monitoring. *Journal of Leadership & Organizational Studies, 12*(4), 27-49.
658. Shrestha, P. R., Timalsina, D., Bista, S., Shrestha, B. P., & Shakya, T. M. (2021). *Generative design approach for product development.* Paper presented at the AIP Conference Proceedings.
659. Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California management review, 61*(4), 66-83.
660. Shrestha, Y. R., Krishna, V., & von Krogh, G. (2021). Augmenting organizational decision-making with deep learning algorithms: Principles, promises, and challenges. *Journal of Business Research, 123*, 588-603.
661. Siderska, J. (2020). Robotic Process Automation-a driver of digital transformation? *Engineering Management in Production and Services, 12*(2), 21-31. doi:10.2478/emj-2020-0009
662. Sidorova, A. (2019). Organizational knowledge creation in the age of AI. Retrieved from https://www.linkedin.com/pulse/organizational-knowledge-creation-age-ai-anna-sidorova/
663. Silva, J. P., & Gonçalves, J. (2022). *Process standardization: the driving factor for bringing artificial intelligence and management analytics to SMEs.* Paper presented at the 2022 10th International Symposium on Digital Forensics and Security (ISDFS).
664. Simon, M. (2011). Assumptions, limitations and delimitations. In: Dissertation and scholarly research: Recipes for success.
665. Sindhgatta, R., ter Hofstede, A. H. M., & Ghose, A. (2020a). *Resource-Based Adaptive Robotic Process Automation*, Cham.
666. Sindhgatta, R., ter Hofstede, A. H. M., & Ghose, A. (2020b) Resource-Based Adaptive Robotic Process Automation: Formal/Technical Paper. In*: Vol. 12127 LNCS. 32nd International Conference on Advanced Information Systems Engineering, CAiSE 2020* (pp. 451-466): Springer.

667. Singh, C., Inala, J. P., Galley, M., Caruana, R., & Gao, J. (2024). Rethinking interpretability in the era of large language models. *arXiv preprint arXiv:2402.01761*.
668. Slaby, J. R. (2012). Robotic automation emerges as a threat to traditional low-cost outsourcing. *HfS Research Ltd*, *1*(1), 3-3.
669. Smith, H. (2014). *Triple Loop-Reflective Learning within Non-Governmental Health Organizations in Sub-Saharan Africa: An Organizational Learning Perspective.* Paper presented at the Fourth Annual International Conference on Engaged Management Scholarship, Tulsa, Oklahoma.
670. Smith, W. K., & Lewis, M. W. (2011). Toward a theory of paradox: A dynamic equilibrium model of organizing. *Academy of management review, 36*(2), 381-403.
671. Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological methodology, 13*, 290-312.
672. Sonenshein, S., DeCelles, K. A., & Dutton, J. E. (2014). It's not easy being green: The role of self-evaluations in explaining support of environmental issues. *Academy of Management Journal, 57*(1), 7-37.
673. Song-zheng, Z., & Xiao-di, Z. (2008). *An empirical study on organizational culture, social capital, organizational learning and enterprise knowledge integration capability.* Paper presented at the 2008 International Conference on Information Management, Innovation Management and Industrial Engineering.
674. Soto-Acosta, P., Popa, S., & Martinez-Conesa, I. (2018). Information technology, knowledge management and environmental dynamism as drivers of innovation ambidexterity: a study in SMEs. *Journal of Knowledge Management, 22*(4), 824-849.
675. Spencer, S., Enge, E., & Stricchiola, J. (2022). *The art of SEO the art of SEO: Mastering search engine optimization* (4 ed.). Sebastopol, CA: O'Reilly Media.
676. Spring, M., Faulconbridge, J., & Sarwar, A. (2022). How information technology automates and augments processes: Insights from Artificial-Intelligence-based systems in professional service operations. *Journal of Operations Management, 68*(6-7), 592-618.
677. Srimarut, T., & Mekhum, W. (2020). The Impact of Compatibility on the Process Integration of the Supply Chain in Improving Firm Performance: The Mediating Effect of Information Technology Capability. *International Journal of Supply Chain Management, 9*(1), 155-167.
678. Stam, W. (2009). When does community participation enhance the performance of open source software companies? *Research Policy, 38*(8), 1288-1299.
679. Stein, B., & Morrison, A. (2014). The enterprise data lake: Better integration and deeper analytics. *PwC Technology Forecast: Rethinking integration, 1*(1-9), 18.
680. Steininger, D. M., Mikalef, P., Pateli, A., & Ortiz-de-Guinea, A. (2022). Dynamic capabilities in information systems research: A critical review, synthesis of current knowledge, and recommendations for future research. *Journal of the association for information systems, 23*(2), 447-490.
681. Stojkovic, J., Choukse, E., Zhang, C., Goiri, I., & Torrellas, J. (2024). Towards Greener LLMs: Bringing Energy-Efficiency to the Forefront of LLM Inference. *arXiv preprint arXiv:2403.20306*.
682. Straub, D., Boudreau, M.-C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information Systems, 13*(1), 24.

683. Strauch, M., Pidun, U., & zu Knyphausen-Aufsess, D. (2019). Process matters–How strategic decision-making process characteristics impact capital allocation efficiency. *Long Range Planning, 52*(2), 202-220.
684. Stuart, R. (2019). Human Compatible AI and the Problem of Control. In: UK, Penguin Random House.
685. Subramani, M. (2004). How do suppliers benefit from information technology use in supply chain relationships? *MIS Quarterly*, 45-73.
686. Sullivan, Y., & Wamba, S. (2022). *Artificial intelligence, firm resilience to supply chain disruptions, and firm performance.* Paper presented at the Proceedings of the 55th Hawaii International Conference on System Sciences.
687. Sullivan, Y., & Wamba, S. F. (2024). Artificial intelligence and adaptive response to market changes: A strategy to enhance firm performance and innovation. *Journal of Business Research, 174*, 114500.
688. Sun, W., Yu, M., Zhang, H., & Zhang, Y. (2022). Does Uncertainty of Trade Environment Promote Green Technological Innovation? Empirical Evidence from China. *Sustainability, 14*(23), 16195.
689. Sun, Z. (2021). An introduction to intelligent analytics ecosystems. *PNG UoT BAIS, 6*(3), 1-11.
690. Sun, Z., Strang, K., & Firmin, S. (2017). Business Analytics-Based Enterprise Information Systems. *Journal of Computer Information Systems, 57*(2), 169-178. doi:10.1080/08874417.2016.1183977
691. Suri, V. K., Elia, M. D., Arora, P., & van Hillegersberg, J. (2019) Automation of knowledge-based shared services and centers of expertise. In*: Vol. 344. 12th International Global Sourcing Workshop, 2018* (pp. 56-75): Springer Verlag.
692. Surya, L. (2015). An exploratory study of AI and Big Data, and it's future in the United States. *International Journal of Creative Research Thoughts (IJCRT), ISSN*, 2320-2882.
693. Suvetha, M., Swathi, S., Rani, M., Vinoth, S., & Suriya, R. (2018). A Study on Artificial Intelligence. *Bonfring International Journal of Industrial Engineering and Management Science, 9 (1), 6, 9.*
694. Szelagowski, M., & Lupeikiene, A. (2020). Business Process Management Systems: Evolution and Development Trends. *Informatica, 31*(3), 579-595. doi:10.15388/20-infor429
695. Škrinjar, R., Bosilj-Vukšić, V., & Indihar-Štemberger, M. (2008). The impact of business process orientation on financial and non-financial performance. *Business Process Management Journal, 14*(5), 738-754.
696. Škrinjar, R., Indihar-Štemberger, M., & Bosilj-Vukšić, V. (2010). Adoption of Business Process Orientation Practices: Slovenian and Croatian Survey. *Business Systems Research, 1*(1-2), 5-19.
697. Tabachnick, B. G., & Fidell, L. S. (2012). *Using multivariate statistics* (6 ed.). Upper Saddle River, NJ: Pearson.
698. Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia manufacturing, 22*, 960-967.
699. Taherdoost, H., & Madanchian, M. (2023). Artificial intelligence and knowledge management: Impacts, benefits, and implementation. *Computers, 12*(4), 72.
700. Taleghani, M., & Talebian, Z. (2013). Investigation of relationship between knowledge management and organizational culture in the National bank branches of Mazandaran province, Iran. *Journal of Basic and Applied Scientific Research, 3*(3), 532-536.

701. Tallon, P. P., Kraemer, K. L., & Gurbaxani, V. (2000). Executives' perceptions of the business value of information technology: a process-oriented approach. *Journal of management information systems, 16*(4), 145-173.
702. Tamayo-Torres, I., Gutiérrez-Gutiérrez, L. J., Llorens-Montes, F. J., & Martínez-López, F. J. (2016). Organizational learning and innovation as sources of strategic fit. *Industrial Management & Data Systems*.
703. Tangen, S. (2005). Demystifying productivity and performance. *International Journal of Productivity and Performance Management, 54*(1), 34-46.
704. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems, 48*, 157-169.
705. Tavana, M., Szabat, K., & Puranam, K. (2016). *Organizational productivity and performance measurements using predictive modeling and analytics*. Hershey, PA, USA: Business Science Reference (an imprint of IGI Global).
706. Taylor, A. B., MacKinnon, D. P., & Tein, J.-Y. (2008). Tests of the three-path mediated effect. *Organizational Research Methods, 11*(2), 241-269.
707. Taylor, J. (2011). *Decision management systems: a practical guide to using business rules and predictive analytics*. Boston, MA, USA: Pearson Education.
708. TechCrunch. (2021). TechCrunch. Retrieved from https://techcrunch.com/
709. Teece, D., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California management review, 58*(4), 13-35.
710. Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319-1350.
711. Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of management perspectives, 28*(4), 328-352.
712. Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning, 51*(1), 40-49.
713. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509-533.
714. Teichert, R. (2019). Digital transformation maturity: A systematic review of literature. *Acta universitatis agriculturae et silviculturae mendelianae brunensis*.
715. Tekic, Z., & Füller, J. (2023). Managing innovation in the era of AI. *Technology in Society, 73*, 102254.
716. Templeton, G. F., Lewis, B. R., & Snyder, C. A. (2002). Development of a measure for the organizational learning construct. *Journal of management information systems, 19*(2), 175-218.
717. The AI Hub of Israel. (2019). StartupHub.ai. Retrieved from https://www.startuphub.ai/startups/
718. The Niso CRediT Standing Committee. (2012). CRediT. Retrieved from https://credit.niso.org/
719. Thong, J. Y., & Yap, C.-S. (1995). CEO characteristics, organizational characteristics and information technology adoption in small businesses. *Omega, 23*(4), 429-442.
720. Thorsen, A. (2018). The Best AI Startups in Europe. Retrieved from https://www.valuer.ai/blog/the-best-ai-startups-in-europe
721. Tippins, M. J., & Sohi, R. S. (2003). IT competency and firm performance: is organizational learning a missing link? *Strategic Management Journal, 24*(8), 745-761.

722. Todor, R. D. (2016). Marketing automation. *Bulletin of the Transilvania University of Brasov. Economic Sciences. Series V, 9*(2), 87.
723. Tortorella, G. L., Vergara, A. M. C., Garza-Reyes, J. A., & Sawhney, R. (2020). Organizational learning paths based upon industry 4.0 adoption: An empirical study with Brazilian manufacturers. *International Journal of Production Economics, 219*, 284-294.
724. Tosey, P., Visser, M., & Saunders, M. N. (2012). The origins and conceptualizations of 'triple-loop'learning: A critical review. *Management learning, 43*(3), 291-307.
725. Trivedi, S., & Patel, N. (2020). The Role of Automation and Artificial Intelligence in Increasing the Sales Volume: Evidence from M, S, and, MM Regressions. *Trivedi, Sandeep and Patel, Nikhil, The Role of Automation and Artificial Intelligence in Increasing the Sales Volume: Evidence from M, S, and, MM Regressions (June 20, 2020)*.
726. Tschang, F. T., & Almirall, E. (2021). Artificial intelligence as augmenting automation: Implications for employment. *Academy of management perspectives, 35*(4), 642-659.
727. Tsou, H.-T., & Chen, J.-S. (2022). How does digital technology usage benefit firm performance? Digital transformation strategy and organisational innovation as mediators. *Technology Analysis & Strategic Management*, 1-14.
728. Tsui, E., Garner, B. J., & Staab, S. (2000). The role of artificial intelligence in knowledge management. *Knowledge based systems, 13*(5), 235-239.
729. Tushman, M. L., & O'Reilly III, C. A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California management review, 38*(4), 8-29.
730. Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research, 81*, 102883.
731. Tyagi, M. A., & Jain, M. R. (2019). Artificial Intelligence a Simulation of Human Intelligence in Jaipur. *BICON-2019*, 141.
732. Uzkurt, C., Kumar, R., Semih Kimzan, H., & Eminoğlu, G. (2013). Role of innovation in the relationship between organizational culture and firm performance: A study of the banking sector in Turkey. *European Journal of Innovation Management, 16*(1), 92-117.
733. Vaculín, R., Hull, R., Heath, T., Cochran, C., Nigam, A., & Sukaviriya, P. (2011). *Declarative business artifact centric modeling of decision and knowledge intensive business processes.* Paper presented at the 2011 IEEE 15th International Enterprise Distributed Object Computing Conference.
734. Vagia, M., Transeth, A. A., & Fjerdingen, S. A. (2016). A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed? *Applied ergonomics, 53*, 190-202.
735. van de Wetering, R., & Besuyen, M. (2021). How IT-enabled dynamic capabilities add value to the development of innovation capabilities. In *Encyclopedia of Organizational Knowledge, Administration, and Technology* (pp. 999-1016): IGI Global.
736. Van de Wetering, R., Mikalef, P., & Helms, R. (2017). Driving organizational sustainability-oriented innovation capabilities: a complex adaptive systems perspective. *Current opinion in environmental sustainability, 28*, 71-79.
737. van der Aalst, W. M., Bichler, M., & Heinzl, A. (2018). Robotic process automation. In: Springer.

