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MASTER'S THESIS

THE ENTREPRENEUR'S NEW TOOLKIT: POTENTIAL BENEFITS, LIMITATIONS, AND IMPLICATIONS OF THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE

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AUTHORSHIP STATEMENT

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ABSTRACT

Generative artificial intelligence (GenAI), as an exciting entrepreneurial tool, provides considerable benefits, limitations, and wide implications. The study employs a mixed-methods approach, integrating survey data and semi-structured interviews, to investigate the impact of GenAI on creativity, innovation, knowledge, decision-making and entrepreneurial workflows. The findings indicate that GenAI promotes ideation, enhances decision-making, and increases efficiency. However, it also presents challenges related to responsible usage, ethics, and regulation. The thesis provides empirical evidence regarding the application of GenAI by entrepreneurs in their daily activities, the tools they predominantly utilise, the barriers hindering its adoption, and the strategies that facilitate more effective usage. In doing so, it shows how GenAI is changing the dynamics and what crucial factors will determine how it will be used responsibly in the future of entrepreneurship.

KEY WORDS: generative artificial intelligence, entrepreneurship, tools, efficiency, creativity and innovation

SUSTAINABLE DEVELOPMENT GOALS



POVZETEK

Generativna umetna inteligenca (GenAI) je razmeroma novo podjetniško orodje, ki prinaša velike koristi in možnosti, a ima hkrati tudi svoje omejitve. V raziskavi se uporablja mešan raziskovalni pristop, ki temelji na podatkih iz vprašalnikov in delno strukturiranih intervjujev. To omogoča vpogled v vpliv GenAI na ustvarjalnost, inovativnost, znanje in odločanje v podjetniških delovnih procesih. Ugotovitve kažejo, da GenAI spodbuja ideje, izboljšuje procese odločanja in povečuje učinkovitost. Vendar pa prinaša tudi izzive, povezane z odgovorno uporabo, etiko in regulativo. Empirični dokazi prikazujejo dnevno rabo orodij GenAI podjetnikov, ovire, ki zavirajo vpeljevanje le-teh v delovne procese, ter strategije za njihovo bolj učinkovito rabo. To kaže, kako lahko GenAI spreminja dinamiko poslovnih procesov ter nakazuje ključne dejavnike, ki so in bodo odločilni za njeno odgovorno in uspešno uporabo.

KLJUČNE BESEDE: generativna umetna inteligenca, podjetništvo, orodja, učinkovitost, kreativnost in inovativnost

CILJI TRAJNOSTNEGA RAZVOJA



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LIST OF ABBREVIATIONS

AGI – Artificial general intelligence

AI – Artificial intelligence

AIET – Enabled Individual Entrepreneurship theory

ANI – Artificial narrow intelligence

API – Application Programming Interface

B2B – Business-to-business

B2C – Business-to-consumer

CAQDAS – Assisted Qualitative Data Analysis Software

CISO – Chief Information Security Officer

CPU – Central processing unit

CRM – Customer Relationship Management

DL – Deep learning

DPO – Data Protection Officer

DSA – Digital Services Act

EU – European Union

GAN – Generative adversarial network

GDPR – General Data Protection Regulation

GenAI – Generative artificial intelligence

GEO – Generative engine optimisation

GPT – Generative Pre-trained Transformer

GPU – Graphics processing unit

H0 – Null hypotheses

H1 – Alternative hypotheses

HHI – Herfindahl-Hirschman Index

HR – Human Resources

ICT – Information and Communication Technologies

IP – Intellectual property

IPA – Interpretative Phenomenological Analysis

IT – Information technology

KM – Knowledge management

KMS – Knowledge management systems

KPI – Key Performance Indicator

LLM – Large language model

MBA – Master of Business Administration

ML – Machine learning

NGO – Non-governmental organisations

R&D – Research and development

ROI – Returns on investment

RQ – Research question

RTA –Reflexive thematic analysis

SD – Standard deviation

SEO – Search engine optimisation

SME – Small and midsize enterprise

SWOT – Strengths, Weaknesses, Opportunities, and Threats (analysis)

TA – Thematic analysis

UI – User interface

1 INTRODUCTION

Can you still tell if a text, picture, or decision was made by a human or by generative artificial intelligence (GenAI)? Such questions show what a tremendous change technology is going through as GenAI quickly spreads through business and society. Goldman Sachs (2023) predicts that the global GDP will grow by 7% in the next ten years, and Eloundou et al. (2023) say that 80% of U.S. workers will experience changes in their professions. Unsurprisingly, GenAI experienced the fastest adoption rate of any digital technology (Chatterji et al., 2025). It is being used in many areas of business, including marketing, customer service, product development, and management. Its advantages include content creation, tailored insights, and decision assistance, etc., which (could) lead to greater efficiency and lower knowledge barriers (Bouschery et al., 2023; Korzyński et al., 2023). Yet with it resurfaced problems that need to be addressed, such as bias, explainability gaps, regulatory uncertainty, and ethical and social dilemmas (Dwivedi et al., 2023). The changes and their implications are especially important for entrepreneurs. GenAI can speed up ideation, improve strategic planning and/or business models, and support communication tasks such as pitches and advertising, however, its value is always contingent on user proficiency, critical assessment, and responsible adoption and use (Short and Short, 2023).

Even with this potential, there is still a clear gap in research. Most studies focus on corporate AI adoption in large organisations, leaving entrepreneurs as well as small and medium-sized enterprises (SMEs) under-represented. Moreover, there has been no research specifically focused on Slovenian entrepreneurs, despite their resource constraints making GenAI adoption particularly pertinent. The aim of this thesis is to address the gap by providing empirical information on the adoption and utilisation of GenAI by Slovenian entrepreneurs, with the goal of evaluating both potential and limitations to guide practice and policy. To this end, it provides survey and interview data that paint a broader picture of its use cases, benefits, drawbacks and implications. The analysis builds on theoretical work in digital transformation, creativity and innovation, knowledge management, and responsible GenAI use. It connects the findings to broader academic debates while clarifying the study's scope (Slovenian entrepreneurs and entrepreneurially minded individuals) and compares those insights with perspectives from corporate stakeholders.

The study uses a mixed-methods approach that combines survey data with semi-structured interviews. This design attempts to achieve both generalisable patterns and nuanced, contextual insights, facilitating a thorough examination of entrepreneurial adoption. Research questions (RQ) that guide it are the following:

- RQ1: What are the potential applications of GenAI tools in entrepreneurship?
- RQ2: How does GenAI influence entrepreneurs' creativity and innovation?
- RQ3: How do different GenAI models and tools vary in their impact on entrepreneurial work?

- RQ4: What are the ethical, legal, and social implications and limitations of GenAI, and how can these be addressed responsibly?
- RQ5: What strategies and best practices enable effective adoption and use of GenAI across entrepreneurial processes and workflows?

2 GENERATIVE ARTIFICIAL INTELLIGENCE

To acquire an understanding of GenAI, the wider general field from which it stems – artificial intelligence (AI), must first be defined and explained. Artificial intelligence is a term that was first coined by McCarthy in the mid-1950s as "the science and engineering of making intelligent machines"; eventually, quite a few other distinguished scientists, such as Turing, Raphael, Minsky, and Rich, contributed their own version of the definition (Toosi et al., 2021). In the book titled Artificial Intelligence: A Modern Approach, Russell and Norvig (2022) propose four potential approaches to defining AI: acting humanly, thinking humanly, acting rationally, and thinking rationally. On the other hand, the McKinsey article (Batra et al., 2018) tries to define it as a "machine's ability to mimic human cognitive functions, including perception, reasoning, learning, and problem-solving."

2.1 Overview of AI development

The history of AI spans more than seven decades. It saw cycles of prosperity and decline, the so-called AI Summers/Winters (Toosi et al., 2021, p. 5). AI Summers can be categorised into three distinct phases (Noguchi et al., 2018, p. 73), the initial phase, "AI as Search Algorithms", which began after the Dartmouth Conference of 1956, often regarded as the birthplace of AI, and continued until the 1970s. The second phase, "Expert Systems Era" of the 1980s, and the current hype cycle that initially centred on machine learning and accelerated into the deep learning era in 2012. Public interest surged with AlphaGo in 2016, subsequently followed by the emergence of ChatGPT and other GenAI tools (Singh et al., 2024, p. 2; Russell and Norvig, 2022, pp. 44–45).

Thus, the next two important terms and subfields of AI are machine learning (ML) and its subsidiary deep learning (DL). Arthur Samuel (a computer scientist) first described ML in 1959 as a computer's ability to learn autonomously without explicit programming (Russell and Norvig, 2022, p. 37). ML algorithms, therefore, detect patterns and learn to make predictions and recommendations based on data processing and experiential learning, rather than through exact instructions (McKinsey and Company, 2024). Nonetheless, its potential was not truly recognised until the 1990s, when a gradual reunification of different subfields such as computer vision, robotics, natural language processing, and speech recognition, along with a renewed focus on data, statistical modelling, and optimisation, led to an improved understanding and outlook on AI (Russell and Norvig, 2022, pp. 37–44). DL, on the other hand, is an advanced version and a subfield of ML and refers to ML using multiple layers of adjustable computing elements (deep neural networks). It's primarily made to

process a wider range of data resources and often produces better results with less human intervention. This method was first used for speech recognition, then visual object recognition, and, with numerous breakthroughs, revived interest in AI among the general public, companies, investors, and governments (Russell and Norvig, 2022, pp. 44–45).

The development and evolution of those AI subfields represent the core technological advancements that unlocked the foundation upon which current AI tools are based. GenAI can also be characterised as the smallest subfield of AI that predominantly falls under the field of DL. Before covering the specifics of GenAI, it is essential to examine foundational aspects of AI, specifically the three technical inputs known as the AI triad: computing power, algorithms, and data, along with human capital, which encompasses talent and scientific expertise. These elements serve as key factors for AI development and, furthermore, contribute to the larger concept of Artificial General Intelligence (AGI) (Sastry et al., 2024, pp. 4–8).

Computing power, or compute, is significant in its singular importance for the development, growth and deployment of AI (as well as GenAI). As computational power increases, general AI performance improves as well, which drives its growth and appeal, especially in the case of large language models (LLMs). It can be defined as computing power that powers AI training and comes from the associated hardware and software. GPUs, which are now powered by general-purpose computer chips called Central Processing Units (CPUs), together with cloud access, enabled the third AI cycle by improving the efficiency, size, and performance of AI system training (particularly deep learning). High-end AI supercomputers now even require special-purpose cutting-edge GPUs (Sastry et al., 2024, pp. 1–2).

Relative to AI, data is defined as the raw material that is processed to train machine learning models and serves as the model's input to make predictions. It can also be said that it is the convergence point between advanced data science and cutting-edge AI technology (Dhoni, 2023, p. 1). On the other hand, Regulation (EU) 2023/2854 of the European Parliament and of the Council of 13 December 2023 on harmonised rules on fair access to and use of data (Data Act), OJ L 2854/22, Article 2, defines data as “any digital representation of acts, facts or information and any compilation of such acts, facts or information, including in the form of sound, visual or audio-visual recording”. AI-related terms include training and inference data. Zha et al. (2025, pp. 129:3, 129:4) define training data as the data utilised during the training phase. Regarding the ML approach, it allows the model to utilise the data for parameter adjustment and formulation of predictions. On the other hand, they define inference data as the data utilised during the inference phase of AI models. This is when the trained AI model uses novel input data to generate predictions (outputs). From this, it can be concluded that the better the quality and amount of the data, the more accurate the results, which in turn provides a higher utility to the users. The better the user experience and satisfaction, the more users there will be, demonstrating AI's enormous data dependence.

The concept of algorithms is as old as the 9th century, but it was not until the 19th century that algorithms were discussed for logical deduction as a way to formalise general mathematical reasoning (Russell and Norvig, 2022, p. 27). Algorithms now govern the processes applied to data, thereby determining the functional capabilities of AI. AI algorithms generate the source code that delineates both the models' architecture and the specific approaches utilised during training (Sastry et al., 2024, p. 8). In the last seventy years, the function of algorithms in AI has vastly developed and broadened. The most notable milestones in contemporary GenAI include the development of Generative Adversarial Networks (GANs) by Goodfellow and his research team in 2014, and the publication of "Attention is All You Need" by Vaswani in 2017, which introduced the transformer architecture. Concerning the public, the paramount development remains OpenAI's GPT series (Generative Pre-trained Transformers), initiated in 2018, as these models establish the benchmark for large language models (LLMs) that are transforming our comprehension and application of GenAI in contemporary contexts and advancing towards AGI (Rai, 2024, pp. 4–22).

The idea of AGI has fascinated philosophers, writers, developers, and scientists since computer technology was invented. Its meaning involved as much science fiction and myths as objectively grounded definitions. In early literature, superintelligence and ultra-intelligent machines meant "a machine that can far surpass all the intellectual activities of any man". Most definitions identify it as the next generation of artificial intelligence and separate it from ANI (artificial narrow intelligence), which is necessary because modern computerised intelligence exceeds human abilities in some areas. McLean et al. (2023) define AGI as a degree of intelligence, previously characterised as an agent's ability to achieve goals in different environments and complex settings; nevertheless, the absence of a scientific consensus on the notion of general intelligence renders the attempts to define AGI meaningless (Mueller, 2024, pp. 3–5).

GenAI encompasses computational methods capable of interacting, responding and generating content like text, code, images, video, and audio that appears to be new and meaningful (Feuerriegel et al, 2024, pp. 111–113; Sastry et al., 2024, p. 9). However, GenAI systems can not only generate creative content mimicking writers, illustrators, designers, and other creators, but can also assist humans as intelligent question-answering general-purpose systems (Feuerriegel et al., 2024, p. 111). This depicts not only a technological advancement but a fundamental paradigm shift and transformation happening in the intersection of digital technologies, its influence on humans (society), and the economy (Abendroth-Dias et al., 2025, pp. 7, 12).

The advancement of GenAI, or more exactly AI algorithms, which learn from extensive datasets, along with the accessibility of high-performance computing and improvements to deep learning architectures, has been crucial for the emerging paradigm shift (Abendroth-Dias et al., 2025, p. 7). More specifically, the rise of GenAI can be attributed to seminal research in machine learning and neural networks (Abendroth-Dias et al., 2025, p. 12), such

as Hinton, Rumelhart and Williams's 1986 paper titled "Learning Representations by Back-Propagating Errors"; the 2013 "Auto-Encoding Variational Bayes" paper by Kingma and Welling; Ian Goodfellow's 2014 paper "Generative Adversarial Nets"; Vaswani's 2017 paper "Attention is All You Need"; and others (Rai, 2024, pp. 12, 18). All relevant research and milestone events touching upon GenAI can be chronologically categorised into four stages: rule-based generative systems, model-based generative algorithms, deep generative methodologies, and foundation models (He et al., 2025, p. 1).

Rule-based generative systems generate data autonomously using expert-designed rules. These systems were only suitable for specific applications (Abendroth-Dias et al., 2025, p. 12). Model-based generative algorithms use statistical or physical models and build on machine learning, neural networks, computer vision, and computer graphics. Deep generative methods, a form of deep neural network, leveraged advancements in computational power and data resources, and so demonstrate superior power in content generation. Therefore, specific models such as autoregressive and diffusion models are used in many real-world situations. Deep learning has also enhanced computer graphics in complex and open areas. Generative pre-trained transformers have revolutionised GenAI. These deep learning models require large models and lots of training data. Scaling provides unparalleled advantages, such as superior content creation, authentic interactions, and multifaceted task execution. Foundational models, therefore, enable content generation across diverse real-life applications and are evolving rapidly due to technological advances and a robust research ecosystem that is already seeing converging capability trends such as agentic AI, multimodal AI, and advanced AI reasoning. This progression shows AI's growing role in technology with commercial and social impacts (He et al., 2025).

A simplified model of the AI lifecycle can be defined and separated into two main phases: development and deployment. AI systems are designed, trained, and refined during development. Design involves datasets, an AI model, and a training technique selection. Learning from large data sets is part of any training phase. A high number of computer processes makes AI training the most computationally intensive part of development. The training computational needs depend on the system's design, size (i.e., trainable weights), amount and quality of data, data reuse frequency, and the training method. Techniques in pre-training such as fine-tuning and reinforcement learning from human feedback, can allow AI systems to perform better and consume fewer computer resources. To solve various tasks during deployment, the AI system uses knowledge and skills acquired during the training phase. Disseminating and using a trained model for various applications and tasks signifies the deployment phase. Here, the model makes input inferences and predictions (outputs). The computational requirements for this are contingent upon the model's architecture, parameter size, and the number of instances. There are many ways to improve inference efficiency, but in general, the larger and more sophisticated AI systems are, the more processing resources per inference they require (Sastry et al., 2024, pp. 9–10).

2.2 Human-machine collaboration

As AI progresses, intelligent machines display human-like abilities such as autonomous decision-making, reasoning, active participation, and contextual awareness. This means they (will) progressively collaborate with humans more and more (Ren et al., 2023, p. 1101). The capacity to collaborate with us has emerged as a benchmark for assessing a machine's intelligence, influencing the breadth and profundity of its applications (Ren et al., 2023, p. 1101). The importance of human-machine collaboration, or at least the need for the adoption of collaborative and symbiotic relationships between humans and technology, is therefore becoming central to the success of the organisations (Seeber et al., 2018, p. 2). With the rise of smart technology, its role is evolving from a "tool" to soon joining our efforts as a teammate. However, especially when AI matures, the questions and opportunities for business and society shift and change. Numerous media outlets (Dwivedi et al., 2023, p. 6) have covered the benefits of this novel AI tool for enterprises, but GenAI models' limitations could pose reputational and legal risks, such as using offensive or copyrighted material, privacy violations, fraud, and misinformation (Seeber et al., 2018, p. 4).

AI definitions usually encompass its ability to demonstrate, replicate, and mimic intelligent human behaviour, thus hinting why it is regarded as the most significant nexus for the human-machine collaboration (Seeber et al., 2018, p. 4). Pioneers of AI thought it would make people smarter so they could solve hard problems, make better decisions, and reach their goals more efficiently (Dwivedi et al., 2023, p. 7). Especially the adaptable and interactive characteristics of this emerging technology (particularly GenAI) now enable its wide application across diverse fields and among a broad spectrum of people. General-purpose models can be easily and seamlessly utilised for downstream use cases without necessitating retraining and are relevant to a wide array of tasks (Abendroth-Dias et al., 2025, p. 7; Gomez et al., 2025, pp. 1–2).

For a long time, the primary question regarding the interaction between humans and machines in the disciplines of informatics, engineering, and humanities, revolved around appropriate user interface (UI) (Schleidgen et al., 2023, pp. 2–3). However, the focus is gradually shifting from merely transferring data and information effectively between humans and computers to a more nuanced understanding of interaction, which can be better characterised as dialogue or communication between humans and machines in a broader context (where humans are not solely considered users and computers are not the only emphasis). Schleidgen et al. (2023) thus conclude that understanding such interactions requires an exploration of multiple dimensions, like subjects, modes, purposes, and the contextual framework in which they take place.

Similarly, it is essential to make intentional decisions when selecting interaction types to achieve specific goals, rather than incorporating excessive interactivity that does not yield improved outcomes. Establishing the appropriate balance of interactivity between humans and AI systems is vital for enhancing user experience, ensuring effective communication

and reliability, and fostering meaningful collaboration. Psychologists and social scientists have extensively analysed human interactions, revealing patterns of reciprocal behaviour. Patterns such as question-answer and request-offer are also very relevant in the realm of human-machine (or AI) interaction. Furthermore, patterns and elements of social communications like greetings, attention, feedback, turn-taking, social cues, and farewell further promote a more organic and effective communication experience for the users. All the above is only possible through AI technologies that integrate natural language capabilities that are added to other elements, including information visualisation and user interface design. In the realm of AI, potential interactions between humans and machines or AI have been categorised based on user control and initiative, task characteristics, and degree of automation (Gomez et al., 2025, pp. 1–3).

The quality of the described interaction primarily depends on the understanding and manner in which users communicate with GenAI models. This is frequently referred to as "prompt engineering." This discipline is, due to its increasing significance, independently addressed in depth in the appendix (Appendix 1: Prompt engineering).

2.3 Potential benefits, drawbacks, limitations, and responsibility

The technology offers various opportunities, accompanied by ethical and legal challenges, and it holds the potential to yield both positive and negative effects on organisations, society, and individuals (Dwivedi et al., 2023, p. 1). GenAI tools have the potential to substantially improve productivity, drive worker engagement and significantly enhance decision-making and versatility across sectors (Abendroth-Dias et al., 2025, p. 7; Milanez, 2023, p. 12). ChatGPT provides expert assistance and advice and is thus becoming a part of modern society (Dwivedi et al., 2023, p. 46). GenAI promises notable gains in banking, hospitality and tourism and any industry related to information technology as it enhances business activities such as management, marketing, and sales (Dwivedi et al., 2023, p. 2). Even so, the problems with the current practices, the threats to privacy and security, and the effects of bias, misuse, and misinformation are very real and need further study and in order to develop approaches on how to deal with the challenges related to accountability, transparency, and governance. (Dwivedi et al., 2023, pp. 2, 14; Abendroth-Dias et al., 2025, p. 7).

Wade (Dwivedi et al., 2023, p. 7) argues that ChatGPT's biggest disruption and potential benefit is knowledge-work productivity, particularly about the influence of its capacity to generate a preliminary draft, as having something to work with is a lot easier than starting something from scratch. However, critical evaluation of the said outputs requires effort, and people frequently depend on instinctual reasoning that disregards the quality of information (Dwivedi et al., 2023, p. 14). Tools like ChatGPT, without much hard work, produce content that looks especially impressive, which puts tasks like writing, coding, planning, and others under increased focus, notably regarding accountability when issues arise, as well as ethical

questions pertaining to authorship and the attribution of intellectual property (Dwivedi et al., 2023, pp. 6, 12). Literature and even the developers acknowledge that the technology is like a black box and fails to completely explain the rationale behind its process and output, and is plagued by discrimination and biases, vulgarity, copyright infringement, plagiarism, and fabricated unauthentic textual content. Notwithstanding its remarkable capacity to produce natural-sounding responses, most of the literature states it lacks compassion, empathy, authenticity, and inventiveness and therefore cannot replace humans in most situations (Bahrini et al., 2023, p. 1). Hence, organisations need to understand, proactively manage and mitigate risks and connected integrity issues resulting from AI adoption (Dwivedi et al., 2023, pp. 6, 46, 48).

Regular risk evaluations must include ethical reviews and bias assessments since the algorithms used are evolutionary, marked by the quickness, diversity, and variety of the huge datasets required to train the models. Context helps identify, assess, prioritise, and mitigate risks, according to research. Technology limitations and downsides are intrinsically connected to training data quality, veracity, and trustworthiness, as well as human designers' and developers' approaches for model refinement. Continued legal and financial responsibility difficulties compound the mentioned limits and drawbacks. The corporate sector should map GenAI adoption by context and application, but a uniform standard is needed to regulate GenAI platforms, which are available in multiple countries (Dwivedi et al., 2023, pp. 6, 10, 12, 46).

The rules and regulations in the EU are already having a big impact on how GenAI is developed and used. The AI Act and the General Data Protection Regulation (GDPR) are pivotal in fostering innovation, transparency, trust, safety, and basic rights (Abendroth-Dias et al., 2025, pp. 6–8). Moreover, limits and responsibilities set forth by the AI Act establish legal requirements that make the technology more transparent and trustworthy while still balancing the challenges and opportunities, as well as alignment with EU democratic values. Additionally, the Digital Services Act (DSA) mandates Very Large Online Platforms and Search Engines to identify and manage systemic risks, including GenAI threats. Regardless, setting frameworks and policies also promotes technology innovation (e.g., trustworthy AI, explainable AI, etc.), watermarking and fingerprinting techniques, that do not just increase responsibility, innovation and sustainability but also lower risk, establish needed ethical oversight, and bring many social and economic benefits to all stakeholders.

The management of AI risks within organisations presents an unprecedented challenge (Dwivedi et al., 2023, p. 14). While the democratisation of AI and the wider adoption of GenAI tools are beneficial, scaling these technologies presents additional/increasing challenges if appropriate responsible AI frameworks are not established. Along with benefits, organisations need to address and limit negative outcomes such as data leakage (losing control over sensitive company information), lack of transparency and hallucinations (hard-to-verify content that sounds convincing but is not), bias and toxicity that were included in the training data for the foundational model, unknown capabilities that the tools

manifest but were not taught ("subliminal learning"), as well as other unknowns that were not planned and accounted for when setting guardrails and risk policies (BSG Global, n.d.; Cloud et al., 2025, p. 1).

Theory provides a framework for conflict resolution within the context of AI risk management, accentuating a flexible, results-driven policy development and evaluation throughout the risk management cycle (Dwivedi et al., 2023, p. 6). Furthermore, the number of people involved in the process has expanded significantly from a small group of knowledgeable professionals to a much larger number of individuals lacking experience in risk management and governance (Dwivedi et al., 2023, p. 14). However, the same goes for cybercriminals and other malicious actors who, with the help of GenAI tools, are targeting organisations regardless of their coding and IT proficiency. Therefore, challenges related to establishing effective controls on ChatGPT and similar tools concerning the dissemination of information for creating phishing and malware software must also be addressed (Dwivedi et al., 2023, p. 46). Addressing these challenges and previously mentioned ethical questions necessitates the involvement of research and development personnel, including engineers and societal representatives, as well as experts from the social sciences and humanities, such as philosophers, linguists, policy analysts, and lawyers (Dwivedi et al., 2023, p. 51).

The contextual importance of AI, therefore, necessitates the inclusion of diverse groups, allowing AI developers, organisations, and policymakers to make informed ethical decisions by thoroughly understanding and evaluating opportunities as well as limitations and potential negative implications. Consequently, it is essential to integrate AI risk management frameworks with diverse ethical and theoretical perspectives and thus ensure that GenAI tools like ChatGPT are used in a way that is socially responsible, beneficial, purposeful, careful, rational, ethical, transparent and inclusive (Dwivedi et al., 2023, pp. 6, 9).

Current research examines the components of inclusive AI, emphasising the imperative of integrating inclusivity during the development and deployment (Dwivedi et al., 2023, p. 10). The integration of GenAI solutions into human-AI hybrid solutions encourages researchers to tackle societal questions concerning access asymmetries. Additionally, the development side is also predominantly carried out by large tech companies like Meta, Google, and OpenAI (Zhang et al., 2023, p. 37). Accumulated disparities contribute to the digital divide, leading to inequalities in income and overall well-being, while worsening unequal access to resources (Dwivedi et al., 2023, p. 12). Furthermore, questions regarding the affordability and usefulness that everyone struggles with are even more common and pronounced in businesses from developing countries (Kshetri, 2023, p. 18). Those issues have been ongoing since the beginning of the IT revolution and are anticipated to grow as individuals and companies with access to and knowledge of ChatGPT and similar tools secure a competitive edge in opportunities and service delivery (Dwivedi et al., 2023, p. 45).

The benefits and drawbacks of GenAI can also be analysed and viewed within the framework of information economics, specifically the four dimensions of quality: certainty,

completeness, symmetry, and perfection. “Certainty” refers to the level of confidence in the reliability of information. Tools like ChatGPT have probably reduced our overall confidence by generating seemingly trustworthy yet inaccurate content. However, even though their capabilities of verifying and consolidating diverse sources are imperfect, they are still valuable. These tools comprehensively address our confidence in the sources of information and the motivations, incentives, or intentions behind their creation. Regarding “completeness”, GenAI tools will probably dilute information quality globally as they seamlessly blend factual content with synthesised, biased, or outright untrue data. “Symmetry,” which was already discussed, touches upon concerns about equal access to information. In this context, tools like ChatGPT can serve as significant equalisers. Access to numerous new capabilities and valued skills is now widespread and easily obtainable. However, it can also lead to amplification of specific viewpoints and misinformation. The fourth and final criterion of information quality is “perfection”, which examines the understanding of roles within processes or transactions. Because GenAI reduces transaction costs and enables the creation of diverse, ubiquitous personal assistants, those using them will experience significant advantages (Dwivedi et al., 2023, p. 51).

ChatGPT (like other GenAI tools) has problems with cultural sensitivity and empathy e.g., commentary on specific personalities, and religious matters. Consequently, it needs to be used with care as different regions may have different sensitivities (Dwivedi et al., 2023, p. 46). GenAI presents both opportunities and challenges for societal progress, as deployment must be conducted responsibly, emphasising the risks associated with disinformation, mental health concerns, deep fakes, and the societal biases that AI outputs may reinforce (Abendroth-Dias et al., 2025, p. 8). It is poised to transform several sectors and automate various mundane and repetitive tasks (Dwivedi et al., 2023, p. 46). Connected with the swift integration of such technology, a notable skills gap is becoming apparent and will require collaborative initiatives among businesses, educational entities, and policymakers to train, upskill, and reskill the workforce (Abendroth-Dias et al., 2025, p. 8). Certain observers express apprehension and fear that specific professions, e.g., copywriters, customer service representatives, transcriptionists, journalists, secondary school teachers, and assistants, may become obsolete (Dwivedi et al., 2023, p. 51). Throughout the literature it is often stated that GenAI will not just impact occupational restructuring but also promote a broader shift in skill demand and impact income inequality (Abendroth-Dias et al., 2025, p. 7). Some even think that adding LLMs to work processes could affect as many as 80% of U.S. workers, and about 19% of those could see their tasks impacted by at least 50%, which means that 300 million jobs could be at risk (Eloundou et al., 2023, p. 3; Merali & Merali, 2023, p. 3). Moreover, organisations should not only look out for labour market shocks and other social impacts but also be aware of GenAI’s environmental and sustainability limitations and drawbacks that come alongside (Bahrini et al., 2023, p. 278). The current relentless and unsustainable approach to the development and improvement of this technology may be unjustified and carries potential environmental consequences like increased demand for

computing power, larger carbon footprints, altered electricity demand patterns, and accelerated depletion of natural resources (Bashir et al., 2024, pp. 1, 2).

2.4 Opportunities for GenAI

Artificial intelligence offers a substantial economic and geostrategic opportunity and represents the revolutionary technology of our generation (Merali & Merali, 2023, p. 2). The cutting-edge technologies like GenAI will impact some sectors faster and to a greater degree (Bahrini et al., 2023, p. 275). Besides business and industry, the academic sector is poised to encounter some of the most significant impacts (Dwivedi et al., 2023, p. 53). Additionally, arts and culture, the creative industry, communication, science and technology, health and medicine, government and politics, infrastructure, banking and finance, hospitality and tourism, cybersecurity and information technology have shown significant applications and opportunities for this technology (Bahrini et al., 2023, pp. 275–278). As of July 2025, as much as 70% of ChatGPT user queries were unrelated to work; however, both work-related and non-work-related enquiries have increased, but the latter has risen at a faster pace (Chatterji et al., 2025, p. 13).

It's no surprise that GenAI can significantly redefine and alter education (Abendroth-Dias et al., 2025, p. 9), as it can fundamentally change the classroom experience and student knowledge and abilities (Dwivedi et al., 2023, p. 20). Almost 77% of all ChatGPT conversations are about asking for practical assistance, seeking information, and writing (Chatterji et al., 2025, p. 14). This shows that education is a big use of the service and that there is a chance for knowledge transfer and self-directed learning. GenAI-based solutions can help with online learning, teaching, writing, research, grading exams, giving feedback on assignments, making educational content, professional growth, and more (Bahrini et al., 2023, p. 276). GenAI can improve overall learning efficiency and so positively impact students' and teachers' productivity (Bender, 2023, pp. 353–354; Dwivedi et al., 2023, p. 52). Furthermore, tools like ChatGPT can successfully pass MBA exams and write or fix code on their own, proving that traditional methods are becoming obsolete (Dwivedi et al., 2023, p. 24). The technology can now facilitate more personalised learning experiences by adapting the difficulty and character of activities according to a student's performance and interests. Likewise, it could democratise access to personal tutoring as well as enable problem-solving, critical thinking and new ways of creativity (Abendroth-Dias et al., 2025, p. 9). Additionally, it is expected to change how students and researchers locate information and write academic publications (Burger et al., 2023). However, there is a risk that AI may be overused for work execution and productivity increase rather than deep conceptual inquiry and learning (Abendroth-Dias et al., 2025, p. 9). Most ChatGPT users do not (completely) comprehend its operations as well as outputs and cannot repeat results manually, which signals that critical thinking and problem-solving may be compromised, together with the role of educators (Dwivedi et al., 2023, p. 9). Therefore, research is needed to determine and get a holistic view of how GenAI might impact and improve teaching and

learning effectively (Dwivedi et al., 2023, p. 9). However, technology will be crucial in the future; thus, banning it for students is unreasonable, and effort should be made to ensure AI tools complement traditional teaching methods, not replace them (Abendroth-Dias et al., 2025, p. 9; Bender, 2023, p. 355).

Literature offers ideas like creating two types of tasks. Firstly, a task that bans ChatGPT use, for example, like a maths exam without calculators, and secondly, tasks that explicitly require ChatGPT, like homework. Unlike the second type, the first type requires only minimal changes. Open-ended homework and tasks involving text composition, on the other hand, should not be used anymore. Instead, teachers should rethink and redesign the learning process, so it promotes soft skills like critical thinking, complex problem-solving, creativity, and decision-making in diverse educational settings using innovative digital resources and pair them with in-person oral assessment (Dwivedi et al., 2023, p. 9).

As the educational sector is trying to adapt to changes and while teachers are considering its use, the students are also seeking direction and/or permission. Using ChatGPT and similar GenAI tools can either have beneficial effects (e.g., can function as either companions or tutors, facilitating self-regulated learning) or it can let students pass exams with little effort (resulting in insignificant learning effects), decrease their creativity and reduce their peer-to-peer and teacher interaction (Bahrini et al., 2023, p. 276). As teachers still teach critical thinking, the main goal and north star remain the same (Dwivedi et al., 2023, p. 9). However, protecting against fraud, manipulation, discrimination, and ethical AI use in education is still crucial (Abendroth-Dias et al., 2025, p. 9). ChatGPT and similar tools may provide responses that appear accurate but are flawed, cause technical issues, raise ethical and security concerns, and as a result put additional pressure on teachers (Bahrini et al., 2023, p. 277).

Similar effects are seen across academia, e.g., in research, where the number of articles is rising rapidly, and questions about research paper text authorship and ownership have raised concerns. Although GenAI may accelerate research akin to statistical software and search engines, thereby obfuscating clarity, it is not the first time AI technology has transformed research methodologies; hence, it can be asserted that alterations to the process are not unprecedented. For example, Grammarly and QuillBot are already known and popular AI academic writing tools. Similarly, an AI chatbot capable of generating R code for statistical analysis, named rTutor.ai and an artificial intelligence application utilised for literature overview and meta-analysis, known as Research Rabbit, are widely utilised (Dwivedi et al., 2023, p. 20).

GenAI is also revolutionising content creation by helping artists, designers, and others to create fresh content by evaluating user preferences and trends as well as co-creating and influencing the whole process. The technology allows AI-generated music, movies, and art, supporting digital-experience-based business models, yet AI models often follow current trends rather than creating new ones, which results in major concern regarding intellectual property rights as it infringes on original artists' work (Abendroth-Dias et al., 2025, p. 9).

In scientific files, GenAI is transforming the scientific process with exceptional efficiency and creativity, fostering new methods to enhance scientific work. It promotes progress by providing access to scientific tools for everyone and encouraging collaboration among fields, speeding up research and innovation. But as everywhere else, its role raises concerns, including biases and the strengthening of existing narratives and questions regarding co-authorship. Increasingly, numerous articles lack creativity and have many undetected errors, as tools like ChatGPT produce papers that are convincing but often wrong. Therefore, it is vital that AI technologies enhance human knowledge and actively work towards preserving scientific integrity and do not contribute to the distortion of scientific facts or incite plagiarism and misinformation (Abendroth-Dias, et al., 2025, pp. 9–10).

In healthcare and medicine, GenAI is increasingly contributing to and improving diagnostic accuracy, providing personalisation of treatment, and analysing large datasets to find trends and predict illness as well as cure development, and so contributing to overall patient management, treatment planning, and decision-making, promoting healthcare efficiency and patient empowerment (Gomez et al., 2025, p. 8). ChatGPT or MedPaLM platforms can improve digital health initiatives and give medical and paramedic staff in remote areas the crucial direction and oversight they need (Dwivedi et al., 2023, p. 45). Furthermore, incorporating these tools could shorten the learning cycle for all participants. Despite that, as already stated, challenges continue to exist, particularly with data privacy and ethical usage, which in this domain necessitate meticulous considerations. There are also concerns about data bias, health inequality, and professional deskilling, which must be addressed and require prudent utilisation within healthcare processes as well as substantial expenditures in information technology infrastructure (Abendroth-Dias et al., 2025, p. 10).

GenAI has the potential to shake up governance, politics and public sector administration and service delivery through increases in responsiveness, efficiency and transparency. By taking advantage of the advantages that come with adopting GenAI, such as better decision-making, community involvement, and resource allocation, everyone involved can see substantial gains. Here again, implementation of such technologies must stress the importance of strong governance and regulatory frameworks to ensure safe, ethical, and legal use (assures transparency, accountability, and monitoring), as otherwise public trust can be quickly eroded (Abendroth-Dias et al., 2025, p. 10).

Hospitality and tourist service businesses can also directly integrate ChatGPT or GenAI-powered chatbots as a widget, e.g., on their websites, and capitalise on the advantages of technology such as contextual awareness and comprehensive text answering. When combined with voice assistants and real-time personalised service, it can act as a 24/7 interactive platform or concierge assistant for clients, offering information about travel, dining, transportation, activities, tourist destinations, local customs, alternative options, and more. This gives clients a whole new level of smart customer service throughout their trip. At the same time as it improves customer experience, satisfaction, multilingual support, and convenience (condensing the laborious and time-consuming task of evaluating several

possibilities into only minutes), it can also reduce labour costs for service providers. However, as this new technology and smart tourism diffuse innovations across tourism services, they irreversibly disrupt already established legacy operational practices, processes, and ecosystems (Dwivedi et al., 2023, pp. 18, 45).

Banks have always been known to constantly adopt and accommodate new technology, and as a result quickly transform their operations. AI has been widely used in banking to analyse its data, understand clients wants and needs, and target them efficiently. Solutions incorporating GenAI now allow banks to improve their back-end operations, data analysis, and financial service marketing. The technology helps marketers create emotive and personalised content with a conversational tone, as it can greatly facilitate the development and execution of marketing communication strategies, consumer demand analysis, and tailored customer offerings. For efficiency and direct client involvement, banks can use GenAI-powered solutions in their front-end operations as well. The chatbot improves client experiences, answers frequently asked questions (FAQs), and simplifies banking; however, human verification of insights and involvement in some parts of the process are still necessary. On the other hand, ChatGPT and similar tools can actually enhance the precision of audit and consulting services, allowing executives in the banking, financial services, and insurance industries to concentrate on other critical responsibilities. Additionally, due to the abilities this technology exhibits, many customers now seek financial advice and investment possibilities outside traditional banks. FinTech custom solutions (Zhang et al., 2023, p. 35) as well as ChatGPT directly face rising customer need for financial services management as they seek to be informed about diverse financial advice, investment options and timing, and money management (Dwivedi et al., 2023, pp. 16–17).

GenAI poses various challenges and opportunities, especially for the IT industry, and at the same time, it already influences its current operations. As already discussed, ChatGPT could disrupt and automate several operations and tasks (e.g., software development, programming, etc., with e.g., GitHub Copilot, ChatGPT, etc.), leading to the displacement of various employees, particularly in IT-related firms (Zhang et al., 2023, p. 35). Besides IT-related skills, ChatGPT has the potential to revolutionise associated consumer experiences as well. This necessitates the establishment of numerous new positions and responsibilities, as well as the redefinition of old ones. Reskilling is a must, as it is widely asserted in IT fields that individuals who leverage technology and artificial intelligence will achieve superior performance compared to those who do not. Corporations and organisations should employ GenAI in innovative and augmenting ways to provide advanced advantages (Dwivedi et al., 2023, p. 48).

In the field of cybersecurity, GenAI possesses the capacity to improve threat detection and response capabilities. However, utilising GenAI technology in cybersecurity can lead to improved and proactive strategies that benefit both professionals and general users. GenAI presents intricate cybersecurity difficulties, encompassing conventional threats and AI-specific weaknesses such as data and model poisoning, adversarial assaults, and prompt

injections. For example, ChatGPT can generate very convincing phishing emails and create harmful programmes with minimal knowledge and/or experience in this field and disseminate rumours or propaganda, however on the other hand, it can also be used for discerning critical elements relevant in social engineering attacks, etc. Therefore, as AI systems increasingly integrate into cybersecurity, it is crucial to ensure their responsible usage and the prevention of new risks, focusing on all five stages of operations (Goldstein et al., 2023, p. 39): model construction (regarding large datasets, AI hardware and AI talent), model access, content dissemination (e.g., impersonation, manipulation, disinformation, distraction, etc.), victim's belief formation stages and its impact (e.g., social engineering, worse decisions, incapacitation, indirect effect, etc.) (Abendroth-Dias et al., 2025, p. 9).