738. van der Aalst, W. M., La Rosa, M., & Santoro, F. M. (2016). Business process management: Don't forget to improve the process! In (Vol. 58, pp. 1-6): Springer.
739. van der Aalst, W. M. P., Becker, J., Bichler, M., Buhl, H. U., Dibbern, J., Frank, U., . . . Zdravkovic, J. (2018). Views on the Past, Present, and Future of Business and Information Systems Engineering. *Business & Information Systems Engineering, 60*(6), 443-477. doi:10.1007/s12599-018-0561-1
740. Van Ee, J., El Attoti, I., Ravesteyn, P., & De Waal, B. M. (2020). BPM maturity and digital leadership: An exploratory study. *Communications of the IIMA, 18*(1), 2.
741. Van Looy, A., De Backer, M., & Poels, G. (2011). Defining business process maturity. A journey towards excellence. *Total Quality Management & Business Excellence, 22*(11), 1119-1137.
742. Van Looy, A., Poels, G., & Snoeck, M. (2017). Evaluating business process maturity models. *Journal of the association for information systems, 18*(6), 461-486.
743. Van Looy, A., & Shafagatova, A. (2016). Business process performance measurement: a structured literature review of indicators, measures and metrics. *SpringerPlus, 5*(1), 1-24.
744. Van Riel, A. C., Lemmink, J., & Ouwersloot, H. (2004). High-technology service innovation success: a decision-making perspective. *Journal of product innovation management, 21*(5), 348-359.
745. Van Schaik, P., & Ling, J. (2007). Design parameters of rating scales for web sites. *ACM Transactions on Computer-Human Interaction (TOCHI), 14*(1), 4-es.
746. Vassakis, K., Petrakis, E., & Kopanakis, I. (2018). Big data analytics: applications, prospects and challenges. *Mobile big data: A roadmap from models to technologies*, 3-20.
747. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., . . . Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems, 30*.
748. Vasylieva, O. (2013). Absorptive capacity in organizational theories: learning, innovation, managerial cognition.
749. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.
750. Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and design in the age of artificial intelligence. *Journal of product innovation management, 37*(3), 212-227.
751. Verma, J., & Abdel-Salam, A.-S. G. (2019). *Testing statistical assumptions in research*: John Wiley & Sons.
752. Viehhauser, J. (2020) Is Robotic Process Automation Becoming Intelligent? Early Evidence of Influences of Artificial Intelligence on Robotic Process Automation. In*: Vol. 393 LNBIP. Blockchain Forum and Robotic Process Automation, RPA Forum, held as part of the 18th International Conference on Business Process Management, BPM 2020* (pp. 101-115): Springer Science and Business Media Deutschland GmbH.
753. Vieira do Nascimento, D. (2013). *Interorganizational learning in the Brazilian bioethanol industry*. Paper presented at the International Scientific Conference on Management of Knowledge and Learning.
754. Vilkas, M., Stankevice, I., Duobiene, J., & Rauleckas, R. (2021). Achieving leanness: the relationship of lean practices with process exploitation and exploration. *Journal of Services and Operations Management, 37*(1), 1-14.
755. Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*.

756. Vugec, D. S., Stjepić, A.-M., & Vidović, D. I. (2018). The Role of Business Process Management in Driving Digital Transformation: Insurance Company Case Study. *International Journal of Computer and Information Engineering, 12*(9), 730-736.
757. W3C. (2018). Web Content Accessibility Guidelines (WCAG) 2.1. Recommendation, W3C (2018). Retrieved from https://www.w3.org/TR/WCAG21/
758. Wade, M., & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS Quarterly*, 107-142.
759. Waldman, D. A., Putnam, L. L., Miron-Spektor, E., & Siegel, D. (2019). The role of paradox theory in decision making and management research. *Organizational Behavior and Human Decision Processes, 155*, 1-6.
760. Wamba-Taguimdje, S.-L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020a). Impact of Artificial Intelligence on Firm Performance: Exploring the Mediating Effect of Process-Oriented Dynamic Capabilities. In *Digital Business Transformation* (pp. 3-18): Springer.
761. Wamba-Taguimdje, S.-L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020b). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal*.
762. Wamba, S. F. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management, 67*, 102544.
763. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356-365.
764. Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: A review and research agenda. *International Journal of Management Reviews, 9*(1), 31-51.
765. Wang, N., Liang, H., Zhong, W., Xue, Y., & Xiao, J. (2012). Resource structuring or capability building? An empirical study of the business value of information technology. *Journal of management information systems, 29*(2), 325-367.
766. Wang, X., Lin, X., & Shao, B. (2022). How does artificial intelligence create business agility? Evidence from chatbots. *International Journal of Information Management, 66*, 102535.
767. Wang, Y. L., & Ellinger, A. D. (2011). Organizational learning: Perception of external environment and innovation performance. *International Journal of Manpower*.
768. Wanner, J., Hofmann, A., Fischer, M., Imgrund, F., Janiesch, C., & Geyer-Klingeberg, J. (2020). *Process selection in RPA projects - Towards a quantifiable method of decision making.* Paper presented at the 40th International Conference on Information Systems, ICIS 2019.
769. Warwick, K. (2013). *Artificial intelligence: the basics*: Routledge.
770. Watson, H. J. (2017). Preparing for the Cognitive Generation of Decision Support. *MIS Quarterly Executive, 16*(3).
771. Weber, C., Curtis, B., & Gardiner, T. (2008). Business Process Maturity Model (BPMM) version 1.0. *Datum des Zugriffs, http://www. omg. org/docs/formal/08-06-01. pdf*, 07-21.
772. Weerawardena, J., O'cass, A., & Julian, C. (2006). Does industry matter? Examining the role of industry structure and organizational learning in innovation and brand performance. *Journal of Business Research, 59*(1), 37-45.

773. Wei, Z., Yi, Y., & Yuan, C. (2011). Bottom-up learning, organizational formalization, and ambidextrous innovation. *Journal of Organizational Change Management*.
774. Weiner, B. J., Helfrich, C. D., & Hernandez, S. R. (2006). Organizational learning, innovation, and change. *Health care management: Organization, design, and behavior*, 382-414.
775. Wellmann, C., Stierle, M., Dunzer, S., & Matzner, M. (2020). *A Framework to Evaluate the Viability of Robotic Process Automation for Business Process Activities*, Cham.
776. Westerman, G., Bonnet, D., & McAfee, A. (2014). *Leading digital: Turning technology into business transformation*: Harvard Business Press.
777. Wiengarten, F., Humphreys, P., Cao, G., & McHugh, M. (2013). Exploring the important role of organizational factors in IT business value: Taking a contingency perspective on the resource-based view. *International Journal of Management Reviews, 15*(1), 30-46.
778. Wijnhoven, F. (2022). Organizational learning for intelligence amplification adoption: Lessons from a clinical decision support system adoption project. *Information Systems Frontiers, 24*(3), 731-744.
779. Wiklund, J., & Shepherd, D. (2003). Knowledge-based resources, entrepreneurial orientation, and the performance of small and medium-sized businesses. *Strategic Management Journal, 24*(13), 1307-1314.
780. Wiklund, J., & Shepherd, D. A. (2008). Portfolio entrepreneurship: Habitual and novice founders, new entry, and mode of organizing. *Entrepreneurship theory and practice, 32*(4), 701-725.
781. Wilkens, U. (2020). Artificial intelligence in the workplace–A double-edged sword. *The International Journal of Information and Learning Technology*.
782. Wilkins, A. L., & Ouchi, W. G. (1983). Efficient cultures: Exploring the relationship between culture and organizational performance. *Administrative science quarterly*, 468-481.
783. Willaert, P., Van den Bergh, J., Willems, J., & Deschoolmeester, D. (2007). *The process-oriented organisation: a holistic view developing a framework for business process orientation maturity.* Paper presented at the Business Process Management: 5th International Conference, BPM 2007, Brisbane, Australia, September 24-28, 2007. Proceedings 5.
784. Willcocks, L. (2020). Robo-Apocalypse cancelled? Reframing the automation and future of work debate. *Journal of Information Technology, 35*(4), 286-302. doi:10.1177/0268396220925830
785. Willcocks, L., Hindle, J., & Lacity, M. (2018). *Keys to RPA Success*. Retrieved from
786. Williams, C., & Mitchell, W. (2004). Focusing firm evolution: The impact of information infrastructure on market entry by US telecommunications companies, 1984–1998. *Management Science, 50*(11), 1561-1575.
787. Williams, D., Allen, I., & McDonough, J. (2018). Using artificial intelligence to optimise robotic business process automation. *EngineerIT, 2018*(May), 24-26.
788. Wong, G. K. (2016). The behavioral intentions of Hong Kong primary teachers in adopting educational technology. *Educational Technology Research and Development, 64*, 313-338.
789. Wu, L.-Y. (2010). Applicability of the resource-based and dynamic-capability views under environmental volatility. *Journal of Business Research, 63*(1), 27-31.
790. Wu, S. J., Melnyk, S. A., & Swink, M. (2012). An empirical investigation of the combinatorial nature of operational practices and operational capabilities:

compensatory or additive? *International Journal of Operations & Production Management*.
791. Yang, C.-H. (2022). How Artificial Intelligence Technology Affects Productivity and Employment: Firm-level Evidence from Taiwan. *Research Policy, 51*(6), 104536.
792. Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach. *Journal of Business Research, 114*, 1-15.
793. Yli-Renko, H., Autio, E., & Sapienza, H. J. (2001). Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms. *Strategic Management Journal, 22*(6-7), 587-613.
794. Yoshikuni, A. C., & Albertin, A. L. (2020). Leveraging firm performance through information technology strategic alignment and knowledge management strategy: an empirical study of IT-Business Value. *International Journal of Research-GRANTHAALAYAH, 8*(10), 304-318.
795. Yoshikuni, A. C., & Dwivedi, R. (2022). The role of enterprise information systems strategies enabled strategy-making on organizational innovativeness: a resource orchestration perspective. *Journal of Enterprise Information Management*(ahead-of-print).
796. Yoshikuni, A. C., Dwivedi, R., & Dwivedi, Y. K. (2024). Strategic knowledge, IT capabilities and innovation ambidexterity: Role of business process performance. *Industrial Management & Data Systems, 124*(2), 915-948.
797. Yu, C. L., Wang, F., & Brouthers, K. D. (2016). Competitor identification, perceived environmental uncertainty, and firm performance. *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration, 33*(1), 21-35.
798. Yu, W., Wong, C. Y., Chavez, R., & Jacobs, M. A. (2021). Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *International Journal of Production Economics, 236*, 108135.
799. Zakir, J., Seymour, T., & Berg, K. (2015). Big data analytics. *Issues in Information Systems*, *16*(2).
800. Zasada, A. (2019). *How Cognitive Processes Make Us Smarter*.
801. Zebec, A., & Indihar Štemberger, M. (2020). *Conceptualizing a Capability-Based View of Artificial Intelligence Adoption in a BPM Context*, Cham.
802. Zebec, A., & Indihar Štemberger, M. (2024). Creating AI business value through BPM capabilities. *Business Process Management Journal*. doi:10.1108/bpmj-07-2023-0566
803. Zelenkov, Y. (2022). Explaining the IT Value Through the Information Support of Decision-Making. In *Digitalization of Society, Economics and Management* (pp. 29-48): Springer.
804. Zero, N. (2020). The Change Management Process for Automation Implementations.
805. Zhang, C. Y. (2019). Intelligent Process Automation in Audit. *Journal of Emerging Technologies in Accounting, 16*(2), 69-88. doi:10.2308/jeta-52653
806. Zhang, J., Long, J., & von Schaewen, A. M. E. (2021). How does digital transformation improve organizational resilience?—findings from PLS-SEM and fsQCA. *Sustainability, 13*(20), 11487.
807. Zhang, Y., Liao, Q. V., & Bellamy, R. K. (2020). *Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making.* Paper presented at the Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency.

808. Zhang, Y., Sharma, K., Du, L., & Liu, Y. (2024). *Toward Mitigating Misinformation and Social Media Manipulation in LLM Era.* Paper presented at the Companion Proceedings of the ACM on Web Conference 2024.
809. Zhang, Z., Zhu, L., Chen, G., Shang, L., Zhao, Q., & Ren, F. (2021). How entrepreneurial team heterogeneity impacts decision-making performance? An input-process-output approach. *Chinese Management Studies*.
810. Zhao, J., Li, Y., & Liu, Y. (2016). Organizational learning, managerial ties, and radical innovation: Evidence from an emerging economy. *IEEE Transactions on Engineering Management*, *63*(4), 489-499.
811. Zheng, S., Zhang, W., & Du, J. (2011). Knowledge-based dynamic capabilities and innovation in networked environments. *Journal of Knowledge Management, 15*(6), 1035-1051.
812. Zhou, C., Zhang, D., Chen, D., & Liu, C. (2023). Business process complexity measurement: A systematic literature review. *Ieee Access, 11*, 47940-47955.
813. Zhuang, Y., Zhu, Q., & Sarkis, J. (2021). Examining antecedents, consequences, and contingencies of proactive environmental strategy. *Sustainable Production and Consumption*, *28*, 1475-1490.
814. Zott, C. (2003). Dynamic capabilities and the emergence of intraindustry differential firm performance: insights from a simulation study. *Strategic Management Journal, 24*(2), 97-125.

APPENDICES

Appendix 1: Daljši povzetek (Extended summary in Slovene language)

POVEZAVA MED PRIVZEMANJEM UMETNE INTELIGENCE IN USPEŠNOSTJO POSLOVANJA ORGANIZACIJE

1 UVOD

Čeprav se je tehnologija umetne inteligence (v nadaljevanju UI) pojavila že v 60. letih prejšnjega stoletja, je šele v zadnjem času pridobila na veljavi zaradi svojih potencialnih poslovnih aplikacij. UI razumemo kot *simulacijo človeških kognitivnih funkcij s pomočjo inteligentnih agentov* (Russel & Norvig, 2016). Velike količine strukturiranih in nestrukturiranih podatkov (velepodatki), računalništvo v oblaku, management podatkov, programska ogrodja in storitve UI so prispevali k novemu valu razvoja, ki zagotavlja lahko dostopno platformo za privzemanje tehnologije UI. V zadnjih letih se organizacije vse pogosteje obračajo k UI, da bi s trajno konkurenčno prednostjo povečale poslovno vrednost (Krakowski, Luger, & Raisch, 2023). UI se je hitro razvila do te mere, da lahko sproži transformacije, ki omogočajo inteligentno avtomatizacijo in avgmentacijo ter ustvarjajo priložnosti za kontinuirane digitalne inovacije (Abbad et al., 2021). Organizacije pa se še vedno soočajo s težavami pri privzemanju in uporabi tehnologij UI za doseganje večje učinkovitosti (Mishra & Pani, 2020).

Kljub obsežnim raziskavam o poslovni vrednosti informacijske tehnologije (v nadaljevanju IT) (De Haes et al., 2020) za tehnologije UI še vedno manjka koherentno razumevanje, kako ustvarjajo poslovno vrednost (Enholm et al., 2021). Predhodne raziskave nakazujejo delni mediacijski vpliv privzemanja UI na uspešnost poslovanja prek organizacijskih zmogljivosti, kreativnosti in agilnosti (Chen, Esperança, et al., 2022; Mikalef & Gupta, 2021; Wamba, 2022), vendar te študije ne upoštevajo vloge poslovnih procesov. Management poslovnih procesov (v nadaljevanju MPP) je priznan kot eden od osrednjih in trajnostnih pristopov v managementu (Rosemann et al., 2004). Njegov strukturiran in strateški pristop dopolnjuje inovativne zmožnosti UI (Ng, Chen, Lee, Jiao, & Yang, 2021a), kar spodbuja raziskave privzemanja UI v kontekstu MPP. Wamba-Taguimdje et al. (2020a) so proučevali mediacijski učinek procesno usmerjenih dinamičnih zmogljivosti in poudarili vpliv na procesni ravni (Wamba-Taguimdje et al., 2020b), vendar ustvarjanje poslovne vrednosti z UI, še posebej prek zmogljivosti MPP, ni deležno dovolj pozornosti (Ahmad & Van Looy, 2020). Ta raziskava si prizadeva prispevati k obstoječemu dialogu z obravnavo raziskovalnega vprašanja *»Kako tehnologije umetne inteligence ustvarjajo poslovno vrednost in kakšno obliko poslovne vrednosti lahko pričakujemo?«.* V ta namen je potrebno celostno razumevanje procesa ustvarjanja poslovne vrednosti UI.