2.5 Future of GenAI tools

Even though human society tands to repeatedly overestimate the imminent capabilities of AI systems “in the very near future” (Singh et al., 2024, p. 1), literature already claims GenAI will influence economic structures through industry transformation and the development of novel business models (Abendroth-Dias et al., 2025, p. 7). With the public’s infatuation with ChatGPT growing, the public and experts alike wait for the first individually established high-valuation start-up (Sawers, 2025; Sullivan, 2025; Smith, 2024) or an emergence of entrepreneurs using GenAI on niche markets without employing any workers (Walkowiak, 2023, p. 3). At the very least LLMs will reduce agency costs and company size, which will in turn encourage more micro-firms and decentralised teams and make the markets more dynamic (Potts, 2023, p. 12).

Therefore, it is no surprise that ChatGPT and GenAI tools were coined as “the industry’s next big disrupter” (Dwivedi et al., 2023, p. 7). Owing to its analytical and computational capabilities, efficiency in generating human-like responses, and continuous availability, substantial productivity gains and job creation across various sectors are anticipated (Dwivedi et al., 2023, pp. 6–7; Abendroth-Dias et al., 2025, p. 7). However, further research and digital maturity are essential for the adoption of GenAI, particularly among SMEs. SMEs must enhance their digital skills, business processes, infrastructure and address enquiries concerning their readiness to invest in advanced generative models; the presence of unregulated tools, and the intention to employ generative models to influence operations (Dwivedi et al., 2023, pp. 6–7; Goldstein et al., 2023, p. 34; Abendroth-Dias et al., 2025, p. 7).

The most accurate way to predict the future of GenAI is to look at the scientific laws that govern this field. These laws are important for advancing AI and providing a systematic way to do so. Recent discoveries relate to the two primary phases of contemporary GenAI models, including pretraining and reinforcement training. Scaling laws related to pretraining (Kaplan et al., 2020, pp. 2–3; Hernandez et al., 2021, pp. 3–6) focus on compute, dataset size, and parameters (neural network size). They demonstrate that increasing the scale of the

pretraining phase in AI leads to a predictable enhancement in performance. The laws have been validated across multiple levels and continue to support the basic ideas behind current AI advancement. Scaling laws in reinforcement training (Gao et al., 2023, p. 10835) indicate a consistent increase in reward, demonstrating that enhanced computational resources during pretraining and reinforcement learning lead to improved model performance. The trajectory of GenAI model development and its future implications can therefore be somewhat discernible. The trend indicates that as GenAI tools evolve to manage more complex tasks, the potential for productivity gains increases significantly, with time savings for humans extending from minutes to hours or even days. This is another scaling law (Kwa et al., 2025, pp. 1–2) which states that the AI's ability to complete long tasks is doubling approximately every seven months, encompassing an increasingly extended task horizon. This evidence indicates that, in the future, AI models or numerous AI models operating collaboratively will be capable of performing tasks currently managed by entire human organisations. Jared Kaplan identifies six key areas essential for the advancement of human-level AI: knowledge, memory, oversight, larger tasks, modality, data integration and scale. He suggests that organisations preparing for the future of GenAI should invest time in developing products that do not quite work yet, prepare to leverage AI for AI integration, and identify areas where adoption may experience exponential growth (Y Combinator, 2025).

3 IMPLICATIONS OF UBIQUITOUS USE OF GENAI IN BUSINESS

A while ago, disruptive technologies such as social media, search engine optimisation, and service-sharing platforms emerged and demonstrated significant potential for businesses (Dwivedi et al., 2023, p. 45). Many organisations were in denial and failed to capitalise on growth opportunities; they recognised and adapted too late, resulting in a loss of competitive advantage. Similarly, the emergence of GenAI has occurred with the public availability of ChatGPT, which has undergone a critical, possibly historical transition and demonstrated significant potential, particularly in business contexts (Dwivedi et al., 2023, p. 45). The primary anticipated impact lies in productivity enhancements, as tools such as ChatGPT facilitate the automation of mundane or repetitive tasks, enabling employees to concentrate on more creative, non-repetitive activities that provide greater added value (Dwivedi et al., 2023, p. 52). In organisations the most significant advantages of GenAI emerge when GenAI initiatives are integrated with essential business functions (applications in operations and management, supply chain management, business analytics, transportation, human resources, marketing, e-commerce, accounting, finance, retail, real estate, and insurance) rather than being limited to experimental applications (BSG Global, n.d.; Bahrini et al., 2023, p. 275). Enterprises achieve greater benefits by advancing beyond isolated pilots and leveraging GenAI to transform foundational workflows (e.g., demand forecasting, inventory and logistics optimisation, supplier selection and evaluation, etc.) aligned with strategic priorities (BSG Global, n.d.; Bahrini et al., 2023, p. 275). GenAI converts manual tasks into

fast, data-driven cycles that lead to measurable increases in productivity, especially in areas like software development, customer service, marketing content, and research and development (R&D) (BSG Global, n.d.).

Studies (Birkinshaw & Cohen, 2013) indicate that 41% of a knowledge worker's time is spent on discretionary activities that yield little personal satisfaction and could be efficiently handled by others. In the context of GenAI tools, this suggests that the technology could perform these tasks instead (Dwivedi et al., 2023, p. 7). This technology, when used appropriately, can yield economic advantages by enabling organisations to decrease agency and governance costs (Allen et al., 2023, p. 5). Furthermore, these expenses are often difficult to quantify; however, they are nonetheless real and can be significant within certain organisational structures. Thus, changes in these costs will fundamentally alter organisations.

People and processes, not the technology itself, present the primary transformational challenge (bottleneck) for GenAI adoption. Numerous organisations faced challenges in scaling the implementation of AI and realising its benefits prior to the emergence of GenAI solutions and tools such as ChatGPT (Fountaine et al., 2021; Dwivedi et al., 2023, p. 13). However, the most successful organisations adopt a 10/20/70 principle. They allocate 10% of their efforts to algorithms, 20% to data and technology, and 70% to the transformation of people, processes, and culture. This transformation encompasses the reconfiguration of everyday work processes and roles, the upskilling of teams, and the promotion of human-AI collaboration, among other things. If those elements do not change, then even the most effective transformation initiatives will not meet their objectives (BSG Global, n.d.).

In addition to the challenges associated with transformation, three other factors contribute to issues related to AI: growth, risk, and urgency. The rapid growth and emergence of new technologies are intensifying competitive pressures among organisations. Simultaneously, risks associated with unfamiliar and poorly understood technologies present distinct challenges. Significant reputational, compliance, or financial repercussions can easily exacerbate these concerns. The urgency factor pertains to the inability to postpone the issue (Dwivedi et al., 2023, p. 13).

However, properly executed, the transformation or integration of GenAI can be economically comparable to reducing the firm's size without altering the production set. This approach may yield the productivity advantages associated with large firms or markets while simultaneously offering the organisational efficiency benefits of smaller firms, including reduced monitoring, agency, and governance costs (Allen et al., 2023, p. 7).

GenAI will not only transform how we prepare the next generation of marketing professionals, but it will also have a profound impact on the operations of the marketing industry (Peres et al., 2023, p. 273). Creativity has been identified as the future of marketing; at the same time, AI is enabling more automation in this field (Ameen et al., 2022, p. 1).

The literature has identified strengths and capabilities of AI that have led to its use in the following areas of marketing: decision-making, customer service, reducing cognitive bias, tracking touchpoints on the customer journey, segmentation, targeting, positioning, personalised recommendations, content creation and curation, customer experience, price and place management, driving engagement, experiential marketing, branding, forecasting sales, and market research (Ameen et al., 2022, p. 1812; Zhang et al., 2023, p. 32; Kshetri, 2023, p. 17). In addition, the use of AI-driven chatbots, drones, algorithms, robots, and digital voice assistants is increasing in multiple areas of marketing (Ameen et al., 2022, p. 1812). For example, ChatGPT can specifically help with building marketing campaigns, developing content marketing, creating content images and art design, service marketing, customer experience, keyword suggestions, marketing research, and brand comparison. Marketers can explicitly use basic prompts such as "Suggest an effective marketing campaign on Instagram," "Suggest an effective marketing campaign on Instagram for a bouquet start-up," and "Analyse the 7 Ps of Pepsi marketing." The more precise the query, the better, more relevant, appropriate, accurate, and creative the results will be (Dwivedi et al., 2023, p. 15). Additionally, tools like DALL·E, and Brandmark.io can help to creatively design products and generate avatars, logos (with many variations), etc. in a very cost-effective way (Dwivedi et al., 2023, p. 15; Zhang et al., 2023, p. 32).

Therefore, agencies and brands are already seeking prompt engineering as a skill set. Effective prompt engineering can facilitate ideation, as well as allow for the exchange of fleshed-out ideas among different team members. It not only improves the performance and quality of marketing content but also significantly reduces its costs and time needed. (Peres et al., 2023, p. 273). By facilitating the generation and evaluation of advertising concepts, AI is also enabling both young and established creators to recognise that creativity is not an exclusive trait but a systematic process that can be enhanced through data and computational methods (Zhang et al., 2023, p. 32). All those advantages of GenAI are particularly evident in developing countries, especially within SMEs, where the knowledge gap is most pronounced, and the tools can effectively address this disparity (Kshetri 2023, p. 17).

It is expected that GenAI tools and powered solutions will be integrated into many existing consumer interfaces, alongside presently popular tools such as ChatGPT. ChatGPT, OpenAI API (application programming interface) and other general AI systems will propel the evolution of chatbots and service robots towards attaining 'general intelligence', allowing them to provide services with a degree of comprehension and adaptability akin to that of modern human frontline workers. Thus, it can be anticipated that a significant shift of comprehensive automation of customer service will ensue. These emerging technologies will propel the digital frontier forward, enhancing both AI models and the design of the user interface. Consequently, customers will likely be unable to distinguish between a digital/AI-powered service provider and a human employee. Furthermore, the study anticipates that customers' concerns about this disparity will be insignificant at that point. Moreover, it is realistic to expect that because of quick availability, round-the-clock service, and

communication in a preferred language most customers will favour digital/AI-powered service providers over traditional human alternatives. Significant cost reductions will also facilitate the transformation, but they will gradually diminish due to market competition and ultimately enhance everyone's experience (Dwivedi et al., 2023, pp. 14, 15).

In the realm of R&D, GenAI tools like ChatGPT can accelerate their progress by offering fundamental knowledge on the subject across several dimensions. Furthermore, such tools can assist in coding and debugging, thereby diminishing the likelihood of duplicative research and development operations that are publicly accessible or open source (Dwivedi et al., 2023, p. 45). Interestingly, merely 4.2% of ChatGPT communications pertain to programming, but almost 33% of work-related messages from other tools such as Claude do (Chatterji et al., 2025, p. 2).

Like any new technology, ChatGPT must overcome various IT-related issues before any enterprise can fully embrace and use it. Privacy and security challenges pose the greatest difficulty in adopting ChatGPT (Dwivedi et al., 2023, pp. 43, 48). The application of machine learning algorithms in ChatGPT involves the processing of extensive data, rendering it vulnerable to cyberattacks, as it may process sensitive data that might be stolen or abused, creating privacy and security risks. Other drawbacks, like the presence of bias in the model's training data, potential propagation of misinformation, awareness of local rules and regulations, should not be overlooked by any IT professionals. Furthermore, many people in the organisations do not understand how it works and are cautious about using it, which slows the adoption and implementation of such new tools and solutions. Additionally, Milanez (2023, pp. 11–12) states that ChatGPT technology heeds hardware, software, and skilled employees to deploy and maintain it, which further shows how important it is to teach, train, and raise awareness. Initial costs related to those factors might cause many problems and difficulties, especially for smaller or less well-founded organisations. Not to mention, it is already quite clear that there is a need for specialised AI and AI-related skills (Dwivedi et al., 2023, pp. 43, 48).

If those challenges are addressed, there are quite a few quick-win opportunities for IT. Automating monotonous processes and improving customer experience are early prospects. Regarding the latter, ChatGPT optimises human resources, allowing staff to handle more complicated questions. Automating monotonous processes on the other hand helps staff focus on important projects, improving morale, productivity, and retention. GenAI tools also help IT professionals directly, as they may help developers generate test cases and data, debug, troubleshoot, write code for specific tasks and be overall more productive (Merali and Merali, 2023, pp. 17–18). It is therefore obvious that ChatGPT and similar tools have considerable potential to uncover new business possibilities, provide extra income streams, and act as a catalyst for innovation (Dwivedi et al., 2023, p. 48).

3.1 Process improvements

The emergence of GenAI has set off a growing interest in its incorporation with software agents, leading to the development of agentic AI. This emerging technology shows enormous potential and increasing deployment; however, its influence on business processes and the necessary management requirements are not yet fully comprehended. Yet AI will most likely have an influence on management work at three levels: administrative, functional, and strategic (Korzynski et al., 2023, p. 9). Currently, most organisations still treat LLMs as agents in a limited sense; they largely automate specific isolated tasks/phases (like discovery, analysis, and monitoring), leaving final decision-making and broader, goal-based autonomy to human users. However, long-term vision involves GenAI not merely as tools for task automation but as intelligent systems capable of adaptability, self-improvement, and bounded autonomy. Despite all advances, some critical challenges remain regarding relevant organisational support frameworks, shifts of employee perspectives, and enterprise architecture (Vu et al., 2025, pp. 4, 13).

OpenAI is for example helping The Associated Press automate writing of public safety incidents, transcribe public meetings, translate weather alerts, recap sporting events and offering descriptive language search through their multiformat content platform (The Associated Press, 2023). Walmart which has positioned itself as an industry leader in the adoption of AI and GenAI within retail, is betting this technology will drive the future of e-commerce (Cavale, 2025). They have a suite of AI-powered agents that improve and streamline operations, help store employees as well as their suppliers and sellers. They also support their customer shopping experience (assists customers with product suggestions, finding the right product and generating whole shopping lists based on their needs, and summarises product reviews). Additionally, Walmart uses GenAI trend-to-product solutions to develop and offer on-trend, affordable items faster and cheaper (Walmart, 2025). Similarly, Instacart partnered with OpenAI to offer GenAI-powered “Ask Instacart feature” that helps customers search, personalise recommendations, and answer their questions (Marr, 2024a). Furthermore, they developed internal GenAI chatbots trained on internal and external data to help their employees access information, analyse data, visualise it and access insights (democratising access within the company).

Ergo, the implementation of next-generation software is expected to automate routine tasks first and enhance 'vertical integration' within a single role by expanding the range of tasks an individual can perform, leading to increased productivity. This organisational effect resembles the reduction of multiple contracts within (with colleagues) or outside the company (with external help). An individual empowered with LLM will therefore execute more tasks within the same time frame, thereby diminishing the necessity for additional contracts and decreasing the transaction, coordination and monitoring costs linked to task execution. This differs from the labour-saving effects of substitution, which may occur when an individual bypasses a contractual situation, such as by hiring a professional service like an accountant, lawyer, or coder. The cost savings in this context include both direct costs

and agency costs, while also reducing expenses related to the transfer of local or specific knowledge from the principal to the agent (Allen et al., 2023, pp. 6–7).

While it frees people to concentrate on other worthwhile endeavours, it raises worries about possible dangers such as bias, over-reliance, job loss, and a lack of transparency. These issues highlight the necessity of a clear and organised governance framework to successfully implement AI/GenAI agents into business processes while making sure that people are still informed, involved, and empowered. Frameworks should include the following six main areas of focus: business context, operational guardrails, human-agent collaboration, customisation, risk management, and adoption. In practice, this means that to ensure compliance with legal requirements, ethical standards, and organisational norms, enterprises must clearly define goals, expected benefits, and related costs for AI agents. Individuals and agents must have clearly defined responsibilities and intervention techniques to work together effectively. Factors of AI agents such as transparency, documentation, autonomy, and oversight must also be tailored to the organisation's unique requirements. Effective risk management is essential for monitoring performance and avoiding unwanted changes. The compatibility of new business systems with current ones must be given top priority throughout adoption, and backup plans must be made to handle any breakdowns (Vu et al., 2025, p. 11).

Regarding human-agent collaboration, organisations, for example, already see many possible roles ChatGPT can assume, including partner, tool, supporter, and teacher/development coach. Its potential for collaboration with individuals entails planning, monitoring, and controlling cognitive, emotional, and behavioural processes. Interestingly, a study (Chatterji et al., 2025, p. 32) found that highly paid professionals tend to use ChatGPT to ask questions (try to learn) instead of executing things, which highlights the importance of support and collaboration with the GenAI tool (working with it and not just using it). The roles of AI in hybrid teams can be classified into two categories: basic roles, including text producer, language editor, and research assistant, and advanced roles, such as coach, innovator, and software developer. ChatGPT (GenAI) has the potential to provide significant contributions to various business tasks, including generating planning and creativity tasks, selecting intellective and decision-making tasks, negotiating cognitive conflict and mixed-motive tasks, and executing contests, battles, and performances. Nonetheless, further investigation is necessary to identify the precise tasks for which ChatGPT (GenAI) tools are most useful, best implementation strategies, and the challenges encountered during their use (Dwivedi et al., 2023, p. 8).

The conventional principles of business process management, encompassing structure, control, and standardisation, are contested by the extensive application and novel dynamics linked to agentic AI, which include autonomy, flexibility, and self-learning. To align these approaches, organisations should take strategic steps, such as creating workflows that balance human and agent input, redefining human roles as supervisors or collaborators, changing static process models to support adaptive agent behaviour, and setting up strong

governance frameworks and metrics to track results. These observations, when viewed collectively, offer a valuable framework for the ethical integration of AI agents. They help businesses make the most of agentic AI while keeping control of the organisation, trust from stakeholders, and the integrity of the process (Vu et al., 2025, p. 13).

3.2 Creativity and innovation

The ability to generate creative, original, and adaptable ideas that may be useful, e.g., in problem-solving, procedures, processes, and products, is what psychologists refer to as creativity (Simonton, 2001; Frare and Beuren, 2021). According to Ameen et al. (2022, p. 1813), creative activities at the organisational, social, and market levels relate to the development of creative ideas inside teams that result in innovation. An individual's creativity is therefore a crucial component in putting new ideas into practice and is a key factor in determining a company's ability to produce innovative goods (Bollinger, 2020, p. 215).

An interesting example of GenAI contributing to the creative process and co-creating an innovative product is Endel's collaboration with Spinnin' Records AI-powered artist "Spinnin' COSMOS" that, in collaboration with human artists, weekly releases new sleep and wellness soundscape-focused records (Yopko, 2025). Another one is H&M's use of AI digital twins and GenAI to recreate fashion model's photorealistic avatars and so revolutionize fashion design, marketing and consequently enhance creativity, internal processes, streamline operations (campaign production), reduce lead time, costs and address sustainability concerns (Arrigo, 2025). Or Ralph Lauren's in-app AI-powered styling companion "Ask Ralph" which not only helps with product discovery but also inspires consumers with Ralph Lauren's unique and iconic take on style (Bransten, 2025).

Researchers in innovation management have concentrated on three categories of drivers influencing AI adoption for innovation (economic, technological, and social) as well as three categories of outcomes resulting from AI adoption, which include economic, competitive, organisational, and innovation aspects. Therefore, the development of new technology, along with product, process, and business model innovation, represents areas of innovation where AI application has significant potential (Mariani et al., 2022).

Text summarisation, sentiment analysis, insight creation, and idea generation are just a few of the jobs that GenAI technologies can do at an astounding scale throughout an invention process. These technologies can enhance human performance in invention and facilitate the evaluation of problem and solution spaces. As AI and humans increasingly interact to produce hybrid intelligence, which amalgamates the best of human and artificial intelligence, we must re-evaluate our strategies for managing and approaching innovation (Bouschery et al., 2023, pp. 140, 149).

As part of a hybrid innovation team, ChatGPT can contribute to the creation of new products by acting as an innovator and facilitator of big-picture thinking, which in turn results in improved innovation performance. Additional research has demonstrated that ChatGPT's generative nature allows it to produce novel concepts and ideas. It can assist human team members in better understanding their issues and solution spaces, even if technology alone still provides fewer original and valuable ideas than humans. AI can also be used as a developer, helping humans with code writing, automating routine tasks like testing, and managing errors during the development and post-deployment phases (Dwivedi et al., 2023, p. 8).

Additionally, it can also serve as a team intermediary and knowledge broker, enabling the exchange of information between various stakeholders and promoting the creation of new knowledge. It can blur the boundaries between internal and external knowledge and boost the number, calibre, and variety of ideas while contributing to the creation of more value at a relatively cheap cost (Bouschery et al., 2023, p. 147).