Predlagano razširjeno ogrodje poslovne vrednosti UI (angl. AI Business Value Framework) vključuje z UI omogočene zmogljivosti kot komponente privzemanja UI, mediacijske zmogljivosti MPP ter izide na procesni ravni in ravni organizacije. Dvojnost uporabe UI za avtomatizacijo in avgmentacijo človeških zmogljivosti za ustvarjanje vrednosti je že prepoznana (Raisch & Krakowski, 2021). Perspektiva avtomatizacije in avgmentacije je integrirana z uvedbo koncepta kognitivne avtomatizacije poslovnih procesov (v nadaljevanju KAPP) kot mediatorja. Visok potencial UI za inovacije, tj. inovacijska ambideksternost, je vključen s postopnimi (v nadaljevanju IPPP) in radikalnimi izboljšavami poslovnih procesov (v nadaljevanju IPPR). Poleg tega vzpostavljamo povezave med organizacijskim učenjem (v nadaljevanju OU) in inovacijsko ambideksternostjo na podlagi zmožnosti UI vplivati na raziskovanje in izkoriščanje procesnih inovacij (Mishra & Pati, 2020). Za boljše razumevanje, kako UI lahko vodi do uspešnosti poslovanja, smo izide razgradili na nižje in višje učinke, ki predstavljajo ločene vplive na ravni procesa in organizacije. Ob upoštevanju mediacijskega učinka ukrepov nižjega reda preučujemo tržno in operativno uspešnost prek učinkovitosti izvajanja procesov (v nadaljevanju UPP) in učinkovitost odločanja (v nadaljevanju UO). To privede do podrobnejšega razumevanja procesa ustvarjanja poslovne vrednosti UI.

Konceptualizirali in operacionalizirali smo komponentno zasnovan pogled na privzemanje UI in KAPP. Oba sta bistvena in temeljna elementa pri naših prizadevanjih za merjenje vpliva in poslovne vrednosti UI. Sledili smo smernicam Podsakoff et al. (2016) za razvoj in validacijo koncepta ter merske lestvice. Izdelani merski lestvici za oba koncepta sta bili združenimi z obstoječimi lestvicami v strukturiranem vprašalniku, ki predstavlja operacionalizirani raziskovalni model. Sestavljen anketni vprašalnik je bil uporabljen v raziskavi na ravni Evropske unije (v nadaljevanju EU), ki je zajemala vzorec 448 organizacij, ki v svojih poslovnih procesih uporabljajo tehnologije UI.

Preostanek povzetka disertacije je strukturiran, kot sledi. Naslednji razdelek predstavi teoretično osnovo raziskovalnih hipotez in predlaganega modela poslovne vrednosti UI. Tretji razdelek opisuje raziskovalne metode, nato sledijo rezultati raziskave. Na koncu so podani razprava in sklepi skupaj z znanstvenimi prispevki, praktičnimi vplivi, omejitvami in predlogi za nadaljnje raziskave.

2 TEORETIČNA IZHODIŠČA IN HIPOTEZE

Za uskladitev te študije z obstoječimi raziskavami (Tabela 1) o privzemanju UI smo kot teoretični okvir izbrali teorijo na temelju virov (TTV). Pretekle raziskave na širšem področju informacijskih sistemov (v nadaljevanju IS) so TTV obsežno uporabljale in ga postavile kot osrednjo teoretično perspektivo za razumevanje, kako viri IS ustvarjajo vrednost in organizacijam omogočajo doseganje boljših poslovnih rezultatov (Patas et al., 2012).

Pri prehodu na vse bolj digitalno poslovno okolje so podatki eden od ključnih virov organizacije, skozi katere dojema in razume lastno poslovanje, ga izboljšuje in se prilagaja okolju (Aydiner, Tatoglu, Bayraktar, Zaim, et al., 2019). UI izkorišča podatke kot jedrni vir in prek zmogljivosti, omogočenih z UI, izboljšuje učinkovitost in uspešnost poslovanja. Za poslovno okolje sta značilni vse večja dinamika in kompleksnost (Wu, 2010). Organizacijske zmogljivosti imajo ključno vlogo pri soočanju organizacij z nepredvidljivim poslovnim okoljem, zato smo v analizi uporabili teorijo na temelju dinamičnih zmožnosti (TTDZ) (Lin & Wu, 2014). Wade and Hulland (2004) trdita, da imajo viri IS lahko številne značilnosti dinamičnih zmožnosti in so zato lahko še posebej koristni za organizacije v hitro spreminjajočem se okolju. Posledično dojemamo TTV in TTDZ kot ustrezen teoretični okvir te študije.

2.1 Umetna inteligenca in uspešnost poslovanja

V tej raziskavi razumemo UI kot simulacijo človeških kognitivnih funkcij z uporabo inteligentnih agentov ali sistemov UI, tj. *sistem, temelječ na strojni opremi, ki za dosego eksplicitnih in implicitnih ciljev na podlagi vhodnih podatkov sklepa, kako ustvariti rezultate, kot so napovedi, vsebina, priporočila ali odločitve, ki lahko vplivajo na fizično ali virtualno okolje. Sistemi umetne inteligence se razlikujejo glede na stopnjo avtonomije in prilagodljivosti po njihovi uvedbi (OECD, 2024).*

Raziskovalci so dokazali, da lahko organizacija učinkovito izkoristi svoje naložbe v IT z razvojem močne IT-zmogljivosti za izboljšanje učinkovitosti procesov in uspešnosti poslovanja (Santhanam & Hartono, 2003). Nedavne empirične raziskave kažejo, da uvedba UI vpliva na organizacijske zmogljivosti in izboljša uspešnost poslovanja (Tabela 1). Predvidevamo, da lahko specifična sposobnost UI za ustvarjanje inteligentnih agentov, ki omogočajo avtomatizacijo in avgmentacijo procesov odločanja ter transformacijo (izboljšanje in preoblikovanje) poslovnih procesov, privede to znatnega povečanja poslovne uspešnosti. To nas vodi do formulacije naslednje hipoteze:

H1: *Privzemanje UI neposredno pozitivno vpliva na uspešnost poslovanja.*

Lui et al. (2022) opozarjajo, da morajo organizacije zaradi zahtevnosti projektov privzemanja UI razmisliti, kako bo njihova naložba v UI vplivala na njihovo poslovno vrednost. Za predvidevanje pričakovanih izidov in zmanjšanje povezanega tveganja zato potrebujemo celostno razumevanje procesa ustvarjanja vrednosti UI.

Tabela 1: Izbrane empirične raziskave o umetni inteligenci in uspešnosti poslovanja

Avtor	Obseg	Teorija	Ugotovitve
Mikalef et al. (2023)	Vprašalnik, 168 javnih organizacij	TTV	(+) Zmogljivost UI → avtomatizacija procesov, kognitivni vpogled, kognitivna vključenost, uspešnost poslovanja
Mikalef and Gupta (2021)	Vprašalnik, 143 višjih vodilnih delavcev ameriških podjetij	TTV, TTDZ	(+) Zmogljivost UI → organizacijska ustvarjalnost in uspešnost poslovanja
Wamba (2022)	Vprašalnik, 205 vodilnih delavcev ameriških podjetij	TTV, TTDZ	(+) Asimilacija UI → organizacijska agilnost, agilnost kupcev, uspešnost poslovanja
Wamba-Taguimdje et al. (2020a)	150 študij primerov, povezanih z UI	TTV, TTDZ	(+) Zmogljivost UI → procesno vodene dinamične zmogljivosti, uspešnost poslovanja
Chen, Esperança, et al. (2022)	Vprašalnik, 394 podjetnikov s področja e-trgovanja	TTV, TTDZ	(+) Zmogljivost UI → ustvarjalnost podjetja, upravljanje z UI, UI vodeno odločanje, uspešnost poslovanja

Se nadaljuje

Tabela 1: Izbrane empirične raziskave o umetni inteligenci in uspešnosti poslovanja (nad.)

Avtor	Obseg	Teorija	Ugotovitve
Rammer et al. (2022)	Nemška raziskava o inovacijah, 2018		(+) UI → učinkovitost inovacij
Bag, Gupta, et al. (2021)	306 izvršnih direktorjev iz Južne Afrike	TUZ	(+) UI, podprta z velepodatki → proces upravljanja z znanjem, slog odločanja, uspešnost poslovanja
Mishra et al. (2022)	Podatki 10-K iz ameriških podjetij		(+) Usmerjenost v UI → uspešnost poslovanja
Kim et al. (2022)	395 podjetij iz ZDA, ki uporabljajo UI (med letoma 2000 in 2018)		(+) Privzemanje UI → uspešnost poslovanja, (+) Privzemanje UI → avtomatizacija
Lui et al. (2022)	62 podjetij iz ZDA (med letoma 2015 in 2019)		(−) Objave glede privzemanja UI → tržna vrednost podjetja (−) Objave glede privzemanja UI → nenavadni tržni donosi
Joseph and Falana (2021)	159 podjetij iz Nigerije		(+) UI → uspešnost poslovanja
Panduro-Ramirez et al. (2022)	80 intervjujev iz Velike Britanije		(+) Integrirana tehnologija UI → uspešnost poslovanja in donosnost
Chetty (2019)	Vprašalnik, 190 respondentov iz Južne Afrike	TTV	(+) UI moderirana zmogljivost analitike velepodatkov → uspešnost poslovanja
Yang (2022)	5.257 tajvanskih podjetij, ki so v obdobju od leta 2000 do leta 2019 vložila vsaj en patent na področju UI		(+) Tehnologija UI → produktivnost in zaposlovanje
Lyu and Liu (2021)	Compustat podatki o sektorju energije v ZDA v obdobju 2010–2019		(+) Privzemanje UI → produktivnost
Chatterjee et al. (2022)	62 ameriških podjetij v obdobju 2015–2019	TTDZ	(+) Privzemanje aplikacij na osnovi UI → uspešnost poslovanja
Naz et al. (2022)	Vprašalnik, 240 pakistanskih podjetij s področja proizvodnje hrane	TTDZ, KT	(+) Podjetniška usmerjenost, zmogljivosti analitike velepodatkov in zmogljivosti UI → uspešnost poslovanja
Ho et al. (2022)	Bloombergov svetovni borzni indeks, povezan z UI, od leta 2019 do 2020		(+) Privzemanje aplikacij na osnovi UI → trajnostna poslovna uspešnost v zahtevnih okoljih
Jain (2019)	Spletna anketa v Indiji; 50 respondentov		(+) UI → upravljanje tehnoloških izzivov (+) UI → gospodarska rast (izboljšanje poslovanja: produktivnost, učinkovitost poslovanja, rast)
Alekseeva et al. (2020)	Compustatu Online objave delovnih mest v ZDA v obdobju 2010–2018		(+) UI → rast prodaje, kapitalske naložbe, EBITDA-marža, naložbe v raziskave in razvoj (+) UI → skupna faktorska produktivnost
Babina et al. (2021)	Objave delovnih mest iz ZDA v obdobju 2010–2018		(+) UI → rast prodaje, inovacije izdelkov, zaposlovanje, tržne ocene; kontrolna spremenljivka: večja podjetja imajo več koristi od naložb v UI
Fotheringham and Wiles (2022)	Analiza dogodkov na ameriškem borznem trgu (2016–2019; 153 objav)	TTS	(+) Objave o naložbah v UI (klepetalni roboti) → nenavadni donosi delnic
Sullivan and Wamba (2022)	Vprašalnik, 107 poslovodnih in IT direktorjev iz Velike Britanije in Francije	TTDZ, TOI	(+) Uporaba UI → odpornost organizacije, uspešnost poslovanja

Opomba. (+) pozitiven učinek; (−) negativen vpliv; ( ) brez vpliva; TUZ = teorija upravljanja z znanjem; KT = kontingenčna teorija; TTS = teorija tržnih sredstev; TOI = teorija organizacijskih informacij.

Vir: lastno delo.

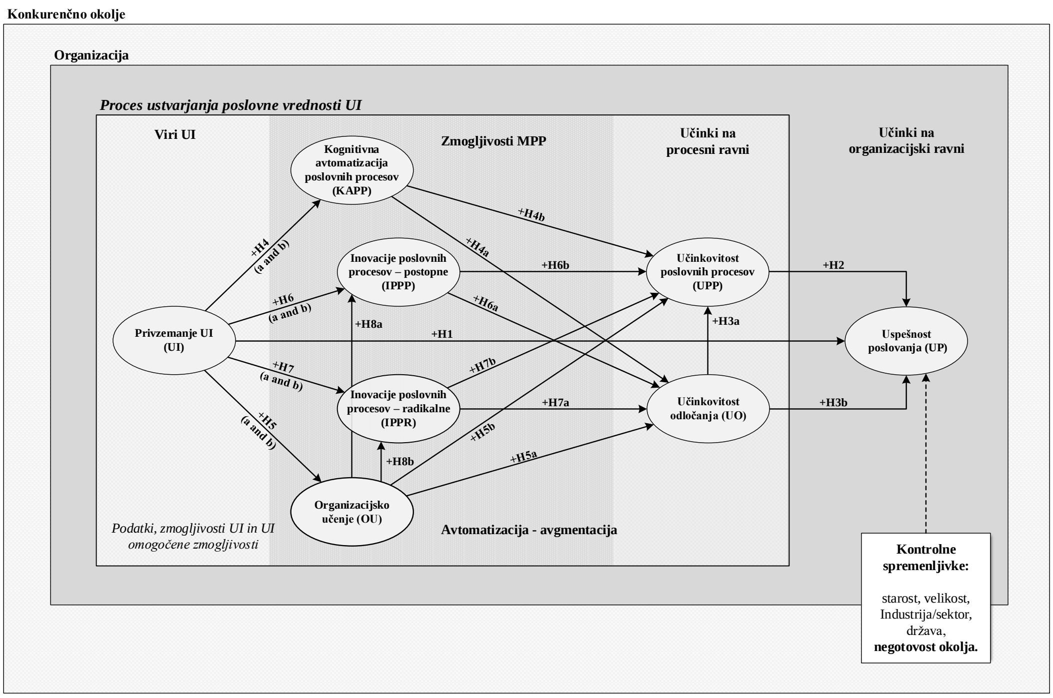
2.2 Model poslovne vrednosti umetne inteligence

Naša uvodna raziskava in obstoječe raziskave o poslovni vrednosti IT (Schryen, 2013) so potrdile, da lahko usklajevanje privzemanja UI s poslovnimi procesi privede do znatnih izboljšav uspešnosti poslovanja. Skladno s tem smo izhajali iz integrativnega modela poslovne vrednosti IT (Melville et al., 2004) za proučevanje privzemanja UI v okolju MPP. Model ponuja ustrezno celostno perspektivo procesa ustvarjanja poslovne vrednosti UI, ki vključuje vire UI, zmogljivosti MPP, poslovne procese, učinkovitost procesov, uspešnost poslovanja (UP) in zunanje okolje.

Obstoječe raziskave (Tabela 1) so pokazale, da je vpliv UI mediiran preko določenih organizacijskih zmogljivosti. Z uskladitvijo virov UI z zmogljivostmi MPP (Kerpedzhiev et al., 2020) smo identificirali tri: KAPP, organizacijsko učenje in inovacije poslovnih procesov (v nadaljevanju IPP), tj. ambideksterni pogled na inovacije, ki združuje operativno zmogljivost postopnih izboljšav procesov in dinamično zmogljivost radikalnih izboljšav procesov. V skladu z modelom poslovne vrednosti IT proučujemo izide na procesni ravni z učinkovitostjo poslovnih procesov in učinkovitostjo odločanja ter tako model razširimo na raven organizacijskega delovanja oziroma uspešnosti poslovanja. Posamezne povezave so predstavljene v nadaljevanju.

Sledili smo smernicam Hong et al. (2014) o kontekstualno specifičnem teoretiziranju za preslikavo modela ustvarjanja poslovne vrednosti IT v kontekst tehnologije UI. Privzemanje UI je osrednji fokus naše raziskave. Slika 1 prikazuje konceptualni model, ki prikazuje stičišče med glavnimi konstrukti.

Slika 1: Predlagani raziskovalni model



Vir: lastno delo.

2.3 Komponentni pogled na privzemanje umetne inteligence

Opirajoč se na delo Aydiner, Tatoglu, Bayraktar, Zaim, et al. (2019) opišemo uvajanje UI kot *implementacijo, uvedbo in uporabo virov UI (podatkov, infrastrukture UI, znanja,* *kompetenc).* Raven privzemanja se meri z razvojem zmogljivosti, ki temeljijo na UI (komponente privzemanja UI). Te zmogljivosti predstavljajo *sposobnost mobilizacije virov UI za specifične poslovne potrebe skozi implementacijo, uvedbo in uporabo aplikacij, orodij ali tehnologij UI.* Ta perspektiva poudarja operativni vidik UI in ne raziskuje dejavnikov, ki prispevajo k njenemu razvoju ali vplivajo na uvajanje (kot so predhodniki ali determinante).

S sprejetjem pogleda na osnovi komponent raziskovalci in strokovnjaki analizirajo oprijemljive dejavnike, ki zahtevajo učinkovito rabo v realnih kontekstih. To je način, ki zagotavlja bolj transparenten in akademski pogled (natančnost in specifičnost, empirično proučevanje, tehnološke vidike, aplikativno usmerjeno analizo) na razumevanje praktičnih posledic in vpliva UI na različnih področjih. Konceptualizacija privzemanja UI opredeljuje pet progresivnih ravni zmogljivosti UI, ki podpirajo poslovne procese in prispevajo k ustvarjanju poslovne vrednosti na osnovi podatkov organizacije.

Pridobivanje in predhodna obdelava podatkov: obsegata manipulacijo velepodatkov (angl. Big Data): *»Sposobnost organizacije, da pridobi podatke iz strukturiranih in nestrukturiranih virov, novih in obstoječih sistemov ter notranjih in zunanjih virov ter jih pripravi za analizo.«*

Kognitivni vpogled: *»Sposobnost organizacije, da uporabi UI za odkrivanje vzorcev v podatkih in razlaganje njihovega pomena.«* Ta dimenzija je konceptualizirana okoli tematik razumevanja konteksta, učenja in analitike.

Kognitivna vključenost: *»Sposobnost organizacije, da uporabi z UI izboljšano človeško-računalniško interakcijo in sodelovanje.«* Vključenost je sestavljena iz več ključnih elementov, vključno z razumevanjem, zaznavanjem namena in domenskim znanjem (Russel & Norvig, 2016). Ta sposobnost omogoča avtomatizirane interakcije, ki podpirajo delo uporabnikov in spodbujajo njihovo sodelovanje (Mele et al., 2018) v poslovnih procesih, usmerjenih k naročniku ali zaposlenim.

Kognitivna podpora odločanju: *»Sposobnost organizacije, da uporabi UI v procesih odločanja.«* Tehnologije UI olajšajo sprejemanje odločitev in ponujajo bolj inteligentno podporo odločanju.

Kognitivne tehnologije: *»Sposobnost organizacije, da integrira tehnologije UI z drugimi IT-viri, storitvami in napravami.«* To dimenzijo smo izolirali za organizacije, ki ne uvajajo in uporabljajo UI zgolj na specifičnem aplikativnem področju kot določen program ali orodje. Zmogljivost kognitivnih tehnologij predstavlja najvišjo raven uvajanja, ko UI globje integriramo s poslovnimi procesi (to pomeni inovativno ali ustvarjalno uporabo UI zunaj njene prvotno predvidene rabe).

2.4 Mediacijska vloga učinkovitosti poslovnih procesov

Melville et al. (2004) uspešnost definirajo kot zmogljivost poslovnih procesov kot tudi uspešnost poslovanja. Model poslovne vrednosti IT ločuje operativno učinkovitost poslovnih procesov od splošne uspešnosti poslovanja, pri čemer naj bi nekateri rezultati poslovnih procesov vplivale na uspešnost poslovanja organizacije (Tallon et al., 2000). Na podlagi njihovega zaključka sklepamo, da viri UI organizacijam pomagajo ustvarjati poslovno vrednost prek vpliva na poslovne procese. Za proučevanje vpliva UI na UPP primerjamo značilnosti poslovne vrednosti UI: hitrost, obseg, granularnost, učenje (natančnost napovedovanja), reševanje problemov in odločanje (Tallon et al., 2000) s ključnimi kazalniki učinkovitosti procesov (čas, strošek), uspešnosti (kakovost) in prožnosti (Dumas et al., 2018).

H2: *Učinkovitost poslovnih procesov pozitivno vpliva na uspešnost poslovanja.*

2.5 Učinkovitost odločanja

UO je sposobnost organizacije za učinkovito in uspešno sprejemanje odločitev. Sistemi UI se uporabljajo za nadomeščanje človeških odločevalcev pri strukturiranih ali delno strukturiranih odločitvah (avtomatizacija) ali kot orodje za podporo pri odločanju za nestrukturirane odločitve na procesni ali strateški organizacijski ravni (avgmentacija) (Duan et al., 2019). Odločanje, podprto z UI, lahko znatno poveča operativno učinkovitost in produktivnost za doseganje boljših poslovnih rezultatov (Ashaari et al., 2021). Poslovni procesi vključujejo številne odločitve, ki neposredno vplivajo na uspešnost (Ghattas, Soffer, & Peleg, 2014), pri čemer vplivajo na različne vidike, vključno z učinkovitostjo in prožnostjo. Komponente odločanja v poslovnem procesu imajo ključno vlogo pri doseganju ciljev procesa in pomembno prispevajo h končnem rezultatu (Raghu & Vinze, 2007). Učinkovit proces odločanja usmerja poslovne procese k uvajanju novih izdelkov in storitev ter jih povezuje z nastajajočimi tehnologijami (Robert Baum & Wally, 2003). Učinkovito odločanje spodbuja inovativnost z razvijanjem ekonomije obsega in sinergij znanja v različnih organizacijskih kombinacijah ter omogoča izkoriščanje priložnosti v dinamičnih okoljih (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019). Povezava je bolj formalno navedena v naslednji hipotezi:

H3a: *Učinkovitost odločanja pozitivno vpliva na učinkovitost poslovnih procesov.*

Proces odločanja na organizacijski ravni vključuje razumevanje trendov in vzorcev v poslovni rasti (Keding, 2021). Natančne informacije se ne pridobivajo samo za operativno odločanje, temveč tudi za uporabo pri strateškem poslovnem odločanju. UO temelji predvsem na znanju (Wiklund & Shepherd, 2008). Tako postanejo IS upravljanja znanja, podprti z UI (tj. inženiring znanja in ekspertni sistemi, sistemi za podporo odločanju), pomembna orodja, ki omogočajo odločanje na podlagi dejstev (angl. evidence-based) in reševanje problemov v kompleksnih poslovnih situacijah. Številni avtorji trdijo, da odločanje na podlagi UI (angl. AI-based) neposredno vpliva na poslovno uspešnost (Ashaari et al., 2021; Chen, Esperança, et al., 2022; Rahman et al., 2021). To nas vodi k naslednji hipotezi:

H3b: *Učinkovitost odločanja pozitivno vpliva na uspešnost poslovanja.*

2.6 Avtomatizacija in avgmentacija

Z vidika učinkovitosti poslovanja predstavljata avtomatizacija in avgmentacija dva glavna primera uporabe v privzemanju UI (Enholm et al., 2021; Raisch & Krakowski, 2021). Avtomatizacija pomeni, da strojna oprema prevzame človeško nalogo; avgmentacija pomeni, da ljudje tesno sodelujejo s stroji pri opravljanju naloge. Oba koncepta se nahajata na nasprotnih koncih spektra sodelovanja človek-stroj (Raisch & Krakowski, 2021). Avtomatizacija sega od popolnoma ročne (tj. človeške) do popolnoma avtomatske (Parasuraman et al., 2000).

Avtomatizacija omogoča organizacijam doseganje stroškovne učinkovitosti, vzpostavljanje hitrejših procesov ter zagotavljanje večje racionalnosti in doslednosti pri obdelavi informacij. Nasprotno pa avgmentacija ponuja dopolnilne prednosti iz vzajemne krepitve človeških spretnosti in strojnih zmožnosti. Integriranje avtomatizacije in avgmentacije vodi do dodatnih sinergij med tema medsebojno odvisnima dejavnostma (Raisch & Krakowski, 2021). Raznolike prednosti kažejo, da kombinacija avtomatizacije in avgmentacije ustvarja komplementarne učinke, ki povečajo učinkovitost (Grønsund & Aanestad, 2020).

Prilagojeno po Dwarkanhalli et al. (2018) ter Zasada (2019) definiramo koncept KAPP kot *avtomatizacijo procesov, ki temeljijo na znanju* (angl. the automation of knowledge-intensive processes). Koncept je bistven za razumevanje vpliva uvedbe UI. KAPP je operativna zmogljivost, torej sposobnost organizacije, da izvaja funkcionalne dejavnosti s pomočjo namensko izbranih skupin virov (Saunila et al., 2020). Wu et al. (2012) navajajo, da se operativne zmogljivosti večinoma preučujejo z vidika izidov, vključno s stroški, kakovostjo, zanesljivostjo, hitrostjo in prožnostjo. Optimizirani procesi imajo največ koristi od avtomatizacije s stroškovno učinkovitostjo, hitrejšo izvedbo ter večjo racionalnostjo in doslednostjo pri obdelavi informacij (kakovost) (Ansari et al., 2019; Berruti et al., 2017; Rocha et al., 2017). Nekateri avtorji pa vztrajajo z bolj pesimističnimi pogledi na kognitivno avtomatizacijo (Daugherty & Wilson, 2018; Raisch & Krakowski, 2021). Trdijo, da pravi digitalni kognitivni mediator (popolna avtomatizacija) še ne obstaja (Rouse & Spohrer, 2018), kar pomeni, da je treba dati prednost delni avtomatizaciji ali avgmentaciji. Za preučitev vpliva avtomatizacije definiramo splošno značilnost koncepta kot *»sposobnost organizacije, da avtomatizira poslovne procese, ki temeljijo na znanju (nepredvidljivi, neponovljivi, visoko prilagodljivi, kompleksni), da simulira delo z znanjem in aktivnosti sodelovanja.«* Osredotočimo se na dve dimenziji: raven avtomatizacije (ročna, podpora odločanju, izbira odločitev, nadzorna kontrola, popolna avtomatizacija) (Sindhgatta, ter Hofstede, & Ghose, 2020b; Vagia et al., 2016) in obseg avtomatizacije (strukturirani,

strukturirani z ad hoc izjemami, nestrukturirani z vnaprej določenimi fragmenti, prosto strukturirani in nestrukturirani procesi) (Di Ciccio et al., 2015; Szelagowski & Lupeikiene, 2020). Glede na teoretiziranje Raisch and Krakowski (2021) ter Karan et al. (2021) lahko pri višji ravni avtomatizacije pričakujemo večji vpliv na odločanje in manjšega na učinkovitost procesov. Glede na to lahko domnevamo vpliv na UO in UPP. Tako oblikujemo naslednji hipotezi:

H4a: *Kognitivna avtomatizacija poslovnih procesov je mediator med pozitivnim vplivom privzemanja UI in učinkovitostjo odločanja.*

H4b: *Kognitivna avtomatizacija poslovnih procesov je mediator med pozitivnim vplivom privzemanja UI in učinkovitostjo poslovnih procesov.*

2.7 Organizacijsko učenje

OU predstavlja stalno prizadevanje za ustvarjanje organizacijskega znanja. Poleg tega prispeva k sposobnosti organizacije, da se učinkovito prilagodi spremembam v poslovnem okolju (Bohanec et al., 2017). Razvije lahko novo, postopno znanje ali posodobi obstoječe znanje. OU razumemo kot *pridobivanje, ustvarjanje, integriranje in distribucijo informacij in znanja* (Templeton et al., 2002; Wang & Ellinger, 2011). Učenje in znanje sta bistvena za več zmogljivosti MPP, predvsem za področje »zaposleni in kultura« (Helbin & Van Looy, 2021; Kerpedzhiev et al., 2020). Posledično lahko OU razumemo kot zmogljivost MPP.

Hitro razvijajoča se vloga in vrednost tehnologije UI za delovanje in konkurenčnost organizacije nas usmerjata k vključitvi ustvarjanja in uporabe znanja na podlagi tehnologije v definicijo organizacijskega učenja (Banasiewicz, 2021). UI ima znaten potencial za razjasnitev organizacijske baze znanja, če je ta predstavljena v velepodatkih. Sistemi UI, ki temeljijo na strojnem in globokem učenju, lahko prepoznajo zapletene vzorce in izvajajo analize, kar jim omogoča preoblikovanje virov znanja v nove zmogljivosti, ki olajšajo proces učenja znotraj organizacije (Jarrahi, Kenyon, et al., 2022).

Končni namen OU je izboljšati informacijsko učinkovitost odločanja (Banasiewicz, 2021). Da bi organizacije ostale konkurenčne v gospodarstvu, ki temelji na znanju, morajo razviti in uporabiti robustne načine za ustvarjanje in izkoriščanje znanja, ki usmerja poslovne odločitve (Banasiewicz, 2021). Za avgmentacijo lahko izkoristimo priložnosti, ki jih ponuja UI, vključno s tehnikami analitičnih podatkov inkodificiranim znanjem za povečanje inteligence človeških odločevalcev (okrepitev inteligence). Čeprav te tehnike ne nadomestijo odločevalcev, lahko pomagajo pri sprejemanju kompleksnih odločitev s pomočjo dobro zasnovanih interakcij učenja med človekom in sistemom UI (Wijnhoven, 2022). Ti premisleki nas vodijo do naslednjih hipotez za preizkus mediacijskega učinka OU prek UO na UPP.