Su et al. (2020, p. 341) contended that the incorporation of AI into marketing creativity will increase a proficient workforce capable of effectively utilising AI in an increasingly complicated environment. In a similar vein, GenAI has the potential to democratise business and cultural endeavours in general. It will make it easier for people to express themselves artistically, like DALL-E does, and it will also let people who are not experts make/write a novel, song, product design, sculpture, painting, video game, and more (Peres et al., 2023, p. 273). GenAI democratises creativity across sectors by significantly lowering the marginal cost of creating creative outputs. This approach lowers entry barriers and promotes hyper-competition in creative and knowledge-intensive industries by enabling a new wave of quick and inexpensive experimentation (Potts, 2023, p. 11).

The agency cost hypothesis of LLM adoption argues that user innovation and problem-solving are enhanced by better availability of specialised knowledge capabilities (lower production costs) and diminished costs associated with organising that knowledge (reduced agency and governance costs). This hypothesis forecasts a more decentralised innovation system that generates further value by utilising local expertise or “sticky information” as resources for innovation (Von Hippel, 2016, pp. 142–145). The “toolkit” model of user invention, formulated by Von Hippel and Katz (Von Hippel, 2016, pp. 99, 125), provides a valuable framework for assessing the advantages of LLMs in innovation. In this paradigm, the trained LLM functions as a resource that decentralised innovators may use and employ for problem-solving by incorporating their own problem context and requirements. Data already indicates the formation of self-organising user groups that exchange prompts and strategies for utilising GenAI tools in problem-solving (Allen et al., 2023, p. 8).

The use of management tools is contingent upon managers' perspectives (Bollinger, 2020, p. 1); hence, coordinating and integrating duties between humans and AI has emerged as a novel responsibility for project leaders (Bouschery et al., 2023, p. 149). They should

prioritise balanced augmentation over automation, whereby the strengths of people and AI are integrated to achieve optimal outcomes (Ameen et al., 2022, p. 1819). AI platforms like ChatGPT still need considerable development before they can function as autonomous agents in innovation processes (Dwivedi et al., 2023, p. 6). For intricate tasks engaging multiple regions of the human brain, such as creative and innovative endeavours, even an effective prompt or prompts seem insufficient for a GenAI system to autonomously produce a distinctly novel and original product (Dwivedi et al., 2023, p. 6).

The integration of AI in business requires high standards for resources, including advanced technology and skilled employees, so recruiting and developing creative professionals with AI, ML, and DL expertise would advance the corporate environment. Furthermore, organisations must ascertain that prospective employees possess the necessary willingness and curiosity to transcend existing boundaries, as human intuitive reasoning is integrated with the accuracy and precision of machines. AI technology assists businesses in coming up with better marketing plans, makes the customer journey better, and changes the ways they acquire, nurture, and convert leads. Consequently, AI may necessitate a re-evaluation of a company's innovation process and promote the transition to the digital organisation of innovation (Haefner et al., 2021, pp. 1–2).

3.3 Knowledge management

Knowledge is a basic resource for organisations, and managing it well can add a lot of value. Knowledge management (KM) deals with how to effectively capture, share, and use knowledge. The advent of GenAI technology has brought about substantial and complex transformations in organisational knowledge management and knowledge management systems (KMS), as GenAI enhances information processing and cognitive functions, thereby facilitating both individual and organisational learning (Alavi et al., 2024, pp. 1–2).

For example, IKEA (Marr, 2024b) is not just providing information to their customers through GenAI-powered chatbot but also pairing it with their “IKEA Kreativ” tool that lets users visualise and design their own living spaces in mixed reality, which enhances and enriches the process of information search and evaluation of alternatives. Furthermore, they developed a GenAI toolbox for their employees with tools like custom Microsoft’s Bing Copilot that enables them to quickly create content and assets that demonstrate products in relevant ways for customers.

GenAI systems integrate aggregated specialised and general knowledge (the trained model) with contextual knowledge (users’ prompts) to create a robust feedback loop (Potts, 2023, pp. 11–12). For example, ChatGPT has begun to realise KM's enduring promise of enhancing access to organisational knowledge through chatbots and automated document and image analysis. The potential exists to improve the productivity of knowledge work through mechanisms that simplify the information search process, thereby assisting organisations in making their knowledge more available (Dwivedi et al., 2023, p. 7).

In the context of knowledge storage and retrieval, GenAI's ability to quickly access vast knowledge bases is revolutionising KMSs and significantly changing how employees interact with these systems (Alavi et al., 2024, p. 1) since LLMs are not autonomous and require human judgement to effectively extract and apply value (Potts, 2023, p. 13). Balancing and harmonising human-derived tacit knowledge with AI-generated explicit knowledge is crucial for ensuring technological advancement and ethical responsibility. McKinsey & Company and Morgan Stanley have already developed and implemented their own GenAI-based Knowledge Management Systems (KMSs) aimed at enhancing collaboration and optimising search, access, analysis, understanding, and synthesis of the firm's knowledge resources for its workforce, while also identifying domain experts within the organisation. The technology's general-purpose nature provides significant versatility, enabling its application across multiple tasks in diverse fields and domains. These systems can alter knowledge creation, potentially shifting the preference from primarily human-generated content to AI-generated insights. Traditional Knowledge Management Systems (KMS) categorise data as facts, information as contextualised data, and knowledge as the sum of human experience and judgement. In contrast, GenAI-powered systems compress the information layer and generate knowledge directly by processing extensive volumes of data. Furthermore, GenAI plays an expanding role in knowledge transfer, especially in training and fostering a culture of learning (Alavi et al., 2024, pp. 1–4).

With the growing dependence of knowledge processes and organisations on automated reasoning and algorithmic governance, new challenges are affecting KM and KMS (Potts, 2023, p. 7). The primary challenge involves structuring organisational knowledge in a manner accessible to GenAI solutions. However, the potential overreliance on AI, the risks associated with disseminating sensitive information, and other challenges organizations generally face related to AI should not be overlooked (Dwivedi et al., 2023, p. 14).

3.4 Decision-making

In general, GenAI tools act as collaborative partners and improve decision-making using data-driven insights, tailored suggestions, and context-aware solutions. This collaboration improves education, healthcare, and business results. However, trust is vital for effective human-AI cooperation; therefore, AI systems must be transparent, explainable, and accountable to build user confidence and trust in human-AI decision-making partnerships (Phillips-Wren and Virvou, 2025, p. 581).

Recent studies and swift incorporation of GenAI in business domains (e.g. already mentioned Walmart or Instacart examples that reduce cognitive load in decision making by helping customers with product discovery, substitution, and search) demonstrate its value as a tool for efficiency, optimisation, and transformative change. Use of GenAI accelerates the whole processes, including spotting opportunities, testing solutions, integrating data-driven insights, and managing information-intensive phases of decision-making, minimising

cognitive overload for managers (Pietronudo et al., 2022, pp. 8–9). For example, GenAI-powered financial and knowledge systems enhance data retrieval, filtering, and classification for strategic decision-making through sentiment analysis and structure financial insights. Consequently, it's perceived as a decision support tool. Its partnership with human intelligence improves business decision-making, cognitive biases, flexibility, and risk anticipation. Furthermore, Chatterji et al. (2025, p. 4) state that ChatGPT likely enhances employee productivity by facilitating decision-making, which is especially important in knowledge-intensive roles because better decision-making boosts productivity. In addition, to support this claim, Albashrawi (2025) gives an example of a domain-specific GenAI model like Real-GPT that can improve real estate investment decisions and even outperform general-purpose models in market analysis. Given industries' growing reliance on data-driven insights, GenAI's ability to process massive amounts of data and produce coherent and contextually relevant outputs could improve decision accuracy and operational efficiency. However, recent studies suggest that GenAI models like ChatGPT and Gemini may not be reliable enough for high-stakes decision-making, especially in academic and research settings. Similarly, as already stated, misinformation and AI faults in consumer-facing apps can hurt financial and tourism users' trust and decisions. Human monitoring and formal governance are needed to preserve confidence and reduce unforeseen dangers (Albashrawi, 2025, pp. 1–5).

Even though GenAI-enabled decision-making shows that all domains can benefit from its effectiveness, it faces distinct problems across industries. All of them have concerns about prejudice, transparency, and ethics. However, domain-specific constraints, such as high oversight requirements in the medical field, customisation concerns in business and education, and automation issues in technology, still hinder wide adoption in relevant areas (Albashrawi, 2025, p. 7).

Nevertheless, some early implementers like the food-tech startup Daily Harvest show their promise. They adopted a GenAI customer service tool that handles routine inquiries and assists its support team with personalised responses, which allows them to speed up customer interactions (responsiveness), drive insights from conversational data, help managers make more informed decisions about their product adjustments, as well as logistic planning (Hightower, 2025a).

GenAI helps people work together and make decisions by organising the communication and getting more people involved, but when it comes to ethical decisions, it pushes boundaries by questioning how open, responsible, and compliant with rules we are. In collaborative decision-making, GenAI promotes inclusion, but in ethical circumstances, its limits require prudence (Albashrawi, 2025, p. 8).

In many applications, decision-making starts with gathering evidence before making a specific choice that has subsequent impacts. This concept views the decision-making process as a human-AI cooperation situation where at least two parties (human and AI) work together

to identify a solution (solution spaces) to the decision problem. Combining human intuition and skill with AI's computational strengths gives better and more robust answers. The traits of this partnership change depending on the situation, so its benefits can range from being used for simple advice to providing more in-depth discussions. Furthermore, collaboration can be anything from parallel work, when AI works on its own but in a way that fits with human goals, to more coordinated activities, such as conversational AI taking turns. To connect algorithmic ideas and human expectations, AI solution designers must use a human-centred approach to establish what information AI should deliver to benefit people while guaranteeing safety and transparency. Understanding how and when to deliver information is key to building successful human-AI interactions. Additionally, current AI systems excel at problem-solving, but they typically focus too much on technology and neglect user interface and experience (Gomez et al., 2025, pp. 1, 2, 10).

The taxonomy of interaction patterns identified in AI-assisted decision-making consists of seven different categories. The categories include AI-first assistance, AI-follow assistance, secondary assistance, request-driven AI assistance, AI-guided dialogic user engagement, user-guided interactive adjustments, and delegation. Generally, the predominant patterns observed were AI-first, AI-follow, and secondary assistance, wherein the human role was primarily confined to supervising AI predictions. AI-first assistance denotes the simultaneous presentation of a decision-making problem alongside an AI-predicted outcome to the user. AI-follow assistance refers to the process in which a user formulates an independent initial prediction concerning a decision-making issue. After the initial judgment, AI's anticipated outcome is provided, possibly with accompanying evidence. This procedure provides the user with a reference point (their initial assessment) for comparison with AI's recommendations and an opportunity to reassess their initial judgement. Secondary assistance commences when AI offers information that is not directly relevant to the decision-making issue at hand. The user must evaluate this supplementary information to assess its significance and determine its integration into the primary decision-making process (Gomez et al., 2025, pp. 5, 6, 9).

The attractiveness of algorithmic decision-making lies in its perceived ability to provide an objective means of addressing human subjectivity, bias, and prejudice. However, numerous algorithms tend to replicate and entrench the biases that are already present in society (Dwivedi et al., 2023, pp. 13–14). AI enhances decision-making processes by promoting inclusivity; however, it can also lead to exclusivity, diminishing participants' roles to that of mere data providers (Pietronudo et al., 2022, p. 10). Excessive dependence on analogous AI algorithms among competitors may result in strategic convergence, thereby diminishing competitive differentiation (Pietronudo et al., 2022, p. 8). AI presents novel challenges in decision-making, such as biases, privacy concerns, and susceptibility to data breaches (Pietronudo et al., 2022, p. 9). Nevertheless, organisations should maintain focus on the cost reduction benefits of AI in prediction, which is essential for decision-making. This enhancement facilitates improved planning, risk management, and the capacity for data-

driven decisions at scale, even with constrained resources, while also fostering strategic agility (Potts, 2023, p. 11). Businesses ought to establish an optimal human-machine collaboration framework that facilitates collaborative decision-making and maximises the strengths of both entities (Geng and Varshney, 2022, p. 61).

4 DISRUPTING THE DISRUPTOR: THE RELATIONSHIP BETWEEN GENAI AND ENTREPRENEUR

The way individuals utilise AI tools determines its impact on humanity. When integrated with entrepreneurship, it becomes an exceptionally versatile "super tool" capable of yielding consequences that may be highly productive or entirely destructive. Industry trends and consultancy firms advocate for diverse AI-related business opportunities for entrepreneurs, highlighting that AI can enhance their overall prospects for entrepreneurial success. Additionally, entrepreneurs can perceive and seize the AI trend and potential, either as AI developers and designers or as a means of support for their entrepreneurial endeavours (Shepherd and Majchrzak, 2022, pp. 1–2).

4.1 Potential for entrepreneurial process

Most of the changes and potential for entrepreneurial processes can be seen regarding the changing relationship between organisational size and competitive advantage, the expansion of individual entrepreneurial capacity, the transformation of market entry barriers, the evolution of traditional firm advantages, and the modification of entrepreneurial risk profiles (Ganuthula, 2025, p. 1).

The emergence of affordable LLMs in business parallels the recruitment of additional competent employees, consultants, or contractors. Similar to capital investment, it enhances worker capabilities by facilitating specialisation, accelerating output, expediting the learning cycle, or incorporating more complex industrial technologies. This approach can profoundly transform the identification, evaluation, and pursuit of opportunities. GenAI diminishes the expenses associated with managing human resources and streamlines procedures, enabling workers and businesses to concentrate on more intricate duties, thereby enhancing their productivity (Allen et al., 2023, pp. 8–9). In order to manage unpredictable choice settings, this study suggested that entrepreneurs now have the capacity to transcend conventional cognitive limits and processing restrictions and possess improved pattern identification, decision-making, and predictive capacities (Ganuthula, 2025, p. 4).

Accordingly, entrepreneurs who use GenAI technology may reduce the effective size of their businesses while, in contrast to conventional wisdom, maintaining or even increasing their capabilities. Furthermore, less venture capital is and will be required to launch a start-up due to the lower team size or quicker execution. By cutting start-up costs, this technology also

encourages competition in most domains, which lowers market rents and will eventually benefit customers (Allen et al., 2023, pp. 8–9).

AI-powered entrepreneurship offers opportunities to access resources with little initial outlay of funds. This change enables solo businesses to experiment and enter markets at scales that were previously unachievable. Simultaneously, GenAI's potential signifies a significant change in the risk profiles of entrepreneurs. AI technologies alter the nature and magnitude of entrepreneurial risk through various mechanisms. Entrepreneurs are less worried about new technology than workers are, and independent contractors who use GenAI have more freedom and control over their work. AI systems' quick prototyping and simulation capabilities offer the potential to drastically reduce the cost of experimentation. The decrease in costs is radically changing the risk-reward analysis in entrepreneurial decision-making, allowing entrepreneurs to test hypotheses and refine company models with minimal resource investment. Additionally, the fast iteration capabilities of AI systems accelerate the learning cycle in entrepreneurial endeavours. AI's ability to quickly change implies that business owners can test and improve strategies more quickly, which saves time and money on exploration. Ultimately, enhancing learning value and reducing sunk costs transform the consequences of failure. AI-enabled entrepreneurship introduces new learning and adaptation patterns that enhance the learning value of failure and reduce its cost. By using AI-driven market analysis, automated marketing, and individualised consumer interaction, AI-enabled entrepreneurship offers new market access patterns that extend beyond conventional organisational limitations. Most notably, AI-enabled entrepreneurship offers fresh approaches to scaling without the need for conventional infrastructure (Ganuthula, 2025, pp. 5–7).

A good example of this is a small eco-friendly company, Repurpose, that scaled its business using AI across the company, including accounting, marketing and HR. AI was especially helpful where they did not have the same resources as their competitors: ChatGPT was used for marketing and copywriting support, then they used a third-party financial platform to improve billing processes and streamline external payments, autofill invoice data etc. as well as AI-enabled review platform with an AI assistant that helps employees and gives them written reviews (Hightower, 2025b).

If entrepreneurs use GenAI tools to the fullest, they could use them in niche markets or aspects without hiring any new or external workers and avoid paying traditional associated costs (Walkowiak, 2023, p. 4). This could usher in new types of business models and start-ups. Entrepreneurs must navigate all the listed repercussions and embrace AI in a balanced way. This means knowing and understanding regulatory frameworks, task dynamics, and industry-specific incentives. Adopting best practices means entrepreneurs will utilise GenAI as a transformative instrument to improve decision-making, stimulate growth, and generate value while acknowledging the necessity for ethical use, regulatory adherence, and adaptability (Gupta, 2024, p. 29).

4.2 Types of GenAI tools used

Based on general-interest articles (Pushkarska & Danielkievych, 2024; AdviceScout, 2025; Kamboj, n.d.), YouTube videos (Ashby, 2025; Stratvert, 2025; Futurepedia, 2025) and other non-scientific sources that touch upon current use of GenAI tools in entrepreneurship, it can be deduced that many tools are being incorporated into business processes. Moreover, the data from Statista (2025) highlights the significant impact and swift acceptance of GenAI by both consumers and enterprises. It has enhanced content production efficiency by 40%, augmented creative output by 75%, and automated workflows by 90%. Grouped into different categories (by purpose and user interaction type), here are those that are mentioned the most:

a) General AI Assistants: ChatGPT, Microsoft Copilot, Gemini, Claude, Perplexity, Grok, Meta AI, DeepSeek, Poe, Siri, Alexa.
b) Routine tasks:
   - Automation: Make, Zapier, n8n, Abacus AI, Manus
   - Research and insights: Genway AI, ViralFindr, NotebookLM
   - Work support and collaboration tools: Trello AI, Notion AI, Otter AI
c) Creative expression:
   - Image and video generating and editing: Runway, PIKA, Kling AI, D-ID, DALL·E, Midjourney, Higgsfield, Ideogram, Leonardo.AI, Adobe Firefly, Sora
   - Audio and music applications: ElevenLabs, Soundraw, Udio, Suno
   - Video and marketing content: Synthesia, HeyGen, Veed, Loom AI, VidlQ, Autopod, Canva (Magic Studio). Creative generating platforms: CapCut, Descript, Opus Clip, Submagic, Captions.
   - Writing and copy tools: Grammarly, QuillBot, Scribe, Bnsn, Rytr, Jasper AI, Surfer SEO, AdCreative.
   - Presentations and visualisation: Gamma, Figma AI, Napkin AI.
d) AI-enhanced software development: GitHub Copilot, AlphaCode, Cursor, Windsurf, Bolt, Lovable, Replit, Hugging Face
e) Relational and social engagement: Character.ai, Replika, Delphi

4.3 Factors impacting the use of GenAI by entrepreneurs

GenAI can give SMEs, especially start-ups, a competitive edge, reinvent their business models, increase business value, and change digitally. Continuous but modest GenAI technology experimentation underpins adoption. The entrepreneur's experience plays a crucial role in this process; nevertheless, factors such as social influence, domain experience, technology familiarity, system quality, training and support, interaction and convenience encourage them as well. These factors encourage entrepreneurs to experiment with the GenAI technology, which increases perceptions of its usefulness, ease of use, and enjoyment, which affect their emotions and willingness to implement it. Thus, GenAI's value

comes from its capacity to match business needs. This means that entrepreneurs who understand their company's needs and are aware of technology's functional capabilities have the greatest potential to determine how GenAI can be used effectively to support their business tasks. The GenAI adoption is, from the entrepreneur's view, therefore dependent on its perceived utility. Yet technology's usefulness depends on users' ability to prompt it effectively and easily; therefore, perceived simplicity of use may still be the most important in acceptance. However, knowing the technology's limitations is also important, as it raises important questions entrepreneurs must consider, such as ChatGPT (GenAI/AI) dependence – full, partial, or none (Gupta, 2024, pp. 1, 2, 29).

A concrete illustration of how those factors such as resource constraints, training/support, and interaction convenience jointly motivate adoption in SMEs is the company Amarra, which integrated third-party GenAI into its core e-commerce workflows. They started using ChatGPT to write product descriptions, which reduced the amount of time needed to create content by roughly 60%; an AI-powered inventory system, which reduced overstocking by roughly 40%; and AI chatbots, which currently handle 70% of routine customer enquiries, freeing up employees to handle exceptions and customisation. In order to minimise model bias and strike the ideal balance between automation and brand voice, leaders emphasised the need for iterative tuning and staff training. The instance shows that when GenAI is matched with particular problems (such as inventory risk, service queues, and catalogue content), its perceived usefulness rises, enabling small teams to boost productivity without hiring more staff (Hightower, 2025c).

This connection is further supported by extensive ChatGPT usage data (Chatterji et al., 2025, p. 20) that shows that nearly half of all communications (45.2%) connect to only three work-related tasks: acquiring information (19.3%), analysing the significance of information for others (13.1%), and documenting/recording information (12.8%). Furthermore, the main work-related tasks are documenting/recording information (18.4%), making decisions and solving problems (14.9%), and thinking creatively (13.0%), which are all important entrepreneurial tasks.

Even though the emergence of low-cost LLMs represents a crucial factor, the overall economic value of AI and GenAI technologies, weighted against their societal and economic cost, is still very important. A framework to access its value is composed of six components that look at its ability to add revenues, enable organisations to differentiate, reduce their costs, optimise risks, innovate, and transform (Dwivedi et al., 2023, p. 42). Furthermore, according to investors, adding ChatGPT or GenAI technology to the company arsenal can have an important impact on publicly traded corporate stocks, as it was shown to drive up companies' returns (Eisfeldt et al., 2023, p. 25).

And finally, the factor of openness to work-GenAI interaction can have a significant effect on productivity and adoption patterns. Start-ups or SMEs that are willing to create open learning environments will gain competitive advantages, as this approach enhances overall

productivity and skill development compared to restrictive policies that can hinder innovation (Walkowiak, 2023, p. 4).

4.4 Effects of GenAI use on the entrepreneurship process

As already discussed, the main GenAI effect on the entrepreneurship process is the same as for other businesses – higher productivity (Walkowiak, 2023, p. 3). By exploiting learning synergies and collaboration between humans and machines, the effect of those tools is even more pronounced regarding entrepreneurs and start-ups, as it enables a smaller number of workers to do more and a wider variety of tasks, and thereby reduces the need for more employees (Allen et al., 2023, p. 8).

A thorough analysis of the implications of GenAI and AI on entrepreneurs is provided by the AI-Enabled Individual Entrepreneurship theory (AIET). The theory (Ganuthula, 2025, pp. 1–3) highlights two key outcomes that the new technology may bring about: the development of resource needs and the democratisation of knowledge. AIET elucidates how individuals can now pursue entrepreneurial endeavours at scales that previously necessitated substantial organisational infrastructure through three fundamental mechanisms: skill enhancement, capital structure transformation, and risk profile adjustment. AI makes information available to everyone and greatly changes how much potential people have as entrepreneurs. AI systems likewise cut down on the costs of processing and retrieving information by a huge amount. This lets users quickly get and use domain-specific knowledge that used to take years of specialised training or experience to learn. AI technologies also turn implicit knowledge into clear, useful insights (facilitate understanding), making expertise that was once limited to certain groups available to everyone. Furthermore, AI systems make it easier to synthesise and apply information in real time, allowing individual business owners to leverage a variety of knowledge areas in ways that were previously only possible inside large organisational structures. On the other hand, AI has caused a substantial shift in the type and number of resources required for entrepreneurial activities, which has led to an evolution in resource needs. AI technologies are changing the balance between human resources and technical progress by making it possible for people to do tasks that used to need big teams or organisational structures. AI technology is also tremendously changing traditional resource-based barriers to entry. AI-powered entrepreneurship creates new ways to get and use resources. Cloud-based AI services and API-driven functions challenge traditional ideas about the minimum effective size and resource needs by letting entrepreneurs use cutting-edge technology without having to make a big initial investment. Additionally, instead of traditional resource management, these changes are creating new forms of competitive advantage based on the ability to effectively leverage AI capabilities. This shift suggests that fundamental assumptions about the relationship between resource ownership, control, and entrepreneurial success need to be re-examined. Lastly, the way that "cloud-based AI services and API-driven functionalities enable entrepreneurs to utilise advanced technological capabilities without substantial initial

investment" challenges conventional beliefs regarding minimum efficient scale and resource prerequisites, thereby illuminating the evolution of resource requirements (Ganuthula, 2025, pp. 1–3).

More specific examples of how ChatGPT use affects the entrepreneurial process can be seen in the wide range of tasks and workflows it can assist and automate. For example, it could be a business assistant that helps research worldwide markets or assists with software development, making or fixing software programs. Entrepreneurs might use ChatGPT's results as hypotheses to guide further research, validation, and verification from a variety of sources of knowledge, including people who are experts in the field. With ethical and appropriate ChatGPT integration into company operations, entrepreneurs can make informed and rational business decisions. This strategy is in line with the quest for more trustworthy business-related data concerning business model elements (Gupta, 2024, p. 2).

Likewise, it is essential to especially highlight GenAI's ability to, in a sense, democratise skills like e.g. marketing, which means small businesses, start-ups, and entrepreneurs can develop whole marketing campaigns (with less experience or knowledge) in addition to customised communications, such as sales materials for funding that are catered to personality types. It may also improve a company's crowdsourcing efforts for visualisation, such as showcasing creative new product designs, packaging, logos, etc. Nonetheless, the efficacy of innovative approaches to content creation for marketing must be methodically evaluated and further examined in a variety of settings (Peres et al., 2023, p. 273).

Despite all those benefits, the AI boom brings forth some pressing negative effects even for entrepreneurs and organisations. For example, according to Financial Times (2025), companies are already skipping the traditional employee progression pipeline and expect new hires to be highly skilled and experienced. This means that new entry-level jobs are disappearing (becoming automated or heavily AI-supported, which reduces their number as well). This shrinking of entry-level roles weakens the talent pool, which in turn means entrepreneurs or firms may soon struggle with recruiting and training young talent. Additionally, this may also negatively affect mentorships, general learning on the job, and social mobility at work. AI's disruptive effect on the job market, in combination with unclear regulatory responses, can lead to adverse cultural effects that can, in turn, further complicate the situation. New theorised organisational structures (e.g., diamond-shaped) that could develop because of diminished entry-level jobs (and a higher need for middle-level roles) may cause many unforeseen events. Companies and decision-makers, as well as entrepreneurs, therefore, need to ask themselves tough questions like where the experienced workers will come from, who and how will nurture the next generation and what happens if they do not.

To summarise, the effect of AI on entrepreneurship emphasised by the AIET is the possible decoupling of organisational size and capacity. Furthermore, the democratisation of knowledge and the evolution of resource requirements could fundamentally change how

individual entrepreneurs identify, evaluate, and pursue opportunities. All these point toward a new theoretical understanding of entrepreneurial capacity that emphasises the ability to effectively leverage AI capabilities rather than traditional measures of resource control or organisational size. This shift has major consequences regarding how entrepreneurial advantage and success in an AI-enabled context are conceptualised (Ganuthula, 2025, pp. 3–4).

5 METHODOLOGY

5.1 Research purpose and goals

The purpose of this master's thesis is to research, gather, and analyse the use of GenAI tools with respect to the entrepreneurial process. It examines the potential benefits, drawbacks, limitations, and implications of GenAI on entrepreneurs, entrepreneurial employees, and their work, as well as identifying best practices of its use. The goals were to investigate and build on the existing theory using empirical, practical, and real-world data by addressing the following research questions:

- RQ1: What are the potential applications of GenAI tools in entrepreneurship?
- RQ2: How does GenAI influence entrepreneurs' creativity and innovation?
- RQ3: How do different GenAI models and tools vary in their impact on entrepreneurial work?
- RQ4: What are the ethical, legal, and social implications and limitations of GenAI, and how can these be addressed responsibly?
- RQ5: What strategies and best practices enable effective adoption and use of GenAI across entrepreneurial processes and workflows?

To enhance the study with a quantitative framework, corresponding null and alternative hypotheses (H0/H1) were formulated alongside the research questions to guarantee the consistency and comparability of the results:

- H0a: The application of GenAI tools is not a regular practice among entrepreneurs.
- H1a: The application of GenAI tools is a regular practice among entrepreneurs.
- H0b: Entrepreneurs with substantial GenAI experience do not have higher mean creativity scores than entrepreneurs with no/minimal GenAI experience.
- H1b: Entrepreneurs with substantial GenAI experience have higher mean creativity scores than entrepreneurs with no/minimal GenAI experience.
- H0c: Entrepreneurs use only one GenAI tool.
- H1c: Many different GenAI tools are used by entrepreneurs.
- H0d: Entrepreneurs do not encounter ethical or legal misgivings about GenAI use.
- H1d: Entrepreneurs encounter ethical and legal misgivings about GenAI use.

- H0e: Widespread organisational-level adoption of GenAI can be achieved through individual initiatives.
- H1e: Widespread organisational-level adoption of GenAI cannot be achieved solely through individual initiatives but requires organisational-level strategies and support mechanisms.

To answer these, the study applied a mixed qualitative methodology: a pre-interview survey was implemented to gather thorough descriptive and exploratory insights, while semi-structured interviews provided detailed qualitative narratives. Simultaneously, the survey functioned as a pre-interview filter that assisted in identifying the most suitable individuals for the mentioned semi-structured in-depth interviews. The data was analysed using thematic analysis (TA) or, more specifically, a reflexive thematic analysis (RTA), which enables the identification of patterned meanings within the dataset while preserving the flexibility to reveal new insights (Byrne, 2022, p. 1392; Braun and Clarke, 2006, p. 32). The analysis relied on RTA, although the interviews were conducted with a phenomenological sensibility informed by Interpretative Phenomenological Analysis (IPA). According to Pietkiewicz and Smith (2014, p. 12) semi-structured, in-depth, one-on-one interviews provide enough room and flexibility for new and unexpected perspectives or topics to come up. This combination ensured that each individual's experience was significant and that the experiences of all participants could be compared.

5.2 Secondary data sources and review process

The theoretical foundation of the thesis is based on secondary data. The literature included encompasses peer-reviewed academic articles, books, and policy documents pertaining to AI, GenAI, entrepreneurship, creativity, innovation, decision-making, knowledge management, and other business processes. Through the analysis of online databases such as ScienceDirect, SpringerLink, ResearchGate, Emerald, JSTOR, Statista, arXiv, and Google Scholar, the most appropriate sources were selected. The majority of the selected sources were published between 2020 and 2025; however, due to the continuously changing nature of the topic, preference was given to sources from 2023 onwards. The inclusion criteria highlighted the use of peer-reviewed, high-quality academic sources, together with regulatory documents from the European Union and the United States. The insights obtained from secondary data directly guided the formulation of the survey and interview questions, ensuring alignment between theoretical and empirical elements. Seven academic papers were selected as key references, as they collectively offer extensive coverage of all five research questions. They provide both conceptual and theoretical foundations of GenAI (Feuerriegel et al., 2023; Abendroth-Dias et al., 2025), evidence regarding its applications and impact on creativity and innovation (Bouschery et al., 2023; Ganuthula, 2024), and critical perspectives on ethical, legal, and governance dimensions (Bahrini et al., 2023; Korzyński et al., 2023; Vu et al., 2025). Together, they ensure the methods are consistent and provide a strong foundation for studying the role of GenAI in entrepreneurship.

5.3 Primary data collection

5.3.1 Pre-interview survey

A pre-interview survey was conducted to assess participants and provide both descriptive and exploratory insights. The survey aimed for a minimum sample size of 100 participants, with the final number being 105. In line with the principle of information power, this was thought to be enough for meaningful descriptive and exploratory analyses while also serving as a basis for identifying possible interviewees. As Malterud et al. (2016, p. 1753) said, the more relevant the information the sample holds, the fewer participants are required. The survey link was disseminated through different channels to ensure it reached a diverse audience and elicited varied responses. However, the accompanying postings, messaging, and survey introduction explicitly indicated that the study focused on individuals utilising GenAI products in their professional or corporate contexts, directing participation towards the appropriate demographic. The dissemination occurred via the researcher's social media platforms (e.g., LinkedIn and Facebook), through cold emails directed at prominent entrepreneurial groups and organisations (e.g., Technology park Ljubljana, Impact Hub Ljubljana, Young Makers Society, and Ljubljana University Incubator; some of which subsequently circulated the information about the survey to their AI-centric groups and communities), and by directly contacting entrepreneurs and appropriate candidates recognised as frequent users of GenAI and otherwise closely aligned with the target demographic.

The survey included twelve demographic enquiries and thirty questions, which were categorised based on the five research areas and their corresponding research questions. The whole survey questionnaire used in data collection can be found in Appendix 2. The evaluation consisted of single- and multiple-choice questions, Likert scales, and ranking questions. The survey was distributed in both Slovenian and English to ensure broad accessibility and minimise unnecessary friction. The results were subsequently translated as necessary for reporting purposes. Descriptive and exploratory statistical techniques were used to examine the responses. The following criteria from the demographic enquiries were employed to assess possible interview candidates: consistent (daily) use of GenAI at work, possession of an entrepreneurial experience, having at least one year of experience with GenAI and having indicated their willingness to participate in an interview. Before data collection, participants were told that their participation was consent under the GDPR. Participants were informed of the study's goal, the scope of data processing, and the short-term data retention period, which is restricted to the completion of this master's thesis. Confidentiality and anonymity were preserved throughout the whole process of collecting, storing, and processing data for academic research purposes. Beyond what was necessary for study, no personally identifiable information was kept, and all data will be safely deleted in accordance with GDPR (Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons concerning the processing

of personal data and on the free movement of such data (General Data Protection Regulation), OJ L 119/1) when the thesis is finished.

5.3.2 Semi-structured interviews

The main empirical data were collected through semi-structured, in-depth interviews. Purposive sampling helped identify 14 entrepreneurs who fulfilled the qualifying requirements from the survey, but only 6 with the highest potential were chosen. The dataset, therefore comprised 6 entrepreneurs, augmented by 2 key GenAI adoption process participants, such as the data protection officer (DPO) and chief information security officer (CISO), who provided more contextual insights and facilitated comparison to the corporate environment. This sample size strikes a balance between practicality and the notion of informational power (Malterud et al., 2016, p. 1759), which asserts that the quality of discourse, precision of objectives, and depth of analysis outweigh sample size. The contributions from the two mentioned experts were separately assessed to corroborate and augment the findings while maintaining the integrity of the primary dataset (entrepreneurs). The interviews were conducted in Slovenian and lasted between 45 and 75 minutes. Each interview was guided using open-ended questions, based on the five research themes (5 RQs), which ensured consistency and rich data for detailed and nuanced analysis while allowing flexibility for emergent topics, all in alignment with TA principles (Braun & Clarke, 2006, p. 82). Automatic GenAI transcription software (Soniox) was employed to document, record and transcribe the interviews. Subsequently, the transcripts were manually verified and anonymised. To ensure rigour, the researcher employed reflexive memoing and acknowledged their dual role as both interviewer and AI practitioner. This reflexive stance aligns with (Byrne, 2022, p. 1393) position that reflexive thematic analysis emphasises the researcher's active role in the development of themes. As already mentioned, all participants were provided with all relevant information and have given their permissions (a consent form can be found in Appendix 3), and all ethical obligations under GDPR Article 5 (consent, confidentiality, data minimisation, and safe storage) were fulfilled.

5.4 Data analysis procedures

The data analysis was divided into three phases: descriptive and exploratory analysis of the pre-interview survey, theme analysis of semi-structured interviews, and synthesis of both components into a unified interpretation. Fundamental descriptive statistics (frequencies, percentages, averages, standard deviations, etc.) and exploratory statistics (non-parametric tests like chi-square, correlations like Spearman's rho, etc.) were employed to analyse the survey data and ascertain demographics, GenAI adoption trends, and attitudes. This methodology is appropriate for exploratory research (Creswell & Plano Clark, 2011, Chapter 7) and served as a screening tool for selecting interviewees. Interview transcripts were analysed using reflexive TA, following Braun and Clarke's six-phase framework (2006, p. 37). The coding employed a mixed inductive-deductive methodology: inductive for

gathering participants' experiences and deductive for analysing the five study topics. Interviews were conducted with phenomenological sensitivity, influenced by IPA, which fosters openness to lived experiences. Coding was conducted manually, supplemented by GenAI tools, although all outputs were meticulously verified to ensure the researcher-maintained oversight and engaged in critical thinking on their actions. The integration phase compared survey patterns with interview topics, enabling triangulation and complementarity that was further enriched with data from 2 key stakeholders (Creswell & Plano Clark, 2011, Chapter 8). This mixed-methods design contextualised broad patterns with more nuanced experience findings. Reflexive memoing, triangulation of data sources, and an audit trail of coding judgements enhanced the rigour of the task. Peer debriefing with the academic supervisor improved transparency and reduced prejudice.

5.5 Methodological limitations

It is critical to acknowledge this study's various methodological shortcomings. Initially, the relatively small sample size limited both statistical power and the ability to conduct trustworthy subgroup comparisons, even though exploratory and inferential techniques (such as cross-tabulations, non-parametric tests, and correlations) enhanced the survey analysis. Consequently, rather than being generalisable, the data remain suggestive. Second, the qualitative dataset was purposively sampled and relatively small, in line with the informational power principle (Malterud et al., 2016, p. 1759); yet it was vulnerable to potential self-selection bias. Entrepreneurs who were already using GenAI were more likely to participate, potentially constraining the perspectives of less active users. Third, a mixed inductive–deductive coding technique was used for thematic analysis, ensuring both sensitivity to new ideas and agreement with study goals. But this approach might put too much focus on predefined categories; however, reflexivity and peer debriefing with the supervisor mitigated this risk. Fourth, during the integration stage, the results of the surveys and interviews were compared to each other to put them in context and triangulate insights. This enhanced validity; however, the clarity of the interactions between the two strands was limited by the absence of formal integration methods. Finally, the results are time-sensitive since GenAI technologies are developing quickly, and translations from Slovenian interviews into English may have resulted in limited meaning change, even with meticulous coding in the original language. The results should be evaluated cautiously and used as a foundation for further study rather than a definitive conclusion, even if efforts were made to improve rigour and the chosen methodologies were generally appropriate for the exploratory scope of the thesis.

5.6 Use of GenAI tools in research

GenAI technologies were employed in conjunction with conventional quantitative and qualitative methodologies. In the phase of collecting and analysing secondary data, ChatGPT assisted in searching, evaluating, and organising different sources; summarising and

categorising extensive texts; highlighting their key findings; generating ideas to improve or find a different perspective; evaluating written text; etc. Moreover, Perplexity AI and SOTRM AI enabled rapid searches of scientific literature and provided initial source summaries, while Consensus assisted in assessing the level of acceptance or contention of findings within the scientific community. QuillBot was used to enhance the written language, paraphrase, check grammar, and detect plagiarism throughout the thesis, particularly during the final editing phase. In the second part, related directly to the primary data collection, ChatGPT similarly helped with idea generation, critical evaluation, codifying the data and with general overall decision-making, especially regarding survey and interview question formation.

Every AI-assisted output used was manually verified and inspected. For example, Soniox was used to transcribe interviews for initial data collection, but it was later reread, manually corrected, and anonymised. Nevertheless, using it reduced transcribing duration and enhanced its accuracy. ChatGPT was also used in a capacity related to Computer-Assisted Qualitative Data Analysis Software (CAQDAS) throughout the analysis phase. It generates initial summaries, categorises candidate codes, and proposes potential topic frameworks. The researcher meticulously evaluated these proposals and retained full control over their interpretation. GenAI technologies were used even though they may present significant risks (e.g., automated transcribing may misinterpret technical terminology or instances of code-switching and may provide biased or fabricated outputs). To mitigate all GenAI-related concerns, e.g. transcripts were assigned pseudonyms prior to uploading to other GenAI tools; sensitive data was omitted; and throughout the research, only paid, GDPR-compliant GenAI tools were used (Soniox, n.d.; OpenAI, n.d.), and all outputs from AI tools were manually verified. Ethical concerns, including GDPR compliance regarding data minimisation, safe storage, and anonymisation, were adhered to. The thesis demonstrates transparency by clearly documenting the use of GenAI tools, critically analysing issues, and framing GenAI as both a subject of investigation and a methodological tool. This reflexive inclusion enhances the originality and relevance of the study.

6 RESULTS AND ANALYSIS OF RESEARCH FINDINGS

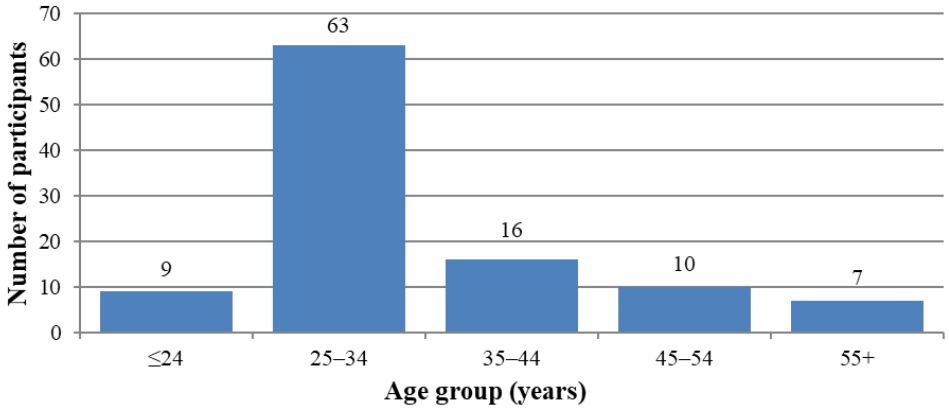
6.1 Results and analysis of pre-interview survey

The pre-interview survey was administered over a 30-day duration, resulting in 106 participants, with 105 replies considered legitimate (n=105). One participant reported that they had never utilised GenAI in a professional context; hence, their statement was omitted from the study. The survey comprised 64 variables, with an average completion time of 12.5 minutes (Md=9 minutes), and was available in Slovenian (70 respondents) and English (35 respondents), and had a 100% completion rate. The dataset offers a robust empirical basis for analysing the utilisation of GenAI products across business and professional domains.