H5a: *Organizacijsko učenje je mediator med pozitivnim vplivom privzemanja UI in učinkovitostjo odločanja.*

H5b: *Organizacijsko učenje je mediator med pozitivnim vplivom privzemanja UI in učinkovitostjo poslovnih procesov.*

OU predstavlja avgmentacijski potencial UI. OU opredelimo kot dinamično zmogljivost, saj integrira, gradi ali preoblikuje kompetence in tako omogoča prilagajanje hitro spreminjajočemu se poslovnem okolju (Eisenhardt & Martin, 2000). Razvoj novega znanja, pridobljenega z OU, zmanjša verjetnost, da bodo kompetence organizacije zakrnele, in omogoča, da ostanejo dinamične in podpirajo povečanje uspešnosti poslovanja (Senge, 1998).

2.8 Ambideksterna inovativnost in organizacijsko učenje

Proces inoviranja se, skupaj s splošno preobrazbo v digitalizirana podjetja, spreminja zaradi povečane implementacije digitalnih storitev in avtomatizacije (Helbin & Van Looy, 2021). UI ponuja možnosti za reševanje dveh specifičnih ovir pri inovacijah. Prva je omejitev pri obdelavi informacij, ki organizaciji omejuje dostop do novih poslovnih priložnosti ali možnih rešitev (Williams & Mitchell, 2004). Haefner et al. (2021) predstavljajo dve zmogljivosti UI, ki ju lahko uporabimo za premagovanje te ovire. Sistemi UI lahko pridobijo informacije iz velepodatkov, prepoznajo in ocenijo bistveno več informacij, jih uporabijo za razvoj idej (npr. *pripovedovanje zgodb na podlagi podatkov, vizualizacija uspešnosti, metaiskanje, prepoznavanje imenovanih entitet*) ter prepoznajo več težav, priložnosti in groženj, ki se lahko uporabijo za ustvarjanje novih idej (npr. *napovedno modeliranje in analitika, odkrivanje anomalij in odklonskega vedenja, napovedno vzdrževanje*). Druga ovira izvira iz neučinkovitih ali lokalnih rutinskih iskanj (Katila & Ahuja, 2002), pri katerih organizacije na splošno iščejo rešitve v domenah znanja, povezanih z njihovo obstoječo bazo znanja (Posen et al., 2018). Posledično bo večina rešitev primerjalno postopnih v svojem inovativnem prizadevanju, saj se zelo tesno opirajo na obstoječe znanje. Da bi organizacije ustvarile bolj kreativne in inovativne ideje ali priložnosti, morajo razširiti svoje iskanje zunaj obstoječih domen znanja na nova področja in zunanje vire podatkov ter biti bolj raziskovalne. Sistemi UI lahko ustvarijo, identificirajo in ocenijo bolj kreativne/raziskovalne ideje (npr. *generativna UI – generativno oblikovanje, inženiring proteinov, odkrivanje materialov, rudarjenje procesov*).

Raziskovalci trdijo, da lahko ambidekstralne organizacije uravnotežijo obe strategiji (izkoriščanje in raziskovanje) in se izognejo težavi prevelikega zanašanja na eno strategijo (Aljumah, Nuseir, & Alam, 2021; Benner & Tushman, 2015). Čeprav O'Reilly III in Tushman (2011) poudarjata pomembnost raziskovanja novih področij in hkratnega izkoriščanja obstoječih za preživetje ter rast organizacije, je jasno tudi, da imajo organizacije s tem pogosto težave (Johnson et al., 2022). Večina organizacij vidi v tehnologiji UI priložnost za raziskovanje, druge pa se osredotočajo na sposobnost UI, da poveča učinkovitost trenutnih operacij (Johnson et al., 2022). V kontekstu MPP pričakujemo izboljšanje procesov s pomočjo vgrajene tehnologije UI ali s pomočjo UI procesa inovacij. Izkoriščanje se nanaša na postopne inovacije (v nadaljevanju IPPP), ki povečajo učinkovitost, kakovost in prožnost poslovnih procesov. Nasprotno pa raziskovanje stremi k radikalnemu izboljšanju (v nadaljevanju IPPR) s pomočjo novih, transformiranih ali preoblikovanih procesov (Norman & Verganti, 2014). Na podlagi tega trdimo, da privzemanje UI omogoča ambidekstralno inovativnost. Za preverjanje trditve predlagamo dva para hipotez za postopno in radikalno inovativnost:

H6a: *Postopne inovacije poslovnih procesov so mediator med pozitivnim vplivom uvedbe UI in učinkovitostjo odločanja.*

H6b: *Postopne inovacije poslovnih procesov so mediator med pozitivnim vplivom uvedbe UI in učinkovitostjo poslovnih procesov.*

H7a: *Radikalne inovacije poslovnih procesov so mediator med pozitivnim vplivom uvedbe UI in učinkovitostjo odločanja.*

H7b: *Radikalne inovacije poslovnih procesov so mediator med pozitivnim vplivom uvedbe UI in učinkovitostjo poslovnih procesov.*

Raziskave kažejo, da OU in njegov rezultat, organizacijsko znanje, prispevata k inovacijam (Almuslamani, 2022). OU preprečuje stagniranje in spodbuja stalne inovacije z obnavljanjem in odkrivanjem novih zmogljivosti tehnologij ter proizvodnih metod (García-Morales et al., 2012). Višja raven inovacij zahteva večjo kritično sposobnost, nove spretnosti in relevantno znanje (Senge, 1998). Po March (1991) lahko organizacija izkoristi obstoječe znanje in raziskuje načine uporabe tehnologije, kot je UI, za ustvarjanje novega znanja. Kljub temu je malo empiričnih dokazov o tem, ali pridobivanje, distribucija in izkoriščanje znanja s pomočjo UI vplivata na učinkovitost procesov s spodbujanjem inovacij. Predlagamo hipoteze za preizkus vpliva:

H8a: *Organizacijsko učenje pozitivno vpliva na postopne inovacije poslovnih procesov.*

H8b: *Organizacijsko učenje pozitivno vpliva na radikalne inovacije poslovnih procesov.*

3 POSTOPEK IZVEDBE EMPIRIČNE RAZISKAVE

3.1 Raziskovalni pristop

Za empirično preučitev raziskovalnega problema smo uporabili anketni vprašalnik. Uporabili smo en sam primarni vir podatkov, zasnovan na samoporočanju respondentov, ki predstavlja prečni prerez (časovno) stanja uporabe UI v organizacijah. Podatke smo zbrali z anonimnim anketnim vprašalnikom v angleškem jeziku, ki je bil distribuiran elektronsko (prek spleta). Organizacija je obravnavana kot analitična enota. Zasnovo, merilne lestvice in vprašalnik smo razvili v skladu s smernicami MacKenzie et al. (2011) ter Brace (2018).

3.2 Zbiranje podatkov in vzorec

Po podatkih (Eurostat, 2022) je leta 2020 v EU 7 % podjetij uporabljalo aplikacije UI. Ocenili smo, da okvir vzorca znaša 8 % aktivnih podjetij, tj. 2,2 milijona podjetij. Z 95 % zanesljivostjo in 5 % napako vzorčenja smo določili 385 respondentov kot minimalno velikost vzorca. Uporabili smo sorazmerno naključno vzorčenje, stratificirano po državah.

Respondente smo pridobili preko LinkedIn Pro in preko podatkov o aktivnih poslovnih domenah po kodah države iz ZoneFiles.io. Ciljna skupina so bili višji managerji in drugi višji odločevalci ali zaposleni, ki so neposredno vključeni v izvajanje strategije UI v organizaciji. Vabila smo poslali po e-pošti v štirih valovih od marca 2022 do junija 2022 ob začetkih mesecev.

Zbran in obdelan vzorec je vključeval 448 organizacij v EU. Reprezentativnost vzorca smo preverili glede na velikost podjetja, panogo, leta poslovanja (starost) in državo. Respondenti so bili večinoma izvršni direktorji (76,34 %) ali srednji managerji (18,75 %) predvsem iz srednje velikih organizacij (89,73 %). Večinoma delujejo v informacijskem in telekomunikacijskem sektorju, storitvah (20,98 %), znanstveno-tehničnih dejavnostih (29,02 %), finančnih in zavarovalnih dejavnostih (7,37 %) ter predelovalni dejavnosti (5,58 %). 40,63 % organizacij je bilo mlajših, 25,22 % pa zrelih, skoraj polovica iz Nemčije (21,43 %), Italije (10,94 %), Nizozemske (10,49 %) in Francije (6,92 %).

3.3 Merjenje spremenljivk

Privzemanje UI smo operacionalizirali s petimi temeljnimi podkonstrukti: pridobivanje in predhodna obdelava podatkov, kognitivni vpogled, kognitivna vključenost, kognitivna podpora odločanju in kognitivne tehnologije. Konstrukt, izpeljan iz konceptualne definicije, je večdimenzionalni drugostopenjski konstrukt reflektivno-reflektivnega tipa I (Jarvis et al., 2003). Kazalniki so bili zasnovani na podlagi pregleda literature, intervjujev s strokovnjaki in pregleda 1.860 projektov iz podjetij, povezanih z UI (MacKenzie et al., 2011). KAPP (prvostopenjski konstrukt z reflektivnimi kazalniki) smo operacionalizirali s kazalniki, ki izhajajo iz pregleda literature (Di Ciccio et al., 2015; Vagia et al., 2016), intervjujev s strokovnjaki in s proučevanjem drugih že obstoječih meritev tega konstrukta. Pri specifikaciji modelov, ocenjevanju lestvic, izpopolnjevanju in ocenjevanju smo upoštevali smernice MacKenzie et al. (2011). Za preostale konstrukte raziskovalnega modela smo prilagodili obstoječe merilne lestvice: IPP (Ng et al., 2015), OU (García-Morales et al., 2012), UO (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019), UPP (Bosilj Vukšić et al., 2017; Dumas et al., 2018; Hernaus, 2016) in UP (Wang et al., 2012).

Specifične značilnosti organizacij smo preverili s štirimi kontrolnimi spremenljivkami: starostjo organizacije, velikostjo, panogo in državo. Spremenljivka panoge je temeljila na kategorijah 1. stopnje šifranta NACE-R2. Državo je določal primarni sedež organizacije po EU-27. Nielsen and Raswant (2018) trdita, da so večdržavne študije dovzetne za težave izpuščenih spremenljivk zaradi kompleksnosti več okoljskih kontekstov (tj. političnega, gospodarskega, sociokulturnega, institucionalnega), zato smo kot kontrolno spremenljivko vključili *negotovost okolja* in jo izmerili z osmimi kazalniki, ki jih predlagajo Rowe et al. (2017).

4 ANALIZA PODATKOV IN REZULTATI

Za izvedbo konfirmatorne faktorske analize (v nadaljevanju KFA) in analize poti (tj. preizkušanje hipotez v konceptualnem modelu) smo uporabili program AMOS, različica 28, z metodo največje verjetnosti (angl. Maximum Likelihood Method).

4.1 Ocena merilnega modela ter zanesljivost in veljavnost konstruktov

Za preizkus veljavnosti merilnega modela smo izvedli KFA. Prileganje modela je bilo ustrezno. Vse faktorske uteži so bile značilne ($p < 0,001$).

Enorazsežnost konstruktov smo merili s Cronbachovim alfa koeficientom. Ocenjena zanesljivost je presegala mejno vrednost 0,70 (Hair et al., 2013; Hancock & Mueller, 2001).

Ocena kompozitne zanesljivosti je pokazala, da so vrednosti skladne z mejno vrednostjo 0,70 (Fornell & Larcker, 1981).

Konvergentna veljavnost je bila preverjena s povprečno izvlečeno varianco (angl. Average Variance Extracted), katere vrednosti so bile znotraj priporočene mejne vrednosti 0,50.

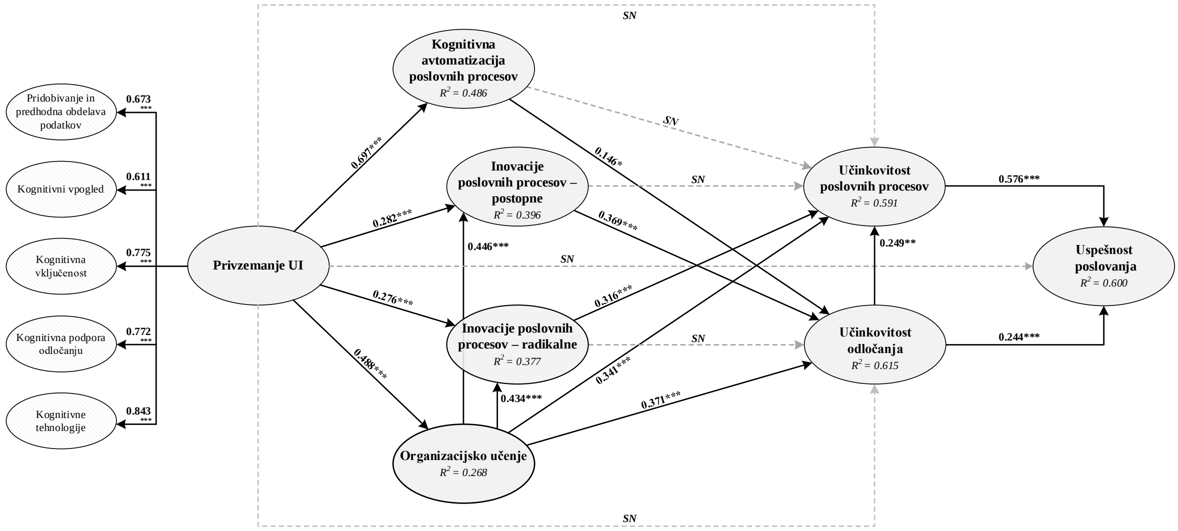
Diskriminantna veljavnost je bila potrjena za vse konstrukte, kjer je bila največja deljena varianca (angl. Maximum Shared Variance) nižja od povprečne izvlečene variance (Hair et al., 2013). Diskriminantno veljavnost smo dodatno potrdili z razmerjem heterotrait-monotrait (Henseler et al., 2015), kjer meja 0,85 ni bila presežena.

Faktorji inflacije spremenljivk so potrdili odsotnost multikolinearnosti vseh napovednih kazalnikov odvisnih spremenljivk. Rezultati so bili nižji od mejne vrednosti 10. Vrednosti tolerance so bile večje od 0,1 (Linton et al., 2020).

4.2 Analiza strukturnega modela in testiranje hipotez

Za testiranje hipotez konceptualnega modela smo izvedli analizo poti ob upoštevanju več mediacijskih učinkov (Collier, 2020). Naknadna analiza moči vzorca s programom semPower (Moshagen & Erdfelder, 2016) je potrdila, da je vzorec primeren za analizo. Rezultate analize prikazuje Figure 21.

Slika 2: Rezultati analize strukturnega modela



+: Standardizirane regresijske uteži.
*p < 0.05, **p < 0.01; ***p < 0.001; SN = Statistično neznačilno.