Before assessing trends, it is essential to delineate the demographics and specify the characteristics of the sample.

Figure 1 shows that most of the respondents in the sample were young, with 63 people (60.0%) between the ages of 25 and 34 and 16 people (15.3%) between the ages of 35 and 44. This shows that most of the people in the sample are professionals in the early to middle stages of their careers who are known for quickly integrating and using new digital technologies. There were 52 (49.5%) female participants and 50 (47.6%) male participants, so the gender split was even. This enhances the data's representativeness and reduces potential gender bias, consistent with literature indicating that gender disparities in GenAI tool utilisation have markedly decreased in recent times (Chatterji, et al., 2025, p. 37). The sampled population is primarily well-educated, with 85.7% of individuals possessing a bachelor's degree (ISCED 6) or higher. This corresponds with expectations for those employing modern digital technologies. Most of the individuals who took part (74, 70.2%) worked for an organisation. Seventeen (15.9%) were self-employed or entrepreneurs, and fourteen (13.9%) were students. This allocation ensures contributions from both organisational employees and individuals with an entrepreneurial focus, while also incorporating the viewpoints of prospective workforce entrants.

Figure 1: Age distribution of participants

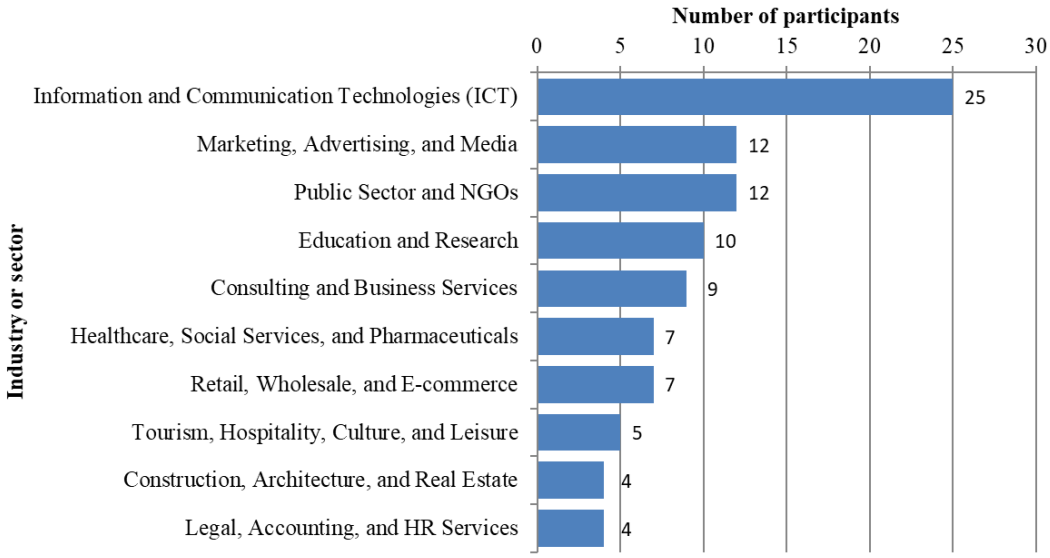


Source: Own work.

Figure 2 clearly demonstrates that the most represented industry or sector by participants was “Information and Communication Technologies (ICT)” at 23.8% (25). In combination with others such as “Marketing, Advertising, and Media” and “Education and Research”, this industry analysis reveals a substantial presence of information- and knowledge-intensive sectors driven by innovation, underscoring circumstances where GenAI adoption is particularly impactful. Regarding organisational classification, 65 respondents (61.9%) were associated with the private sector, 37 respondents (35.2%) with the public sector, and 3 respondents (2.9%) with non-governmental organisations (NGOs). A total of 41 respondents, representing 39.0%, were from large enterprises; 32 (30.5%) from medium enterprises; 10 (9.5%) from small enterprises; 15 (14.3%) from micro enterprises; and 7

(6.7%) were sole proprietors. The incorporation of tiny, micro, and sole proprietorships offers a significant perspective on agile organisations, which frequently encounter unique limitations while demonstrating flexibility and quick integration of new technologies.

Figure 2: Most represented industries among participants

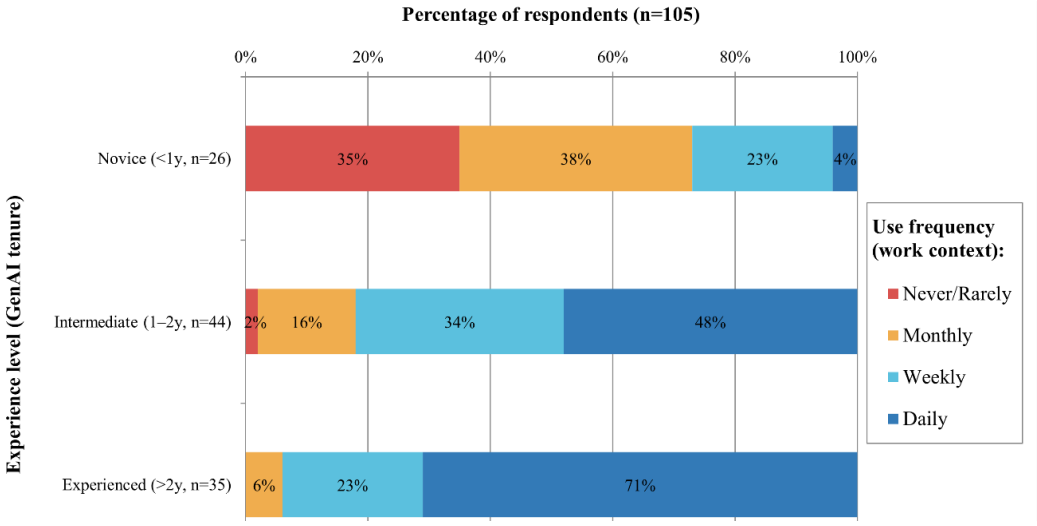


Source: Own work.

The primary functions reported by most respondents are "information technology (IT) and digital development", accounting for 27 individuals or 25.7%. The next largest group (16, 15.2%) was involved in "Marketing and Sales", and the smallest group (13, 12.4%) consisted of entrepreneurs with diverse duties. The category of "Research, Development, and Innovation (R&D)" comprised 12 responders, accounting for 11.4%. This distribution, similar to the industry analysis, shows the most common situations in which GenAI is used and adopted. When asked about their hierarchical roles, a large majority (72 respondents, 68.6%) said they were individual contributors instead of managers. At the same time, 20 people (19.0%) said they were team leaders or middle managers, and 8 (7.6%) said they were executives or C-level executives. This structure suggests that the information mainly comes from people who work in operational and creative roles, but it also includes ideas from people who work in strategic and decision-making roles. This distribution is important for figuring out how GenAI is used every day and how it affects the whole organisation. The results also show how much people have used and worked with GenAI tools before (experience). A significant proportion of participants (44, 41.9%) reported utilising GenAI for 1–2 years, while 35 individuals (33.3%) indicated usage exceeding 2 years. Twenty-six individuals (24.8%) had experienced exposure for a period of less than one year. Additionally, approximately half of the sample (52, 49.5%) reported using GenAI at work daily (when measuring frequency). Twenty-four people (22.9%) said they used it every week, and nineteen people (18.1%) said they used it once a month. Figure 3 outlines how surveyed individuals have consistently and significantly integrated GenAI into their procedures, which is especially clearly seen when segmented into groups by duration of

GenAI use and compared on their frequency of use. This provides a robust empirical base for analysing adoption trends.

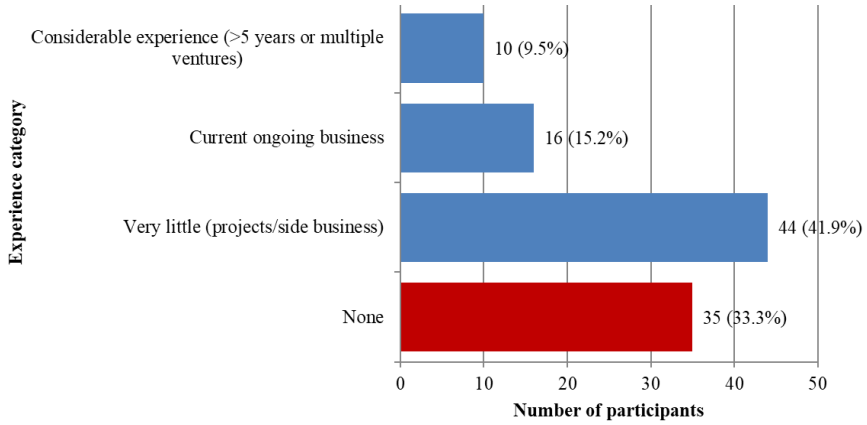
Figure 3:Work-use frequency of GenAI rises with experience



Source: Own work.

The demographic section also asked about entrepreneurial experience, which is highly relevant. Figure 4 summarises this and shows that a third of the respondents (35) said they had never started a business before and that 66.7% had at least some experience as an entrepreneur (with the majority of those having very little experience). This composition, therefore, facilitates a comparison between entrepreneurs and non-entrepreneurs concerning GenAI adoption.

Figure 4: Entrepreneurial experience by category



Source: Own work.

When using a Likert scale, a 5-point scale was utilised throughout the survey. For example, it was used to evaluate participants' perceptions of their proficiency with GenAI. A majority of respondents (62%) indicated possessing moderate to high levels of proficiency (Levels 3–

5), hence affirming the sample's validity about practical experience and confidence in utilising GenAI.

The demographics and industry sectors of the respondents to the pre-interview survey indicate a workforce that is young, well-educated, tech-savvy, knowledgeable about GenAI, and shows an active entrepreneurial inclination. This profile provides a robust framework for analysing the integration of GenAI into business environments, alongside its correlation with entrepreneurial behaviour and strategies for innovation. The differences in responsibility, experience, and skill level make the dataset more useful and better equipped to find different patterns of GenAI adoption in business settings. Consequently, the sample provided a robust basis for identifying suitable candidates for the in-depth semi-structured interviews, as specified in the methodology, thereby facilitating a smooth transition from the survey phase to the subsequent qualitative analysis.

6.1.1 General application information

The main reasons people start using GenAI tools are productivity and efficiency enhancement (65 mentions), idea generation and creativity improvement (52 mentions), and curiosity/personal interest (48 mentions). A lot of participants also indicated they use it to automate routine or repetitive tasks (38 mentions) and to overcome limitations in knowledge or skills (31 mentions). Table 1 shows tool adoption by participants and highlights that ChatGPT (OpenAI) was by far the most popular GenAI tool. Notably, regardless of the duration of time participants used GenAI tools, ChatGPT was still the most popular choice across all experience groups (91–96%). Novice users exhibit a greater reliance on Microsoft Copilot (42% compared to 31%), whereas experienced users demonstrate more diversification (higher Perplexity utilisation: 23% against 12%) and the adoption of more specialised tools.

Table 1: Tool adoption by participants

GenAI tool	**Users (n)**	**Share (%)**
ChatGPT	99	93.4
Gemini	35	33.0
Copilot	35	33.0
Canva AI	25	23.6
Perplexity	14	13.2
Midjourney	9	8.5

Source: Own work.

The majority of users assess their competence as moderate (M=3.01), with 34.3% at the median level and 27.6% perceiving themselves as above average. When looking for between-group differences summarised in Table 2, a robust, statistically significant correlation was found between the duration of GenAI usage (experience levels) and self-

reported competency. Users with greater experience regularly assess their competence more favourably, with a dramatic disparity observed between novices (less than 1 year: 53.8% self-rate as below average) and experienced users (more than 2 years: 0% self-rate as above average). This indicates that proficiency evolves progressively with continuous use over time. In the context of business applications of GenAI, text preparation and editing account for 78.6%, followed by data analysis at 55.3% and idea generation at 53.4%. The level of utilisation regarding the text preparation and editing significantly increases from novice to intermediate users, rising from 65% to 93%. Data analysis also increases with user experience (46% to 60%); however, idea development diminishes with experience (58% to 49%).

Users expressed a moderate incorporation of GenAI into their assignments (mean frequency: M=3.22; mean degree of daily integration: M=2.91), with the most significant perceived influence in IT/digital development (49.1%) and marketing/sales (43.4%). The integration pattern demonstrates highly significant disparities with linear progression and substantial effect sizes in both frequency and degree of integration, which is reported in Table 2, with the most pronounced difference observed between novice and experienced users; nonetheless, the most notable increase is evident among intermediate users. The primary distinction in perceived influence between novices and experienced users lies in the shift from an R&D focus (beginners) to an emphasis on marketing/sales and customer support applications (experienced). The data indicates a maturity trajectory in which users evolve from basic, experimental usage to advanced, integrated business applications as they acquire proficiency with GenAI tools. The referenced studies on the incorporation of GenAI in business contexts, e.g., Ameen et al. (2022, p. 1812), also indicated that marketing, sales, customer support, and software development are initially prevalent applications of GenAI in organisations. Conversely, advanced automation and operational optimisation were also less emphasised. This alignment suggests that in multiple contexts, GenAI is predominantly perceived as a tool for enhancing knowledge work and written communication, while its role in process automation and workflow transformation remains in an emerging stage, with users currently prioritising quick wins and immediate productivity enhancements.

Table 2: Between-group differences for key measures (ANOVA)

Outcome	Test	F(df)	p
Competency ~ Experience	One-way ANOVA	F (2,102) = 18.49	< .001
Frequency of use ~ Experience	One-way ANOVA	F (2,102) = 13.38	< .001
Degree of integration ~ Experience	One-way ANOVA	F (2,102) = 9.81	< .001
Competency ~ Age	One-way ANOVA	F (2,102) = 4.304	.016
Frequency of use ~ Age	One-way ANOVA	F (2,102) = 4.124	.019

Source: Own work.

Additional noteworthy disparities pertained to age demographics, indicating that age substantially influences GenAI adoption patterns. As shown in Table 2, self-assessed competency exhibited a significant difference among the middle group (which had the highest mean score and is shown in Table 3), the young group and the senior group. A similar pattern recurred with the frequency of GenAI utilisation, exhibiting comparable significance. Middle-aged professionals have the highest competency and usage, whereas seniors demonstrate a considerable deficit, suggesting diverse training and support requirements across age groups. Consequently, employees can be categorised into three groups: "digital natives" (≤34), exhibiting moderate proficiency and significant adoption potential; "digital adopters" (35–54), demonstrating the highest proficiency and usage; and "digital learners" (≥55), possessing the lowest proficiency and requiring targeted support. Despite an equal gender distribution, there are no statistically significant disparities in GenAI adoption patterns between men and women regarding this segment.

Table 3:Self-reported competency by age group

Age group (years)	Mean (M)	SD	n
Young (≤34)	2.96	1.07	72
Middle (35–54)	3.38	0.98	26
Senior (≥55)	2.14	0.69	7

Source: Own work.

6.1.2 Creativity and innovation

Approximately 70% (73) of users indicate that GenAI led directly to new ideas and solutions, demonstrating a significant impact on innovation and potential. Only 11.4% (12) of the people who answered said it impaired creativity. When divided by how long people have been using GenAI, experience reduces uncertainty. New users are much less sure (34.6% unsure), while experienced users have shown an increased level of trust in innovation benefits (77.1%). Later, though, 44.8% of individuals who took part unexpectedly agreed with the claim that GenAI tools offer generic solutions that limit creativity. Nevertheless, this proved highly polarising, as 32.4% explicitly disagreed with the assertion. The comparison is easily comprehended when looking at Figure 9, which shows the results of

creativity-related questions divided into experience groups and can be found in Appendix 4. This conflict suggests that GenAI's creative value depends on context and how it is used: as a direct final output (too generic to be useful) or as an integral part of the process.

The response to GenAI's impact on creative tasks is shown in Table 4 and indicates that the impact was largely neutral, with 35.3% indicating substantial change. The frequency of idea generation, was slightly above average, with 45.7% of users employing GenAI regularly for this purpose. Interestingly, for GenAI's enhancement of collaboration, respondents tended to express a neutral or minimal stance, with merely 20% indicating substantial improvement in collaboration. Nonetheless, when analysing the duration of GenAI usage, the findings indicated that the advantages of GenAI in creativity and innovation are significantly contingent on experience (all p-values < .01), implying that organisations should prioritise long-term skill development instead of anticipating immediate creative outcomes from novice users. The pronounced learning curve effect is evident, particularly in the significant improvement of scores across all metrics (variations of roughly 1.0 point across all measures show strong practical advancements, demonstrating a clear universal transition from novice to experienced user, with the greatest benefits noted between the groups of novice and intermediate users).

Table 4: Summary Statistics for Creativity-Related Outcomes

Outcome	**Mean**	**Median**	**SD**	**% (scoring 4–5)**
Creative task impact	3.07	3.00	1.13	35.3
Idea generation frequency	3.25	3.00	1.19	45.7
Collaboration enhancement	2.50	2.00	1.20	20.0

Source: Own work.

The most common application (already) mentioned was text preparation and editing, with 78.6% of respondents indicating they engaged in such a task. This indicates that content-related activities, particularly those requiring efficiency and linguistic accuracy, remain the primary domain of GenAI use. The second most prevalent application was data analysis and research (55.3%), indicating an increasing number of individuals are utilising GenAI to guide decision-making and acquire information. 53.4% of respondents used GenAI to generate new ideas, indicating its significance as a creative and exploratory instrument. Ultimately, 30.1% of users reported utilising process automation, revealing that although automation is increasingly significant, it remains less prevalent than content creation and knowledge-related tasks.

The findings affirm and reiterate existing literature stating that the application of GenAI predominantly aims to augment cognitive (Alavi et al., 2024) and creative abilities (Potts, 2023), while operational automation remains uncommon (as elaborated in chapter “1.5 Future of GenAI tools”, it represents the subsequent phase of GenAI evolution and is anticipated to become more prevalent in the near future). This analysis indicates that GenAI

technologies are more effective as enhancers of individual creativity (high impact) than as platforms for collaborative invention (low impact). The data shows an existing need to enhance individual creative skills rather than improving collaborative capabilities. Literature supports this, as text creation and summarisation are listed as two prevalent applications. A thorough investigation (Chatterji et al., 2025) analysing ChatGPT usage patterns indicated that writing tasks were the primary application of work (42%), followed by information retrieval and interpretation (32%).

As stated in the "5.1.1 General application information" section, there were no statistically significant differences between genders. Furthermore, age and industry showed little influence; although seniors face greater challenges, the disparity between young and middle-aged users is negligible. The experience with GenAI technologies, time investment, and skill development underscores the necessity for investment in long-term training programmes.

6.1.3 Factors and comparative impact

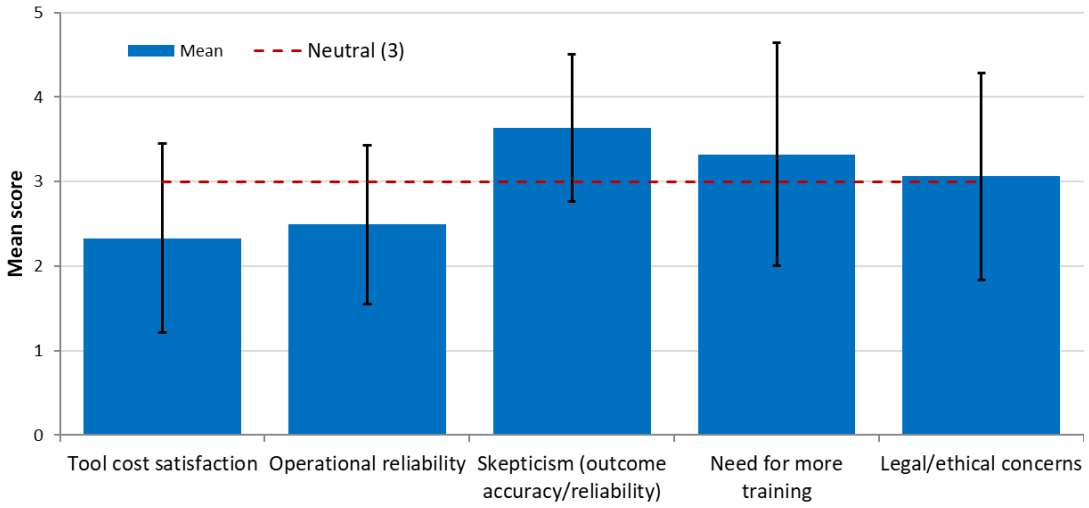
The responses indicate that when choosing GenAI tools, participants put the most weight on things like task utility (56.2%), free or freemium options (48.6%), accuracy (47.6%), ease of use (44.8%), reliability (24.8%), and price or subscription cost (26.7%). This means that users want tools that help them reach their work goals. When divided by age, "digital natives" focus on free or freemium options and ease of use; "digital adopters" focus on accuracy and task-specific utility; and "digital learners" focus on task-specific utility and ease of use. Thus, organisational adoption strategies should not categorise employees as a homogeneous entity. Moreover, men are more concerned with accuracy than women (58% vs. 36%), while women are more likely to prefer free tools (freemium options) than men (57.7% vs. 38%). Notably, concerning organisational size, small organisations (≤49 employees) are primarily cost-driven and task-oriented, seeking methods that effectively address their issues at minimal expense. Conversely, large organisations (with over 250 employees) emphasise reliability and accuracy because they have the financial capacity to invest in quality and consistency.