Vir: lastno delo.

Pregled neposrednih učinkov (Figure 21) ne kaže podpore za H1 (β = 0,036, t = 0,691, p > 0,05), kar kaže, da privzemanje UI nima neposredne povezave z UP, vendar pa je razmerje statistično značilno v odsotnosti mediacijskih spremenljivk s skupnim učinkom 0.418 (t = ,584, p < 0,001, 95 % CI: LL = 0,314 to UL = 0,521). Nasprotno je potrditev H2 (β = 0,576, t = 9,488, p < 0,001) skladna s predhodnimi raziskavami, ki kažejo mediacijsko vlogo UPP kot povezavo UP (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Melville et al., 2004). Potrditev hipotez H3a (β = 0,249, t = 3,532, p < 0,001) in H3b (β = 0,244, t = 4,050, p < 0,001) utemeljuje pričakovani vpliv UO na UPP in UP (Aydiner, Tatoglu, Bayraktar, & Zaim, 2019; Fredrickson & Mitchell, 1984). Potrditev hipotez H8a (β = 0,446, t = 8,442, p < 0,001) in H8b (β = 0,434, t = 7,001, p < 0,001) razkriva, da ima OU pomembno neposredno povezavo z inovacijami procesov, tj. IPPP in IPPR.

Za identifikacijo mediacijskih učinkov je bil analiziran celoten model. Glede na rezultate v tabeli 3 je KAPP mediator med pozitivnim vplivom privzemanja UI in UO (podpora za H4a), ne pa na UPP (ni podpore za H4b). Rezultati v Table 84 kažejo, da je OU mediator med pozitivnim vplivom privzemanja UI na UO in UPP (podpora za H5a in H5b). Za testiranje učinkov UI na inovacije procesov sta bila vstavljena dva vzporedna konstrukta IPPP in IPPR. Rezultati v Table 84 kažejo, da je IPPP mediator med pozitivnim vplivom privzemanja UI in OU (podpora za H6a), vendar pa IPPP ni mediator med UI in UPP (ni podpore za H6b). Nasprotno IPPR ni mediator privzemanja UI in UO (ni podpore za H7a), mediira vpliv na UPP (podpora za H7b).

Tabela 2: Rezultati analize posamezne mediacije, tj. mediacijski učinki

Pot	Relacije	Nestandardizirane uteži	Učinek	Z-ocena	Mediacija
UI → KAPP → UO	UI → KAPP	0,715 (0,063)	0,104* (0,050)	2,271$^{\xi *}$	Podpora za H4a
	KAPP → UO	0,146 (0,063)			
UI → KAPP → UPP	UI → KAPP	0,715 (0,063)	–0,042 (0,059)	–0,713$^{\xi}$	Ni podpore za H4b
	KAPP → UPP	–0,058 (0,073)			
UI → OU → UO	UI → OU	0,576 (0,065)	0,185*** (0,040)	5,482$^{\xi ***}$	Podpora za H5a
	OU → UO	0,321 (0,046)			
UI → OU → UPP	UI → OU	0,576 (0,065)	0,190*** (0,045)	4,673$^{\xi ***}$	Podpora za H5b
	OU → UPP	0,330 (0,060)			
UI → IPPP → UO	UI → IPPP	0,304 (0,058)	0,106*** (0,034)	4,076$^{\xi ***}$	Podpora za H6a
	IPPP → UO	0,350 (0,054)			
UI → IPPP → UPP	UI → IPPP	0,304 (0,058)	–0,013 (0,023)	–0,622$^{\xi}$	Ni podpore za H6b
	IPPP → UPP	–0,042 (0,067)			
UI → IPPR → UO	UI → IPPR	0,241 (0,052)	0,021 (0,023)	1,237$^{\xi}$	Ni podpore za H7a
	IPPR → UO	0,086 (0,067)			
UI → IPPR → UPP	UI → IPPR	0,241 (0,052)	0,099*** (0,031)	3,410$^{\xi ***}$	Podpora za H7b
	IPPR → UPP	0,413 (0,082)			

+ Standardne napake pri zagonu so navedene v oklepajih. *p < 0,05, **p < 0,01, ***p < 0,001. $^{\xi}$2-repna Z-ocena = $\frac{a*b}{\sqrt{b^2*SEa^2+a^2*SEb^2}}$ za enkratni mediacijski učinek. ~ Neposredni učinek ni statistično značilen.

Vir: lastno delo.

Brez mediatorjev KAPP, OU, IPPP in IPPR je vpliv UO na UPP in UP pozitiven in statistično značilen, vendar pa analiza celotnega modela ne razkrije pomembnega neposrednega vpliva privzemanja UI na UO. Kljub temu lahko v Table 86 opazimo, da je posredni vpliv OU pozitiven, ko je postavljen kot sekundarni mediator v zaporednih razmerjih večkratne mediacije. UO ima torej mediacijsko vlogo in je v celoti mediiran.

Podobno je vpliv UI na UP, mediiran s strani UPP, pozitiven in statistično značilen, če izključimo mediatorje KPPA, OU, IPPP, IPPR in UO. To ne velja pri analizi celotnega modela. V Table 86 lahko opazimo, da je mediacijski učinek UPP pozitiven, ko je postavljen kot sekundarni mediator v zaporednih razmerjih večkratne mediacije. UPP ima mediacijsko vlogo in je v celoti mediirana.

Tabela 3: Rezultati analize zaporedne večkratne mediacije, tj. zaporedni mediacijski učinki

Pot	**Relacije**	**Nestandardizirane uteži**	**Učinek**	**Z-ocena**
UI → KAPP → UO → UP	UI → KAPP	0,715 (0,063)	$0{,}022^{*}$ (0,012)	$1{,}981^{\xi\xi*}$
	KAPP → UO	0,146 (0,063)		
	UO → UP	0,215 (0,053)		
UI → KAPP → UO → UPP → UP	UI → KAPP	0,715 (0,063)	$0{,}013^{*}$ (0,008)	
	KAPP → UO	0,146 (0,063)		
	UO → UPP	0,278 (0,079)		
	UPP → UP	0,455 (0,048)		
UI → OU → UO → UP	UI → OU	0,576 (0,065)	$0{,}040^{***}$ (0,013)	$3{,}261^{\xi\xi***}$
	OU → UO	0,321 (0,046)		
	UO → UP	0,215 (0,053)		
UI → OU → UO → UPP → UP	UI → OU	0,576 (0,065)	$0{,}023^{**}$ (0,010)	
	OU → UO	0,321 (0,046)		
	UO → UPP	0,278 (0,079)		
	UPP → UP	0,455 (0,048)		
UI → OU → UPP → UP	UI → OU	0,576 (0,065)	$0{,}086^{***}$ (0,024)	$4{,}191^{\xi\xi***}$
	OU → UPP	0,330 (0,060)		
	UPP → OP	0,455 (0,048)		
UI → IPPP → UO → OP	UI → IPPP	0,304 (0,058)	$0{,}023^{***}$ (0,010)	$2{,}875^{\xi\xi**}$
	IPPP → UO	0,350 (0,054)		
	UO → UP	0,215 (0,053)		
UI → IPPP → UO → UPP → UP	UI → IPPP	0,304 (0,058)	$0{,}013^{***}$ (0,006)	
	IPPP → UO	0,350 (0,054)		
	UO → UPP	0,278 (0,079)		
	UPP → UP	0,455 (0,048)		
UI → IPPR → UPP → UP	UI → IPPR	0,241 (0,052)	$0{,}045^{***}$ (0,016)	$3{,}209^{\xi\xi***}$
	IPPR → UPP	0,413 (0,082)		
	UPP → UP	0,455 (0,048)		

+ Standardne napake pri zagonu so navedene v oklepajih. *p < 0,05, **p < 0,01, ***p < 0,001. $^{\xi\ \xi}$ 2-repna Z-ocena = $\frac{a*b*c}{\sqrt{a^2*b^2*SEc^2+a^2*c^2*SEb^{2+}b^2*c^2*SEa^2}}$ za učinek zaporedne večkratne mediacije.

Vir: lastno delo.

Iz Table 86 je razvidno, da posamezne zaporedne (verižne) relacije KAPP, OU, IPPP, IPPR, UO in UPP vzpostavljajo povezavo med UI in UP. Statistično neznačilno neposredno razmerje, ki ga določa H1, kaže, da je razmerje med UI in UP v celoti mediirano.

Pri kontrolnih spremenljivkah le velikost organizacije pomembno vpliva na spremenljivki UP in OU. Večje organizacije dosegajo višjo raven uspešnosti kot manjše. Nasprotno pa je OU v večjih organizacijah na nižji ravni. Druge kontrolne spremenljivke niso bile statistično značilne.

4.3 Moderirani učinki

Preučili smo moderacijsko vlogo zrelosti managementa poslovnih procesov (ZMPP), digitalne zrelosti, podatkovno vodene kulture (PVK) in organizacijske kulture (klanovska, adhokracija, tržna, hierarhična) na vseh konceptualnih poteh med latentnimi spremenljivkami. Po izključitvi nepomembnih interakcij predstavljamo značilne moderirane učinke.

Študija je ocenila vlogo ZMPP kot moderatorja na povezavi med UI in OU, kjer so rezultati pokazali statistično značilen negativen vpliv ZMPP (β = –0,148, t = –3,579, p < 0,001). Podobno tudi za povezavo med OU in IPPP, kjer so rezultati pokazali statistično značilen negativen vpliv ZMPP (β = –0,151, t = –3,628, p < 0,001).

Rezultati so potrdili vlogo PUK kot moderatorja na povezavi med IPPP in UPP. Razkrili so tudi statistično značilen pozitiven vpliv (β = 0,098, t = 2,422, p < 0,05).

5 RAZPRAVA IN SKLEPI

Čeprav sta tehnologiji velepodatkov in UI v ospredju IT-investicij, mehanizmi in pogoji, ki ustvarjajo poslovno vrednost, v empiričnih raziskavah na splošno ostajajo neraziskani. Nedavne raziskave poudarjajo potrebo po napredku z uporabo ustreznih mediacijskih spremenljivk za razumevanje razmerja med viri UI, zmogljivostmi MPP in UP.

5.1 Razprava in teoretični prispevki

Na podlagi uveljavljenega modela poslovne vrednosti IT smo z uporabo kontekstualnega teoretiziranja model preslikali v kontekst tehnologije UI. Z uporabo kompleksnega nomološkega ogrodja smo vključili več perspektiv za ustvarjanje poslovne vrednosti iz investicij v UI, s čimer smo obogatili nastajajočo literaturo o UI.

Najprej predstavimo alternativni koncept privzemanja UI, da bi zajeli bolj natančen in splošno veljaven pogled vpliva UI na UP. Eksogena, komponentno zasnovana spremenljivka, je povezana z ravnijo implementacije, dejanske uporabe ali izkoriščanjem specifičnih aplikacij in tehnologij UI. V nadaljevanju ta študija razširja razvijajočo se literaturo o UI s tem, da ponuja nomološko mrežo, ki povezuje privzemanje UI z UP. Medtem ko predhodne raziskave domnevajo delni mediacijski vpliv privzemanja UI na uspešnost poslovanja, mediiran s strani organizacijskih zmogljivosti, povezanih s kreativnostjo in agilnostjo (Kim et al., 2022; Mikalef & Gupta, 2021; Mishra et al., 2022; Wamba, 2022), naše ugotovitve potrjujejo, da je ta vpliv odvisen od zmogljivosti MPP, UO in UPP. S postavitvijo avtomatizacije, kot pomembnega mediatorja, smo konceptualizirali in operacionalizirali koncept KAPP. V kontekstu MPP z merjenjem ravni in obsega avtomatizacije razumemo sposobnost organizacije za avtomatizacijo poslovnih procesov, ki temeljijo na znanju. Nazadnje smo z obsežno raziskavo organizacij iz EU empirično dokazali pozitiven vpliv privzemanja UI na uspešnost poslovanja.

Različni avtorji (Raisch & Krakowski, 2021) teoretizirajo, da je popolna avtomatizacija kompleksnih procesov odločanja zaradi tehničnih in socialnih omejitev zahtevna. Naši rezultati kažejo, da privzemanje UI v resnici večinoma vodi k avgmentaciji in izboljšanju procesov odločanja. Predvsem je odločanje v celoti odvisno od avtomatizacije procesov in organizacijskega učenja, dveh inherentnih značilnosti UI, odločanja in inženiringa znanja. Ugotovitve kažejo, da privzemanje UI enako vpliva na postopno in radikalno inovacijo, zato je primerno za vzpostavitev uravnotežene in ambidekstralne postavitve za spodbujanje raziskovanja in izkoriščanja znanja ter tehnologije. Kot je splošno priznano v literaturi, naši empirični dokazi potrjujejo, da postopne izboljšave vplivajo na učinkovitost odločanja, radikalne izboljšave pa bistveno povečajo učinkovitost procesov.

5.2 Ključni prispevki za prakso

Rezultati poudarjajo pet različnih zmogljivosti UI, ki vplivajo na poslovanje:

- Visoko razvita *zmogljivost pridobivanja in predobdelave podatkov* je temelj za uspešne projekte UI.
- *Pridobivanje in interpretacija vpogledov* (angl. insights) sta predvsem povezana z napovednim modeliranjem, ki temelji na UI.
- Sposobnost *UI omogočene podpore interakcij med človekom in računalnikom* za napredno sodelovanje s strankami in zaposlenimi.
- Sposobnost *avgmentacije in avtomatizacije procesov odločanja* prek sistemov za avtomatizacijo odločanjam omogočenih z UI, inženiringa znanja, ekspertnih sistemov in sistemov za podporo odločanju.
- *Sposobnost integracije tehnologij UI* z obstoječimi IT-viri, storitvami in napravami.

Rezultati so potrdili predlagani polni zaporedni model večkratne mediacije, kar pomeni, da privzemanje UI posredno vpliva na UP. Managerji lahko pričakujejo največji vpliv na učinkovitost in kakovost procesov, čeprav nekoliko manj na prilagodljivost procesov. Na operativni ravni se vrednost kaže v povečani učinkovitosti izvajanja procesov prek hitrosti, obsega, natančnosti in podrobnosti obdelave informacij. UO smo obravnavali kot ločen konstrukt in njegovo vlogo mediatorja med privzemanjem UI in UPP. Ugotovitve kažejo, da UI bistveno vpliva na odločanje, izboljšuje kakovost, hitrost in učinkovitost (na primer, hitrejše pridobivanje in distribucija znanja) v operativnih procesih in na strateški ravni ter tako neposredno vpliva na UP.

Glede dileme avtomatizacija ali avgmentacija je bilo ugotovljeno, da je splošno stanje avtomatizacije poslovnih procesov v organizacijah na nadzorni in podporni ravni odločanja za strukturirane in nestrukturirane procese. To pomeni, da čeprav KAPP nima pomembnega neposrednega vpliva na UPP glede učinkovitosti izvajanja ali razširljivosti, ima v nasprotju s tem pričakovano pomemben neposreden vpliv na UO. Vpliv privzemanja UI je viden predvsem na koncu spektra sodelovanja med človekom in računalnikom (avgmentacija) v obliki bolj učinkovitega odločanja.

Preučili smo vpliv UI na znanje v organizaciji z mediatorjem OU. Rezultati potrjujejo vpliv prek UI omogočenih in povečanih zmogljivosti managementa znanja na UO, UPP (prek procesov, ki temeljijo na znanju) in IPP. Ugotavljamo, da je OU mediator med privzemanjem UI in postopno ter radikalno IPP. To bi lahko nakazovalo, da je UI posebna tehnologija, ki lahko hkrati omogoča in spodbuja izkoriščanje ter raziskovanje inovacij v procesih, kar managerjem pomaga doseči izmuzljivo ambidekstralno organizacijo (prek procesa privzemanja UI) – ta pa glede učinkovitosti in uspešnosti poslovanja presega druge organizacijske tipe (O'Reilly III & Tushman, 2011).

Transformativni učinki privzemanja UI so ugotovljeni z mediatorjem postopnih izboljšav procesov, ki pomembno vpliva na UO, medtem ko radikalne izboljšave procesov neposredno vplivajo na UPP. Ugotovitve so v skladu z obstoječimi raziskavami o inovacijah procesov (Cao & Jiang, 2022), kar kaže, da so postopne izboljšave večinoma povezane z odločanjem s pomočjo UI in imajo manjši vpliv na učinkovitost kot radikalne izboljšave, kjer se UI uporablja za zasnovo novih ali preoblikovanje obstoječih procesov, kar ima največji vpliv na učinkovitost izvajanja procesov. Tako bi morale organizacije dati prednost razvoju znanja in spretnosti na področju UI, da bi zaposleni lahko učinkovito spodbujali postopne in radikalne izboljšave s pomočjo orodij UI.

Nazadnje predstavljene ugotovitve kažejo potrebo, da se managerji odločijo za strukturiran pristop k širšemu privzemanju UI, vključujoč vse organizacijske procese. Managerji naj upoštevajo pet predlaganih zmogljivosti, omogočenih z UI, in obravnavajo avtomatizacijo procesov, inovacije in organizacijsko učenje kot ključne sposobnosti MPP za ustvarjanje poslovne vrednosti iz UI, preden lahko pričakujejo merljivo povečanje uspešnosti poslovanja.

5.3 Omejitve raziskave in smernice prihodnjega raziskovanja

Raziskava ni brez omejitev. Za potrditev predlaganega raziskovalnega modela smo uporabili presečno raziskavo. Za to raziskovalno zasnovo so značilne omejitve, kot sta pristranskost pri samoocenjevanju in samoporočanju ter endogenost (Jordan & Troth, 2020). V nadaljnjih raziskavah bi lahko razmislili o longitudinalnem pristopu, da bi ugotovili razlike pred in po privzemanju UI. Po drugi strani bi raziskava s študijami primerov lahko rešila vprašanja endogenosti, vendar to ne bi prispevalo k posploševanju ugotovitev. Ker raziskava temelji le na merjenju zaznane učinkovitosti in uspešnosti, bi bilo priporočljivo v nadaljnjih raziskavah uporabiti tudi nekatere objektivne kazalnike za izboljšanje natančnosti rezultatov. Pridobivanje objektivnih meritev za široko zastavljeno raziskavo je sicer zahtevno. Dodatna omejitev raziskave je, da se opira na enega samega respondenta iz vsake organizacije. Za triangulacijo bolj zanesljivih meritev bi lahko uporabili več respondentov ali različne vire podatkov iz določene organizacije. Nazadnje, v organizacijah se lahko vloge zapolnijo z algoritmi UI, kar nakazuje nove zahteve glede preglednosti in predvidljivosti pri izvajanju. Algoritmi UI morda ne bodo več delovali v predvidljivih kontekstih, kar zahteva zagotavljanje varnosti in inženiring etičnih premislekov glede UI. Prihodnje raziskave bi zato morale proučiti socialne posledice ter etične in moralne dileme, povezane z UI in njeno uporabo.

Appendix 2: Supplemental Materials

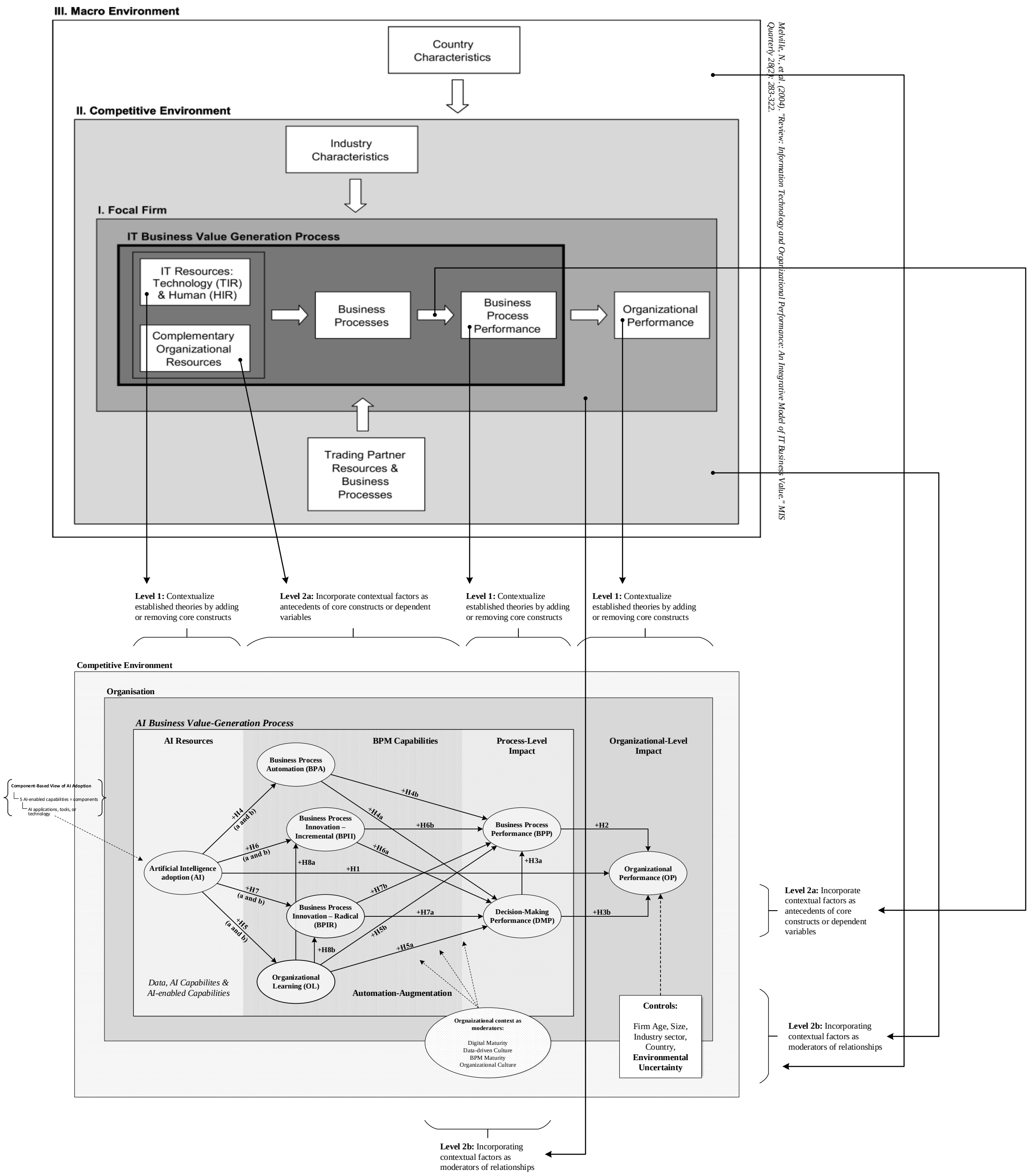
#	Filename	Description
1	Zebec (2023) Data Sample80.sav	The pilot study data for AI adoption and CBPA validation. The sample size is 80. SPSS Statistics data file.
2	Zebec (2023) CBPA First-Order Initial Formal Measurement Model Sample80.amw	CBPA first-order initial formal measurement model. Data source: pilot study data. AMOS syntax file.
3	Zebec (2023) CBPA First-Order Abridged Formal Measurement Model Sample80.amw	CBPA first-order abridged formal measurement model. Data source: pilot study data. AMOS syntax file.
4	Zebec (2023) Data Sample451 Remove3.sav	Main study data. The sample size is 451. Includes later removed cases 482, 2310, and 2509. SPSS Statistics data file.
5	Zebec (2023) Data Sample451 Remove3 NonResponse200.sav	The main study data. The sample size is 651 (451 valid cases and 200 nonresponse cases). Includes later removed cases 482, 2310, 2509. SPSS Statistics data file.
6	Zebec (2023) Data Sample448.sav	The main study data. The sample size is 448. SPSS Statistics data file.
7	Zebec (2023) Data Sample448 NonResponse200.sav	The main study data. The sample size is 648 (448 valid cases and 200 nonresponse cases). SPSS Statistics data file.
8	Zebec (2023) CBPA First-Order Final Formal Measurement Model Sample448.amw	CBPA first-order final formal measurement model. Data source: main study data. AMOS syntax file.
9	Zebec (2023) CBPA First-Order Final Formal Measurement Model Nomological Validity Sample448.amw	CBPA first-order nomological validity model. Data source: main study data. AMOS syntax file.
10	Zebec (2023) AI Adoption Second-Order Formal Measurement Model Sample80.amw	AI adoption second-order initial formal measurement model. Data source: pilot study data. AMOS syntax file.
11	Zebec (2023) AI Adoption First-Order Initial Formal Measurement Model Sample80.amw	AI adoption first-order initial formal measurement model. Data source: pilot study data. AMOS syntax file.
12	Zebec (2023) AI Adoption First-Order Abridged Formal Measurement Model Sample80.amw	AI adoption first-order abridged formal measurement model. Data source: pilot study data. AMOS syntax file.
13	Zebec (2023) AI Adoption First-Order Abridged Formal Measurement Model CMV Sample80.amw	AI adoption first-order abridged formal measurement model with common method variance test. Data source: pilot study data. AMOS syntax file.
14	Zebec (2023) AI Adoption Second-Order Formal Measurement Model Sample 80.amw	AI adoption second-order formal measurement model. Data source: pilot study data. AMOS syntax file.
15	Zebec (2023) AI Adoption Formal Measurement Model final One-Factor CMV Sample80.amw	AI adoption one-factor formal measurement model. Data source: pilot study data. AMOS syntax file.
16	Zebec (2023) AI Adoption Second-Order Formal Measurement Model Sample448.amw	AI adoption second-order final formal measurement model. Data source: main study data. AMOS syntax file.
17	Zebec (2023) AI Adoption Second-Order Formal Measurement Model Nomological Validity Sample448.amw	AI adoption second-order nomological validity. Data source: main study data. AMOS syntax file.
18	Zebec (2023) Formal Measurement Model.amw	Formal measurement model. Data ource: main study data; N = 451. AMOS syntax file.
19	Zebec (2023) Formal Measurement Model Common Latent Factor.amw	Formal measurement model with common latent factor test. Data source: main study data; N = 451. AMOS syntax file.
20	Zebec (2023) Formal Measurement Model Harman Single Factor.amw	Formal measurement model with Harman single factor test. Data source: main study data; N = 451. AMOS syntax file.
21	Zebec (2023) Structural Model With Controls.amw	Structural model with controls. Data source: Main study data; N = 448. AMOS syntax file.
22	Zebec (2023) Structural Model Total Effect With Controls.amw	Structural model total effect with controls. Data source: main study data; N = 448. AMOS syntax file.
23	Zebec (2023) Structural Model Without Mediators With Controls.amw	Structural model without mediators and with controls. Data source: main study data; N = 448. AMOS syntax file.
24	Zebec (2023) Structural Model With Moderators With Controls Mean.amw	Structural model with moderators (mean) and with controls. Data source: main study data; N = 448. AMOS syntax file.
25	Zebec (2023) Structural Model With Moderators With Controls Low.amw	Structural model with moderators (low) and with controls. Data source: main study data; N = 448. AMOS syntax file.
26	Zebec (2023) Structural Model With Moderators With Controls High.amw	Structural model with moderators (high) and with controls. Data source: main study data; N = 448. AMOS syntax file.

27	Zebec (2023) Assessment Report.pdf	An example of a preliminary assessment report with personalized results.
28	Zebec (2023) GDPR.pdf	Privacy and GDPR compliance statement for the questionnaire. An explanation of how the respondent's data will be collected, stored, and used, including any third-party processors with access the data.
29	Zebec (2023) Informed Consent.pdf	Informed consent form from conducted interviews.
30	Zebec (2023) Semi-Structured Interview Guide.xlsx	The semi-structured interview guide.
31	Zebec (2023) Invitation Letter.pdf	The survey invitation letter.

Supplemental materials are available at https://www.buyitc.si/documents/supplemental_materials.zip (password AIBusinessValue).

Source: Own work.

Appendix 3: Contextualization procedure



Source: Own work.