ChatGPT is the most suggested tool, receiving 76.73% of endorsements, followed by Microsoft Copilot at 10%, Google's Gemini at 7%, and Perplexity at 4%. When categorised by organisational size, individuals from medium-sized organisations exhibit more balanced tool choices, evidenced by the lowest factor concentration (HHI=1.051) and the minimal dominance gap of 3.1 points. This may suggest that they assess various criteria more equitably and employ a thoughtful and deliberate selection strategy. Conversely, smaller organisations exhibit focused criteria (HHI=1.586) while demonstrating a diverse exploration behaviour (highest tool variety), indicating they are exploring many options but know exactly what they want. This may be due to constrained resources necessitating meticulous evaluation. Nevertheless, large organisations have the lowest tool concentration (HHI=1.228) and a modest balance in factor selection, indicating a consensus-building

approach in tool suggestions. This is probably a consequence of varied departmental requirements.

In Figure 5 the data demonstrates that users are generally content with tool costs and operational reliability, although some exhibit scepticism regarding the accuracy and reliability of outcomes (Figure 5). They indicate considerable requirements for further training and experience apprehensions regarding the legal and ethical ramifications of GenAI use.

Figure 5: Descriptive statistics for perceptions of GenAI tools



Source: Own work.

Notably, when examined based on the duration of GenAI usage, the learning curve effect reappears, with novice users explicitly recognising their need for further training (M=3.92) and demonstrating increased apprehensions about technological reliability (M=3.04). The latter significantly decreases as users gain experience (M=2.34). Furthermore, findings indicate that users seldom alternate between tools during the same task (M=2.11, SD=1.1) and exhibit minimal worry or encounter any substantial integration issues (M=2.28, SD=1.02). As expected, experienced users create more intricate processes, regularly switching between tools to enhance their results (M=2.54). It is noteworthy that intermediate users exhibit the least apprehension over reliability and legal/ethical issues, indicating a "confidence peak" prior to acquiring the more sophisticated concerns characteristic of highly experienced users. These insights and traits substantiate the idea that organisations adopting GenAI tools require different training and support approaches for novice, intermediate and experienced users.

6.1.4 Implications and responsibility

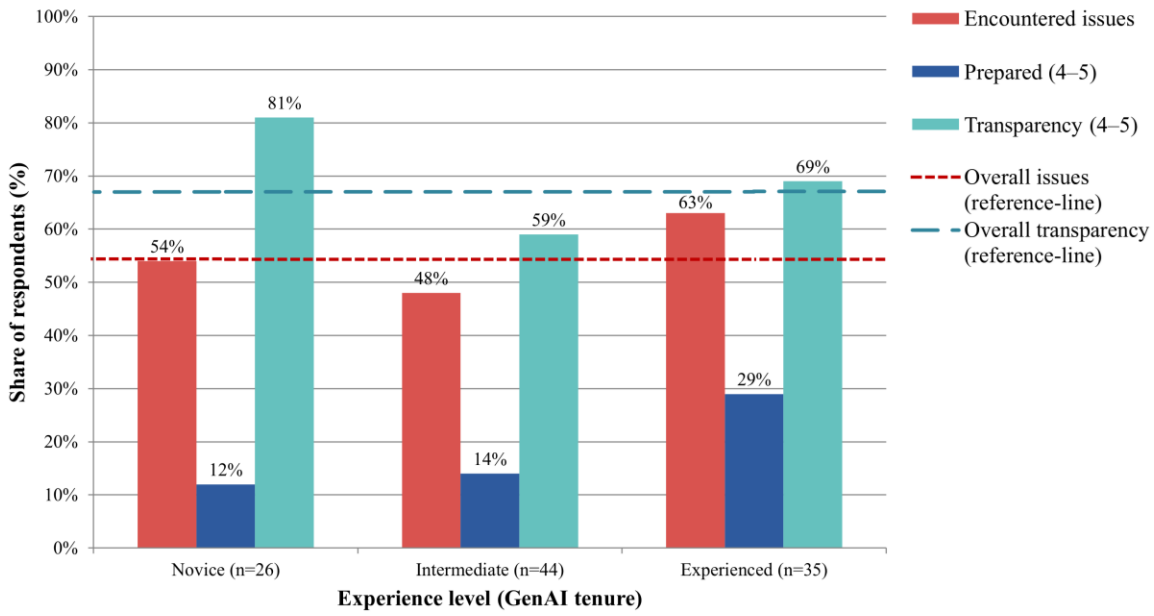
As many as 72.4% of participants recognise that GenAI is transforming their work, indicating that GenAI is perceived as a significant disruption in the workplace. Given that just 18.1% report no changes, it can be inferred that the majority of professionals are experiencing and acknowledging the effects of GenAI. A distinct progressive pattern emerges when categorised by duration of GenAI use: 50% of novice, 77.3% of intermediate users, and 82.9% of experienced users recognise changes. Longer utilisation of GenAI leads individuals to increasingly perceive its transformative influence on their professional lives, indicating that the transformation becomes more evident with continuous experience.

More than half (54.3%) have encountered ethical or legal issues, proving that these challenges are not only theoretical. Moreover, 61.0% express a lack of preparedness to confront those legal difficulties. This is consistent across all segments; nonetheless, experience with GenAI utilisation has demonstrated enhanced legal preparedness. The results indicate a significant desire for transparency, with 67% rating it as important or extremely important (M=3.9), further confirming its status as a top concern. Consequently, 61.9% of participants express a need for increased regulation. This is particularly evident among the group with the least experience in GenAI usage, as they exhibit the highest pro-regulation stance (76.9%), likely indicative of their uncertainty and caution. This conveys unequivocal messages to researchers, policymakers, and organisations that the necessity for organisational transparency policies, legal training programmes, and regulatory frameworks is not a future consideration but a pressing reality demanding an urgent need for proactive development and implementation.

A U-shaped experience-based learning pattern appears when categorising groups based on the duration of GenAI usage regarding ethical and legal issues. Likewise, akin to the “confidence peak” associated with reliability, the pattern recurs in relation to ethical and legal considerations. Figure 6 shows that new users exhibit moderate concern levels, intermediate users demonstrate lower concern, and the most experienced users indicate the highest rates of concern. This suggests that extensive experience reveals more significant ethical complexities; however, the analysis must consider the limited sample size (n=105) and recognise that the statistical power of this finding is correspondingly restricted (chi-square test p-value of 0.4201, with a small Cramer's V coefficient of 0.136). The pattern may still be useful in practice, even though it is not statistically significant. Interestingly, novice users place a high value on transparency (M=4.12), which means that their onboarding should focus on being open, transparent, and clearly showing how to follow regulations. The data show that confidence affects how much transparency is needed. Because of this, training and teaching more experienced users should focus on other, more complex ethical issues. Given that there are big differences between the groups that use GenAI for different amounts of time (experience), further suggestions and implications could be deduced by policymakers. When creating regulatory frameworks, it is important to consider the different needs that come from different levels of experience. It is

also important to cover a wide range of topics in professional development programs, that are related to legal, ethical, and regulatory preparation or transparency mandates. It would be interesting if future studies and research looked into this issue with this kind of segmentation.

Figure 6: Encountered issues, preparedness, and transparency by experience level



Source: Own work.

Interestingly, the data also indicates that gender significantly predicts individuals' attitudes about using GenAI, although organisational size does not. Individual traits appear to have a greater impact on GenAI adoption than the organisational setting. For instance, women regularly demonstrate more cautious, pro-transparency, and regulation-focused attitudes regarding GenAI technology than men, which may influence implementation tactics and policy development.

6.1.5 Adoption Strategies

Initially, merely 31.4% of participants said that their companies have established structured procedures and guidelines regarding the use of GenAI tools. Moreover, hardly 10.5% indicated the existence of any processes for evaluation of GenAI's value (e.g., ROI, impact, or added value assessment), and only 8.6% reported having efficiency metrics in place (e.g., job completion speed, time savings, increased quality of output, etc.). Nonetheless, 44.8% of respondents reported that their companies offer some form of training or educational programmes related to GenAI, while 41.0% indicated that they had a designated budget for GenAI initiatives. Secondly, the primary obstacle seems to be the knowledge gap (M=3.99). While policy clarity (M=3.37) and time restrictions (M=3.34) are the subsequent concerns, whereas cost (M=3.11) is unexpectedly the least significant obstacle to GenAI use. Finally,

there are some encouraging metrics, as 60.6% (M=3.83) of participants advocated for the adoption of GenAI (integration into professional or organisational workflows), coinciding with a robust culture of knowledge and work-insight sharing among colleagues, with 51.4% sharing often. The investigation indicates that organisations are eager for GenAI but lack structured methodologies for its adoption and evaluation.

In this part, the most relevant segmentation variable was organisational size. The age and gender of the participants did not significantly influence this portion of the research topic. Large and medium enterprises exhibit a significantly higher prevalence of formal GenAI procedures, with rates of 41.5% and 43.8%, respectively, in contrast to small organisations at 8% and individual freelancers at 0%. As anticipated, large organisations are at the forefront of offering GenAI training (61%), followed by medium organisations (50%), whilst small organisations lag significantly (16%).

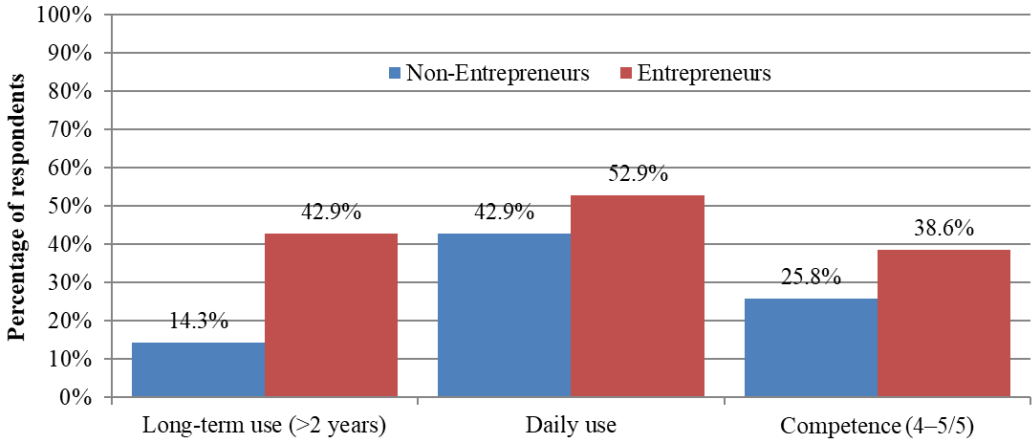
Segmenting participants by the duration of GenAI usage reveals that experience significantly influences attitudes and individual behaviours. Recommendation levels rise with expertise (M1=3.50 to M2=3.77 to M3=4.15; p=0.042) as well as knowledge sharing (M1=2.69 to M2=3.30 to M3=3.71; p=0.002). Experienced users transform into advocates and knowledge sharers. Organisational practices exhibit remarkable stability, with only a 5.1 percentage point difference between high-frequency users, that work in organisations with established procedures and those who do not. This indicates that established structured procedures, guidelines, and support mechanisms do not substantially affect adoption. This is visualised in Figure 10, that can be found in Appendix 4. Conversely, the primary impetus for utilising GenAI tools arises from individual factors, as 77.4% of all chosen initial motivations were classified as individual motivations, compared to 22.6% attributed to organisational motivations. Consequently, one could contend that the survey indirectly corroborates and supports the null hypothesis “H0e: Widespread organisational-level adoption of GenAI can be achieved through individual initiatives,” as the analysis indicated no significant influence ($p>0.5$ for all relevant variables) or a small practical effect (Cohen's $d<0.13$) of organisational procedures and guidelines on individual employee GenAI usage behaviours.

6.2 Entrepreneurial perspectives and dimensions in survey results

Comparing and segmenting GenAI users by their entrepreneurial experience is presented in Table 7 and reveals some significant and intriguing findings. The two participant groups were categorised as follows: entrepreneurs (individuals with at least some entrepreneurial experience, n=70) and non-entrepreneurs (individuals without any entrepreneurial experience, n=35). Entrepreneurs possess markedly greater experience with GenAI technologies, with 42.9% utilising them for over two years compared to merely 14.3% of non-entrepreneurs (p=0.002), and they employ these tools much more often (p=0.02). which is shown in Figure 7. Thus, self-evaluated competence was markedly greater (p=0.006) among entrepreneurs compared to non-entrepreneurs. This is noteworthy, as the analysis

must consider participants had already been vetted and were more likely to engage in the survey, if they used the GenAI tools. Entrepreneurs may be early adopters, who utilise GenAI more strategically for their business endeavours. Furthermore, because the data from the entrepreneurs' group is disproportionately aligned with the already robust general survey evidence (refer to the previous chapter "5.1.1 General application information") that discusses significant use in business, research can reject the null hypothesis (H0a). It can be asserted that the evidence – 84.3% of entrepreneurs are long-term users and 52.9% are daily users, with the inclusion of weekly users raising this figure to 81.4% – is highly significant ($p>0.001$) and strongly supports the hypothesis "H1a: The application of GenAI tools is a regular practice among entrepreneurs."

Figure 7: GenAI use and competence by entrepreneurial status



Source: Own work.

The analysis of the initial motivation for GenAI usage revealed no significant difference among the groups ($\chi^2=61.071$, $p=0.581$). Entrepreneurs indicate marginally elevated rates of GenAI leading to new ideas (72.9% vs 62.9%), although this disparity lacks statistical significance. Entrepreneurs showed a tendency for greater impact on creative tasks (42.9% compared to 20%) and a more frequent application for idea development (51.4% against 34.3%); however, again, neither reached statistical significance (only approaching it; $p=0.067$). Entrepreneurs reported markedly superior cooperation enhancements using GenAI, with 30% rating the collaboration impact as 4-5 (showing major improvements), but 0% of non-entrepreneurs assigned such high ratings ($\chi^2=15.238$; $p=0.004$). The disparity is notable, which may indicate that entrepreneurs may be employing GenAI tools more intentionally in their interactions with teams and clients.

Both categories predominantly endorse ChatGPT, with 75.4% of entrepreneurs and 67.6% of non-entrepreneurs recommending it. Non-entrepreneurs have marginally greater diversity in recommendations, featuring Microsoft Copilot at 14.7% compared to 7.2%. Both entrepreneurs (35.7%) and non-entrepreneurs (26.5%) exhibit a strong propensity to suggest

GenAI tools (rating 5), with no statistically significant difference between the two groups. This indicates favourable prospects for future adoption, regardless of entrepreneurial status.

No significant differences were again observed in the factors influencing tool selection or in the assessment of which tools are deemed least useful. Moreover, both cohorts exhibit comparable apprehensions regarding accuracy (χ^2=1.022, p=0.796), with the majority of participants (45.7% entrepreneurs, 37.1% non-entrepreneurs) categorising this as a moderate concern. Entrepreneurs exhibit marginally greater concern (37.1% rating 4) than non-entrepreneurs (20.0% rating 4); however, the disparity is not statistically significant (χ^2=4.180, p=0.382).

The perspective on performance issues is similarly regarded as a moderate concern (no significant difference: χ^2=2.719, p=0.606). 32.9% of entrepreneurs strongly disagree that costs are excessive (rating 1), but only 14.3% of non-entrepreneurs share this sentiment; nonetheless, there was no statistically significant difference overall: χ^2=6.486, p=0.166. This indicates that entrepreneurs may exhibit a greater propensity to invest in GenAI solutions. No significant difference was seen concerning ethical hazards (χ^2=4.363, p=0.359), with both groups exhibiting modest worry about legal and ethical issues.

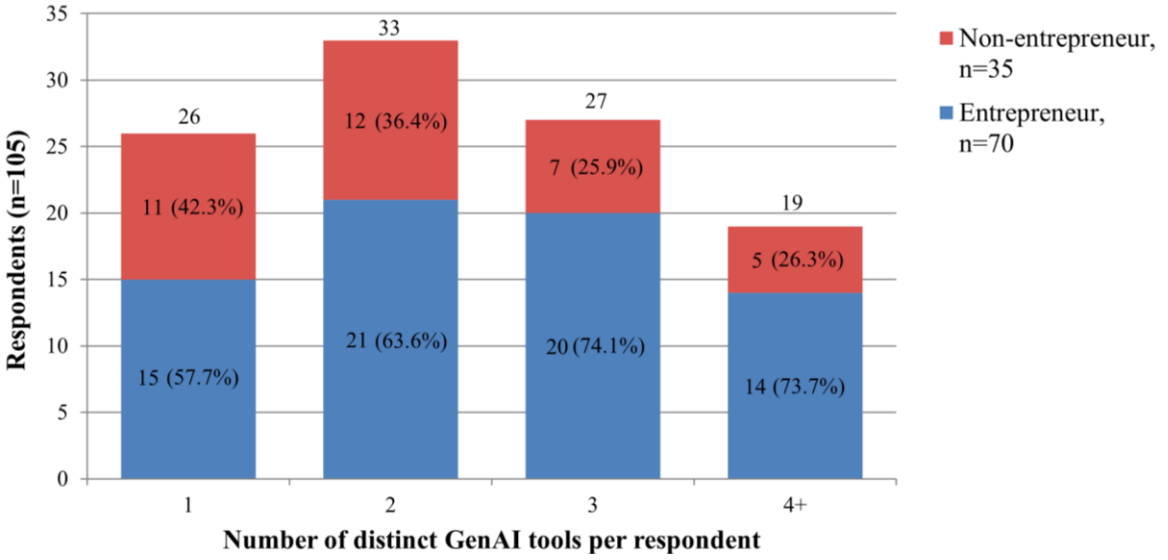
Except for a few variables, it can be concluded that entrepreneurs and non-entrepreneurs exhibit few differences in their usage of GenAI for work and that prior general findings (with the specified exceptions) are applicable to entrepreneurs as well. To validate or refute the remaining three hypotheses, only data from the entrepreneurs' group (n=70) will be used; nevertheless, a larger sample (all participants, n=105) may still serve as a valuable reference.

We can reject the null hypothesis “H0b: Entrepreneurs with substantial GenAI experience do not have higher mean creativity scores than entrepreneurs with no/minimal GenAI experience.”, hence supporting the alternative hypothesis. A Welch's t-test comparing entrepreneurs with significant GenAI experience to those with negligible experience indicates that the former group scores around 1.30 points better on the 1–5 creativity scale (t=2.838, df≈15.29). The intended one-tailed test is significant (p=0.0061) and even a more conservative two-tailed test remains significant (p=0.0123). Furthermore, the survey data, indicating that 70% of respondents report new ideas, strongly substantiates that GenAI has an important positive impact on creativity and innovation (refer to the preceding chapter “5.1.2 Creativity and Innovation”). Specifically, among entrepreneurs, 72.9% attribute new ideas or solutions directly to GenAI, while 77.1% observe significant alterations in creative methodologies, and 78.6% regularly utilise GenAI for idea generation, with all statistical analyses yielding high significance ($p<0.05$), resulting in this conclusion.

The null hypothesis “H0c: Entrepreneurs use only one GenAI tool” is rejected. In addition to the overall survey findings (detailed in the preceding chapter “5.1.1 General application information”), data specific to entrepreneurs reveals that a diverse array of GenAI tools is employed, with 78.6% of entrepreneurs utilising multiple tools (binomial test p-value is

0.000002). Figure 8 which depicts the number of different GenAI tools used by each respondent, further supports the H1c.

Figure 8: Number of different GenAI tools used by each respondent



Source: Own work.

Nevertheless, while examining the data exclusively pertaining to entrepreneurs concerning the null hypothesis "H0d: Entrepreneurs do not experience ethical or legal concerns regarding GenAI utilisation," the analysis was unable to entirely dismiss it. The partial support of H0d arises from data indicating that entrepreneurs do suffer concerns, albeit the evidence is less robust than that for the overall population. Although entrepreneurs exhibit ethical and legal apprehensions (54.3% have faced issues), only their legal preparedness demonstrates statistical relevance, indicating that entrepreneurs may possess a higher risk tolerance while acknowledging their lack of readiness for legal challenges.