Appendix 4: Initial Anti-Image Correlation Matrix

	DACQ	CI	CE	CDA	CT	CBPA1	LEVEL	EXTENT	OL1	OL2	OL3	OL4	IPII	IPIII	RAD1	RAD2	EFFC	EFFT	BPP1	BPP2	BPP3	OPER	MP
DACQ	**0.926**[a]	-0.165	-0.068	-0.114	-0.281	-0.041	-0.094	0.070	-0.049	-0.009	0.074	-0.029	-0.093	0.016	0.038	0.078	0.056	-0.027	-0.082	0.012	0.105	-0.002	-0.036
CI	-0.165	**0.906**[a]	-0.303	-0.073	0.111	-0.144	0.139	-0.089	-0.002	-0.017	0.031	0.008	0.013	-0.031	-0.022	0.007	0.006	-0.008	0.039	0.004	-0.009	-0.031	-0.102
CE	-0.068	-0.303	**0.920**[a]	-0.237	-0.271	0.043	-0.073	-0.098	-0.010	0.040	-0.025	-0.068	0.023	0.001	0.068	-0.067	0.025	0.005	0.003	0.012	-0.009	-0.057	0.045
CDA	-0.114	-0.073	-0.237	**0.939**[a]	-0.270	-0.077	-0.028	-0.105	0.050	-0.009	-0.066	0.112	0.008	0.025	-0.142	0.055	-0.078	-0.055	-0.047	0.021	0.021	0.033	0.005
CT	-0.281	0.111	-0.271	-0.270	**0.918**[a]	-0.268	0.016	-0.014	-0.071	0.017	-0.001	-0.049	-0.032	0.033	0.000	-0.038	0.049	-0.037	0.049	-0.085	0.024	-0.002	0.035
CBPA1	-0.041	-0.144	0.043	-0.077	-0.268	**0.939**[a]	-0.256	-0.121	-0.046	-0.052	0.052	0.055	-0.108	-0.005	0.110	-0.124	-0.147	0.100	0.001	-0.063	-0.021	0.010	0.026
LEVEL	-0.094	0.139	-0.073	-0.028	0.016	-0.256	**0.882**[a]	-0.425	-0.022	0.017	-0.041	0.056	0.088	-0.059	-0.072	0.060	0.053	-0.080	0.058	0.003	-0.064	0.017	-0.073
EXTENT	0.070	-0.089	-0.098	-0.105	-0.014	-0.121	-0.425	**0.911**[a]	-0.022	0.033	0.028	0.003	-0.084	0.050	-0.093	-0.020	-0.036	-0.025	-0.087	0.059	0.070	0.090	-0.081
OL1	-0.049	-0.002	-0.010	0.050	-0.071	-0.046	-0.022	-0.022	**0.932**[a]	-0.479	-0.241	0.005	-0.100	0.052	-0.049	0.025	-0.010	0.026	-0.007	-0.094	0.018	-0.043	-0.053
OL2	-0.009	-0.017	0.040	-0.009	0.017	-0.052	0.017	0.033	-0.479	**0.910**[a]	-0.269	-0.227	0.043	-0.026	-0.030	-0.024	0.024	-0.039	-0.098	0.127	-0.119	-0.075	0.058
OL3	0.074	0.031	-0.025	-0.066	-0.001	0.052	-0.041	0.028	-0.241	-0.269	**0.938**[a]	-0.192	-0.053	0.048	0.113	-0.137	0.004	-0.056	0.047	-0.037	0.002	0.038	-0.099
OL4	-0.029	0.008	-0.068	0.112	-0.049	0.055	0.056	0.003	0.005	-0.227	-0.192	**0.948**[a]	-0.014	-0.089	0.006	0.039	-0.104	-0.141	0.062	-0.126	-0.071	0.073	-0.007
IPII	-0.093	0.013	0.023	0.008	-0.032	-0.108	0.088	-0.084	-0.100	0.043	-0.053	-0.014	**0.893**[a]	-0.625	-0.116	0.017	-0.022	-0.077	0.018	-0.083	0.065	0.034	-0.002
IPIII	0.016	-0.031	0.001	0.025	0.033	-0.005	-0.059	0.050	0.052	-0.026	0.048	-0.089	-0.625	**0.873**[a]	0.015	-0.114	-0.052	-0.088	-0.027	0.086	-0.022	-0.114	0.081
RAD1	0.038	-0.022	0.068	-0.142	0.000	0.110	-0.072	-0.093	-0.049	-0.030	0.113	0.006	-0.116	0.015	**0.880**[a]	-0.461	-0.021	0.038	0.116	-0.082	-0.048	-0.074	-0.031
RAD2	0.078	0.007	-0.067	0.055	-0.038	-0.124	0.060	-0.020	0.025	-0.024	-0.137	0.039	0.017	-0.114	-0.461	**0.911**[a]	0.005	-0.034	-0.165	-0.018	0.005	0.092	-0.077
EFFC	0.056	0.006	0.025	-0.078	0.049	-0.147	0.053	-0.036	-0.010	0.024	0.004	-0.104	-0.022	-0.052	-0.021	0.005	**0.907**[a]	-0.600	-0.137	0.079	-0.131	-0.147	0.055
EFFT	-0.027	-0.008	0.005	-0.055	-0.037	0.100	-0.080	-0.025	0.026	-0.039	-0.056	-0.141	-0.077	-0.088	0.038	-0.034	-0.600	**0.912**[a]	0.051	-0.038	0.008	0.052	-0.074
BPP1	-0.082	0.039	0.003	-0.047	0.049	0.001	0.058	-0.087	-0.007	-0.098	0.047	0.062	0.018	-0.027	0.116	-0.165	-0.137	0.051	**0.914**[a]	-0.514	-0.135	-0.100	-0.076
BPP2	0.012	0.004	0.012	0.021	-0.085	-0.063	0.003	0.059	-0.094	0.127	-0.037	-0.126	-0.083	0.086	-0.082	-0.018	0.079	-0.038	-0.514	**0.900**[a]	-0.295	-0.166	0.060
BPP3	0.105	-0.009	-0.009	0.021	0.024	-0.021	-0.064	0.070	0.018	-0.119	0.002	-0.071	0.065	-0.022	-0.048	0.005	-0.131	0.008	-0.135	-0.295	**0.944**[a]	0.061	-0.079
OPER	-0.002	-0.031	-0.057	0.033	-0.002	0.010	0.017	0.090	-0.043	-0.075	0.038	0.073	0.034	-0.114	-0.074	0.092	-0.147	0.052	-0.100	-0.166	0.061	**0.886**[a]	-0.565
MP	-0.036	-0.102	0.045	0.005	0.035	0.026	-0.073	-0.081	-0.053	0.058	-0.099	-0.007	-0.002	0.081	-0.031	-0.077	0.055	-0.074	-0.076	0.060	-0.079	-0.565	**0.888**[a]

Note: a. Measures of Sampling Adequacy

Source: Own work.

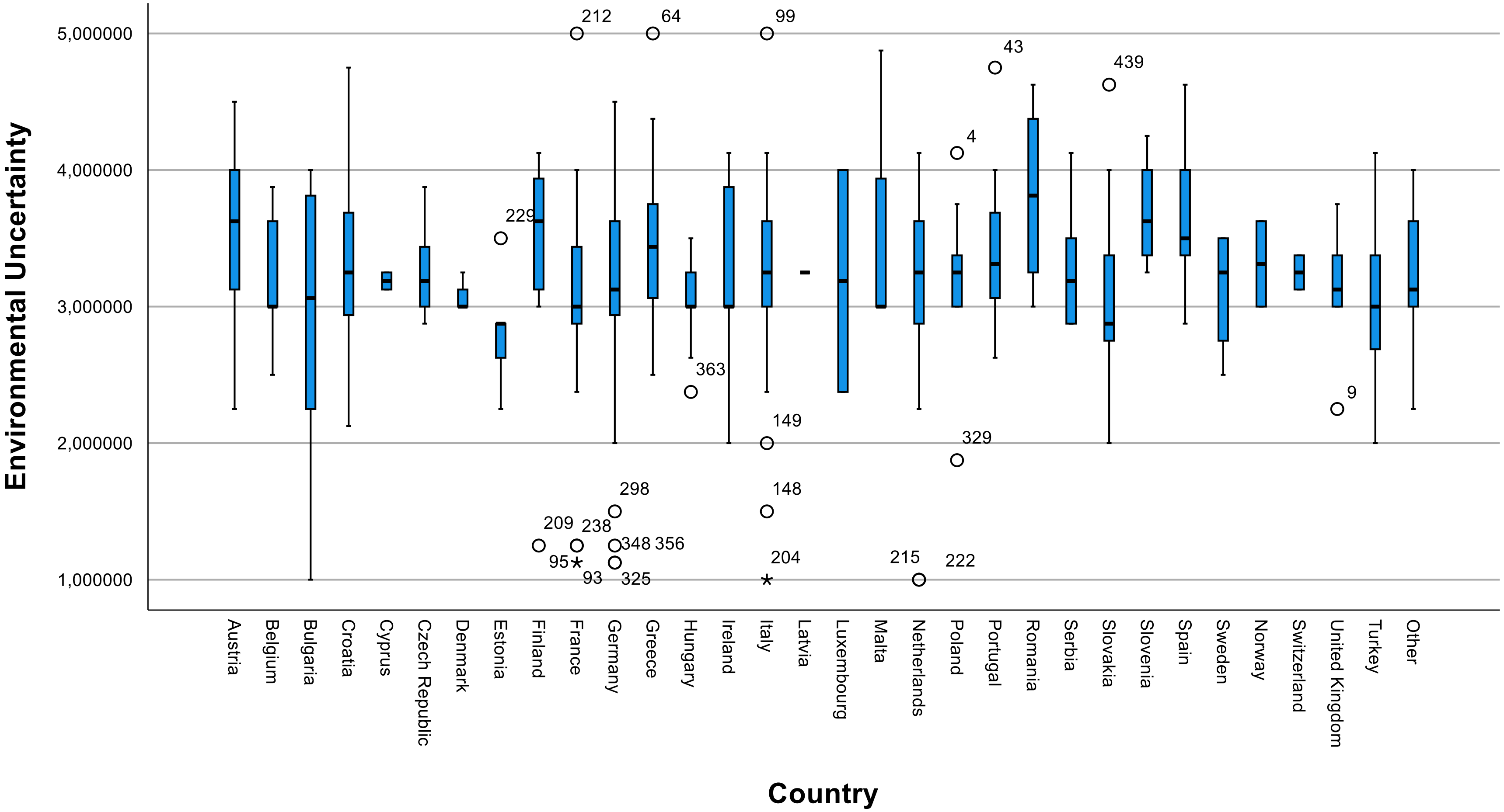
Appendix 5: Final Anti-Image Correlation Matrix

	DACQ	CI	CE	CDA	CT	LEVEL	EXTENT	OL1	OL2	OL3	OL4	IPII	IPIII	RAD1	RAD2	EFFC	EFFT	BPP1	BPP2	BPP3	OPER	MP
DACQ	**0.913**[a]	-0.172	-0.067	-0.117	-0.303	-0.108	0.066	-0.051	-0.012	0.077	-0.027	-0.098	0.016	0.043	0.073	0.050	-0.023	-0.082	0.009	0.104	-0.002	-0.035
CI	-0.172	**0.911**[a]	-0.300	-0.085	0.075	0.107	-0.109	-0.009	-0.025	0.039	0.016	-0.003	-0.032	-0.006	-0.011	-0.015	0.006	0.040	-0.005	-0.012	-0.030	-0.099
CE	-0.067	-0.300	**0.916**[a]	-0.235	-0.270	-0.064	-0.094	-0.008	0.043	-0.027	-0.070	0.028	0.001	0.064	-0.063	0.031	0.001	0.003	0.015	-0.008	-0.058	0.044
CDA	-0.117	-0.085	-0.235	**0.928**[a]	-0.302	-0.049	-0.115	0.047	-0.014	-0.062	0.117	0.000	0.024	-0.135	0.046	-0.091	-0.047	-0.047	0.016	0.020	0.034	0.007
CT	-0.303	0.075	-0.270	-0.302	**0.917**[a]	-0.057	-0.049	-0.086	0.003	0.014	-0.035	-0.063	0.033	0.031	-0.075	0.010	-0.011	0.051	-0.106	0.019	0.001	0.043
LEVEL	-0.108	0.107	-0.064	-0.049	-0.057	**0.880**[a]	-0.476	-0.035	0.004	-0.028	0.073	0.063	-0.063	-0.046	0.029	0.016	-0.056	0.061	-0.014	-0.072	0.020	-0.069
EXTENT	0.066	-0.109	-0.094	-0.115	-0.049	-0.476	**0.889**[a]	-0.028	0.026	0.034	0.009	-0.098	0.050	-0.081	-0.035	-0.055	-0.013	-0.087	0.052	0.068	0.092	-0.078
OL1	-0.051	-0.009	-0.008	0.047	-0.086	-0.035	-0.028	**0.929**[a]	-0.482	-0.239	0.007	-0.106	0.052	-0.044	0.019	-0.017	0.030	-0.007	-0.097	0.017	-0.042	-0.052
OL2	-0.012	-0.025	0.043	-0.014	0.003	0.004	0.026	-0.482	**0.908**[a]	-0.267	-0.225	0.037	-0.027	-0.024	-0.031	0.016	-0.034	-0.098	0.124	-0.121	-0.074	0.059
OL3	0.077	0.039	-0.027	-0.062	0.014	-0.028	0.034	-0.239	-0.267	**0.937**[a]	-0.195	-0.048	0.048	0.108	-0.132	0.012	-0.062	0.047	-0.034	0.003	0.038	-0.100
OL4	-0.027	0.016	-0.070	0.117	-0.035	0.073	0.009	0.007	-0.225	-0.195	**0.946**[a]	-0.008	-0.089	0.000	0.046	-0.097	-0.148	0.062	-0.123	-0.070	0.072	-0.009
IPII	-0.098	-0.003	0.028	0.000	-0.063	0.063	-0.098	-0.106	0.037	-0.048	-0.008	**0.889**[a]	-0.630	-0.106	0.003	-0.039	-0.067	0.018	-0.090	0.063	0.036	0.000
IPIII	0.016	-0.032	0.001	0.024	0.033	-0.063	0.050	0.052	-0.027	0.048	-0.089	-0.630	**0.867**[a]	0.016	-0.115	-0.053	-0.088	-0.027	0.086	-0.022	-0.114	0.081
RAD1	0.043	-0.006	0.064	-0.135	0.031	-0.046	-0.081	-0.044	-0.024	0.108	0.000	-0.106	0.016	**0.886**[a]	-0.453	-0.005	0.027	0.117	-0.075	-0.046	-0.075	-0.034
RAD2	0.073	-0.011	-0.063	0.046	-0.075	0.029	-0.035	0.019	-0.031	-0.132	0.046	0.003	-0.115	-0.453	**0.912**[a]	-0.014	-0.022	-0.166	-0.026	0.002	0.094	-0.074
EFFC	0.050	-0.015	0.031	-0.091	0.010	0.016	-0.055	-0.017	0.016	0.012	-0.097	-0.039	-0.053	-0.005	-0.014	**0.908**[a]	-0.594	-0.138	0.071	-0.136	-0.147	0.060
EFFT	-0.023	0.006	0.001	-0.047	-0.011	-0.056	-0.013	0.030	-0.034	-0.062	-0.148	-0.067	-0.088	0.027	-0.022	-0.594	**0.913**[a]	0.051	-0.032	0.010	0.051	-0.077
BPP1	-0.082	0.040	0.003	-0.047	0.051	0.061	-0.087	-0.007	-0.098	0.047	0.062	0.018	-0.027	0.117	-0.166	-0.138	0.051	**0.911**[a]	-0.515	-0.135	-0.100	-0.076
BPP2	0.009	-0.005	0.015	0.016	-0.106	-0.014	0.052	-0.097	0.124	-0.034	-0.123	-0.090	0.086	-0.075	-0.026	0.071	-0.032	-0.515	**0.896**[a]	-0.297	-0.166	0.062
BPP3	0.104	-0.012	-0.008	0.020	0.019	-0.072	0.068	0.017	-0.121	0.003	-0.070	0.063	-0.022	-0.046	0.002	-0.136	0.010	-0.135	-0.297	**0.942**[a]	0.061	-0.078
OPER	-0.002	-0.030	-0.058	0.034	0.001	0.020	0.092	-0.042	-0.074	0.038	0.072	0.036	-0.114	-0.075	0.094	-0.147	0.051	-0.100	-0.166	0.061	**0.882**[a]	-0.565
MP	-0.035	-0.099	0.044	0.007	0.043	-0.069	-0.078	-0.052	0.059	-0.100	-0.009	0.000	0.081	-0.034	-0.074	0.060	-0.077	-0.076	0.062	-0.078	-0.565	**0.884**[a]

Note: a. Measures of Sampling Adequacy

Source: Own work.

Appendix 6: Environment Uncertainty box and whisker plot by Country



Source: Own work.