6.3 Results and analysis of the interview data

To maintain confidentiality, all participants' personal or otherwise sensitive information has been anonymised. They are only referred to by letters (for example, the entrepreneur from one of the interviews is here named by the letter J). Because of the personal and sensitive data that is interwoven into the answers only a random part of one of the interviews is presented in the appendix (Appendix 5). Furthermore, even though a full coding matrix is provided (Appendix 6), only the coding process for this sample of the interview J is shown (Appendix 7). All interviews were carried out in the Slovenian language, and the quotes were translated into English so they could be analysed. To make it easier to read and compare them, they were sometimes edited and summarised without changing their meaning.

The analysis is structured according to the five research questions (RQ1–RQ5). For each question, the author examined the codes and categories that were relevant. This makes things clear and shows how each quote fits into the bigger analytical themes, such as general applications, creativity and innovation, factors and comparative impact, implications and responsibility, and adoption strategies. The same method was used for the two extra interviews with key stakeholders (the Data Protection Officer (DPO) and the Chief Information Security Officer (CISO)). In the analysis, their insights are referred to as DPO or CISO. Their contributions add unique added value because they come from experts employed at large companies, which adds to the perspectives of the entrepreneurs, who were either solo founders or worked in SME.

6.3.1 General application information

In the first part of the interviews, the questions addressed the potential applications of GenAI tools in entrepreneurship. From the beginning, it quickly became clear that GenAI can be applied in many entrepreneurial contexts. Process applications, communication assistance, strategic roles, and industry-specific activities dominated these usages. Everyone's adoption was diverse in depth and complexity, but there were evident trends of convergence, especially in automation, content development, and administrative efficiency.

Regarding the process uses, GenAI was widely praised and sought for meeting transcription and summaries (some already use it, some are trying out different tools, and the rest want to implement it in the near future). Fathom, Fireflies, Otter.ai, and MetaView were increasingly mentioned to record talks and create organised records. Participant A noted, "We also use it in meetings for summaries, recordings, and so on," while D evaluated "almost every voice-to-text transcriber on the market" before "for now" choosing Fireflies. The majority of interviewees argued that transcription speeds up work, eases the cognitive load of the notetaker, and encourages active participation (if used, all present are free to participate in the meeting and do not need to multitask). Participant P also announced plans to use Soniox after seeing its potential during the interview, which shows how open, prepared and eager entrepreneurs are to find a good tool that can help them in such work processes.

ChatGPT was used to edit, repair, and reformat texts for workflow, communication, and language improvement tasks. D stated he just "puts things into ChatGPT, writes 'please fix mistakes', and 99% of the time it works." J and L also employed GenAI to simplify procedures and automate repetitive email and CRM routines (in combination with other non-AI automation tools). These examples demonstrate that GenAI is a daily writing aid that improves professional communication across all interviewees.

Human resource management uses apps for hiring and following norms. D called Loxo ATS "a very useful system" for candidate management due to native AI-powered search. However, data privacy is always a concern. He preferred fully internalised solutions "to be more GDPR compliant", whereas B advised caution "before I put any sensitive data into

ChatGPT or anywhere else." Results show a recurrent tension between efficiency improvements and compliance limitations. Here, the CISO's view brings an interesting insight, as he said, "the biggest risk is that a user forgets they're still on the personal [GenAI tool's] profile and accidentally enters [the company's] sensitive data," which he later elaborated they mitigate "mainly with awareness – mandatory yearly training, phishing simulations, and constant reminders."

The second major category encompassed email and marketing communications. Most people use GenAI to write, edit, and improve emails. P noted that "everyone uses it when writing emails," and A is currently trying inbox-management software like Superhuman (but first for his personal use). L said he sends "250,000 emails a month" and has automated sales and response channels (part of the process itself was designed with the help of ChatGPT, as it helped with reasoning, multiple options/combinations, text, discovering features and possibilities of complicated software used, etc.). GenAI can therefore be easily seen as becoming crucial for managing client connections in SME due to its volume and customisation needs.

Pitch and presentation preparation were also another typical use. D said that using Gamma he could "make a ten-slide presentation that really sums up everything quite well," and then further improve it in PowerPoint or Canva. J mentioned the Gamma AI as well, especially for presentations. B also tried Gamma, indicating a rise in AI-driven slide-based solutions as a shared practice among entrepreneurs. These methods combine creativity with automation. GenAI helps entrepreneurs save time while leveraging their judgment to improve their work. It's important to note that everyone emphasised that when any of the GenAI tools are extensively used, you can feel and see the tools' limitations, like generic and recognisable output design; however, e.g., regarding Gamma, they still found it very useful for low-stakes, casual and/or large numbers of presentations.

B and L's GenAI use in marketing content stood out, as they both attempted many things (blogs, item descriptions, FAQs, social media posts, etc.). B who has a background and expertise in marketing, has described his role as "content manager and coordinator", using GenAI (ChatGPT and Perplexity) to create and manage both while keeping an eye on the final editorial ("For social media posts, I use GenAI, but in the end, I rework it to add a human layer, authenticity"). He says that his experience showed AI-generated posts were less engaging because "users notice and engage less." This emphasises the need for humanising AI outputs. On the other hand, L sometimes authored 2,000-word posts in minutes, using structured blog templates, multiple GenAI tools, their combinations, and SEO content templates. His exact quote is, "A blog that would normally take me half a day is ready in 10–30 minutes." GenAI also assisted P and D with SEO-driven blogging, while B actually started to do generative engine optimization (GEO) for his website. While J predominantly used GenAI to quickly investigate and search for information, he emphasized his use of Midjourney and other modes to generate photographs and videos.

These findings reveal that entrepreneurs favour GenAI for its speed and scale but worry about its authenticity and quality. Interestingly, one of the D's offhand remarks included an example that touches this topic and illustrates surprising counterintuitive evidence against the claim that GenAI content repels customers. When doing their A/B tests for social media posts, they found that when the text stayed the same, people clicked more on the one with a GenAI-generated photo and not the one with the stock photo.

Project applications, market research, and help with legal concerns were also considered strategic uses for GenAI. A and P were planning to use ChatGPT (as an API and custom GPT solution) to write grant and incubator applications. Participant A said they built "a custom GPT to help write applications," which strongly increased their number of monthly applications. P said that ChatGPT created documents and explained the more unknown or new laws: "We put in all the data, and it tells us the exact legal framework." Even the DPO of a larger organisation uses ChatGPT in the same way: "If I have a specific legal problem, I ask what the procedures are... so that I can check whether I have overlooked or forgotten something." Efficiency in tender processes was also underlined. These examples demonstrate that entrepreneurs use GenAI as a core growth tool, which helps them either gain a deeper understanding of topics they do not consider themselves experts in or accelerate/scale the processes they have already mastered.

Market analysis and competition information dominated J's interview. He commented, "For analysing competitors, it is a very good tool," and utilised ChatGPT to scrape websites and compare them to his portfolio. GenAI accelerated his market evaluations, SWOT analysis, and go-to-market plan creation. Most of the participants utilised Perplexity and ChatGPT together. Perplexity helped B, L and J get "more legit outputs" when researching, supplementing ChatGPT. They indirectly pointed out that this two-tool strategy balances ease of use and dependability with the depth, complexity, and breadth of the analysis.

Legal and regulatory difficulties were another strategic priority. P touted DeepL and ChatGPT for handling paperwork and saving money over employing lawyers: "If you don't have a lawyer employed, it is too expensive." She discussed using it for compliance risk assessment and inspection response. Both B and D verified similar practices, although they were more cautious because they realised that sharing private data with external systems was risky. A CISO who works for a large company said that the "initial hardening" before using the GenAI tool is critical for safe use, especially in bad situations, like "if someone pastes confidential business information into a prompt", as their "DLP is integrated with ChatGPT and Copilot and will block the transfer" of sensitive files/information. GenAI makes learning or better understanding some specific expert fields like the law a lot easier, but entrepreneurs are conscious about its shortcomings and risks. The majority of interviewees view it primarily as a tool to better understand when and why they need outside expert help, as well as how to explain their needs more effectively, allowing them to reach crucial points faster and avoid wasting time and money on general information.

Some applications of GenAI were also related to more specific professions. L in e-commerce discussed Klaviyo and CRM flows and anticipated AI-powered customer service chatbots to reduce calls. J and B made multimedia, but copyright and IP risks kept them cautious. P stressed DeepL's role in translating technical documents to make items usable in her field. These examples demonstrate how GenAI adapts to varied scenarios, with sector needs determining its adoption order.

Despite differing scales and circumstances, certain aspects were similar. First, everyone utilised GenAI to create content, from individual emails to large-scale SEO blogging. Second, time savings and efficiency (no need to have additional employees/outside help) were most common. D said MetaView AI features "really saves the most time," while L supplied a blogging time reduction statistic. Third, it is important to maintain quality and trust by ensuring the output is verifiably true. B wanted to examine all AI-generated content, while P cited ChatGPT's poor translations that required another tool that is more specialised and is not LLM-based (DeepL). The CISO's view on the matter is clear, as he says, "You are always responsible for the data. Even if it came from AI. You must always double-check and verify it. Saying 'I got it from AI' is not an excuse."

The extent to which entrepreneurs have adopted various technologies varies. L and B have well-organised workflows with compatible GenAI and non-AI tools. But P and A used GenAI more as a helper. However, curators B and J underlined the significance of checking and adjusting GenAI outputs multiple times. D focused on tool-testing and exploration and actively sought GDPR-compliant options, while A and L prioritised production efficiency and occasionally exhibited some reduced regulatory concerns. Finally, interviews revealed diverse perspectives. A's concentration on bespoke GPTs for project applications and P's use for tenders demonstrate strategic grant-seeking. B's content quality views matched L's efficiency-focused blogging. Together, they advised entrepreneurs to balance speed and transparency. The findings reveal that GenAI applications in entrepreneurship are complicated and impact operations, communication, strategy, and wider industry factors. Highlighted technologies help entrepreneurs reduce paperwork, accelerate content development, improve contact with customers, and make strategic decisions. Compliance, authenticity, and reliability are also important to entrepreneurs and are often mentioned together. GenAI is used differently, but it has swiftly become part of entrepreneurial processes, transforming everyday chores and long-term growth goals.

6.3.2 Creativity & Innovation

GenAI's effect on entrepreneurs' creativity and innovation, and the answer to RQ2: How GenAI influences entrepreneurs' creativity and innovation, is especially evident from the quotes, categories/themes and topics discussed in this chapter. Broadly, the interviews quite quickly revealed how GenAI influences entrepreneurs' creative thinking and production of new concepts. Participants actively used GenAI for brainstorming and drafting, but they

stressed that meaningful innovation requires human initiative, supervision, and development. However, while analysing, four interconnected overarching dimensions emerged: creative stimulation, innovation processes, creativity limits, and perception of the human role.

GenAI was thought to assist people in brainstorming and generating new ideas. Participant A claimed ChatGPT was great "for brainstorming and for various innovations," because it could swiftly expand or test concept/idea feasibility. J also finds that GenAI helps "start brainstorming content" or refine concepts. On the other hand, P appreciated its help with the next steps of idea generation (collaboration and evaluation), as she stated that she liked to see "how it perceives my idea, and I always get some feedback." These testimonies make GenAI look more like a conversational buddy that accelerates the early creative thinking stage, rather than an idea generator. Furthermore, GenAI was also appreciated for comments and criticism. J uses it to check his instructional materials to make sure they are current and useful. P also stressed the importance of feedback loops for new blog or product ideas. Therefore, the analysis can conclude that GenAI facilitates the process and serves as a reflective partner to enhance creativity, thereby assisting entrepreneurs in testing and refining their ideas. Several other interviewees further supported this by indicating that GenAI assisted them in developing and enhancing their concepts. For example, participant A described multiple instances where ChatGPT interactions turned a vague product idea into "a well-developed foundation". Participants emphasised that understanding and contextualising these "creative" outputs was crucial. P observed that GenAI's outputs could be "very generic, not really very creative," while A asserted that many users quickly found satisfaction in "basic outputs without putting in any additional effort." These observations support the argument that while GenAI offers new possibilities, it doesn't always innovate and may even limit the user if they accept the output at face value.

Throughout their creative process, different GenAI tools were utilised, but together they actively supported entrepreneurs' creative activities. Again, ChatGPT and Perplexity were the most popular, and all entrepreneurs used a diversified approach dependent on which creative stages they were in. GenAI also provides initial/core drafts and templates to inspire creativity. L remarked, "I have a template for writing blogs, and in the first phase, I give it to Perplexity," and A further mentioned that GenAI wrote his draft email replies and disclaimers. This indicates that businesses that use templates don't always have to develop content from scratch. Instead, they may improve and provide value. This function shows how GenAI offloads everyday activities to free up cognitive resources for ideation. Though this was a lot less emphasised than brainstorming.

We also discussed how GenAI integrates creativity into innovation. As already discussed, A said brainstorming with ChatGPT turned a vague product idea into a developed one, demonstrating how ideation and creativity work together. J integrated GenAI into analysis, product positioning, and automatic preparation of offers. This showed that technology is employed for strategic innovation, not just small, isolated tasks. This embedding suggests

GenAI accelerates the process from conceptualisation to implementation. It is easier to iterate quickly, allowing entrepreneurs to test and enhance concepts before investing much in development.

Everyone who used GenAI understood it wasn't really creative, despite its benefits in the creative process. For example, P stated, “We haven't gotten any good ideas yet,” and “strategic or creative work is still on us.” A common complaint was how generic and repetitious things were. P further elaborated that outputs were often unoriginal and needed much improvement. On the other hand, L claimed that only organised intentional urging and active human-led correction could improve ChatGPT’s outcomes. Some interviewees also touched upon the fact that the user's level of digital literacy can also hinder AI's capabilities. “Older employees already have trouble with basic tasks on the computer, let alone GenAI tools,” showing how user readiness can limit GenAI's creativity.

The major finding is that individuals firmly believe creativity and innovation require human action. All participants thought entrepreneurs should have their own original ideas. P said, “The idea always came from us, and then it (GenAI) helped us make that idea better.” The AI draft first and human polish second strategy was prevalent in interviews. L said he developed “at least a draft with some GenAI tools,” which he improved upon before using it. Using AI-generated drafts for communication activities also emphasises the need for direction and revision. B especially used and enhanced initial drafts from Perplexity and ChatGPT. He said layering them required intentional orchestration but at the end sped up and improved early production while he ensured the end output was high-quality, original, and contextual.

To illustrate the need for a holistic approach, D emphasised the effect of the company culture on the whole creative and innovation process: “It’s only because we are very AI-forward and strongly encourage AI use that employees’ innovation and willingness to share their own ideas comes forth.” Interviews’ results frame creation and innovation as a human-led process with AI/GenAI as a tool, which codependently changes how people work as well as helps change and reinforce the organisation's identity and culture. The results also demonstrate that entrepreneurs have complementary and contrasting views on GenAI's creative role. A and B saw GenAI as a co-creator who might influence product development and content, but P saw its contributions as generic and unimportant. Nevertheless, GenAI is considered a creative partner that acts as a catalyst by some entrepreneurs and a partially limited helper by others. A slightly different view with the same conclusion was proposed by the DPO in reference to the visualisation tool Napkin AI, who said, “It is more creative than I am, but still the engine behind it is the human-driven... I still believe the real creativity is human.”

6.3.3 Factors and comparative impact

When trying to find answers to the RQ3 that asks how different GenAI models and tools vary in their impact on entrepreneurial work, the analysis first has to address if and what

effects different GenAI types have on the entrepreneurial process. The interview analysis shows that indeed they do have an effect, and it does depend on the type of tool. Furthermore, other factors are also important, e.g., how much prompting is needed, the organisation, and the industry. These differences can be understood on three levels: micro (individual productivity), macro (organisational efficiency and cost), and contextual (industry and size).

As previously addressed in RQ1 (chapter 5.3.1 General application information), all participants realised enhancements in efficiency via GenAI, especially in tasks related to content drafting, meeting transcription, and communication. Here, when looking at the RQ3 part, it is shown that the difference is in how different tools made these savings.

For example, MetaView (participant D) and other specialised tools (mentioned by A, L, and P) always gave quick, low-effort, but long-term, substantial value. On the other hand, generalist LLMs (like ChatGPT and Perplexity) sped up many tasks, like writing and summarising emails or planning meetings, but they needed to be prompted and improved all the time. Regarding this, the CISO's quote was very informative about how some large organisations already do this daily: "With Copilot, I can compare 30 internal regulations in hours instead of a week. It identifies duplicated content, missing clauses, and even exact articles. The organisation first had to test it extensively, including doing some penetration tests, before trusting it, but now it saves me a lot of time and work." So, even though both types of tools made people more productive, they did so in different ways: specialised tools were easy to use right away, while generalist models required more skill but could be used in more situations.

In RQ2 (chapter 5.3.2 Creativity & Innovation), the analysis discussed how important prompting skills are when entrepreneurs talked about "AI draft + human polish". This also affected how different tools were used here. Participant A emphasised that "you have to prompt it so much", know how to do it effectively (also pointed out by D and J), and try many methods, e.g., "reverse prompt tactics." This shows how frustrating it can be when tools are flexible but require significant effort (active prompting and refinement). He even suggested making an internal newsletter to share useful prompts, which shows that coworkers can and should compare and collectively learn from each other. In contrast, transcription platforms like Fireflies needed almost no prompting and gave the same benefits without any work. So, the difference between how easy a tool was to use and how much prompting it needed was a key way that entrepreneurs looked at while evaluating its impact.

At the organisational level, participants stressed differences between setup costs and returns on investment (ROI). D said that the effect of new tools "won't be visible right away; there is setup, cost, and time before they pay off." This was different from the immediate benefits of lightweight apps like email automation or transcription (mentioned by A and J). Interestingly, a large organisation the CISO works for stood out the most, as it had a clearly established evaluation framework. He said that "when you get a Copilot licence, your KPIs

automatically go up. Some roles even require creating three GPT use cases per year. Those who don’t use AI really lag behind their colleagues.”

Some benefits were easy to measure (like L's estimate that he saved “at least four hours a day” or he wouldn't even have time for it at all), while others were more trial-and-error, with D saying, “Sometimes after a year you see it wasn't worth the money, but at least you have the experience.” Interviewee P took this conversation in a more speculative direction by saying that efficiency gains could one day lead to “shorter workdays and more time for ourselves.” Her comment, which looks to the future, shows that entrepreneurs see different value horizons depending on the tool, and the implementation of different tools may not be motivated solely by immediate gains but represent possible future ones (a good foundation for the future).

As stated in RQ1, GenAI was used in marketing, legal, IT, and compliance settings. In RQ3, the analysis looked at how the effect changed depending on the type of task and sector. In marketing, J pointed out that GenAI can “optimise marketing and sales pipelines,” which fits with goals that are fast-moving and focused on growth. B used ChatGPT to edit and write legal and compliance content, but he stressed, “I always read it again because it sometimes makes things up.” So, this tool was helpful but had limited usefulness. However, the research already discussed a positive impression P has in exactly this field/type of task, which means that again it depends on how, who, and why exactly it's used. This sentiment is also expressed and seen in the fields of IT and digital services, as A pointed out that both scaling up and trusting it to follow the rules can be problematic, and that the usefulness of tools depends on “what the purpose of use is.” These differences show that the same tool or model can change things in one area while needing close supervision or prove unhelpful in another.

The effect of tools also changed based on the size and age of the organisation. Smaller businesses used GenAI in a practical way to get quick help, often using ChatGPT for research or communication tasks that used to take a lot of time. Larger companies, on the other hand, had longer adoption cycles and more difficult integration problems. Overall, everyone agreed that the adoption or implementation of GenAI tools can easily become very risky, especially if the results or returns cannot be seen immediately. All participants concurred that the adoption or implementation of GenAI tools can pose significant risks, particularly when immediate results or returns are not visible. Nevertheless, J warned against adopting too quickly: “It's still better to go somewhat slower and more carefully before you break established and working systems that are already in place.” This shows that quick wins are best for small businesses, while scaling up adoption is harder and riskier for larger or more established ones.

Therefore, three major dimensions summed up how models and tools had different effects in all of the interviews: ease of use vs. need for prompting, return on investment right away vs. later, and context-dependence. The results also show that GenAI tools have different effects on entrepreneurial work depending on usability, prompting demands, cost-return

timelines, and contextual alignment with tasks and industries. Transcription platforms and other specialised tools gave quick, dependable benefits with little work. Generalist LLMs like ChatGPT and Perplexity were much more flexible, but they needed a lot of user prompting and careful human oversight. In short, entrepreneurs see GenAI as a complex system where the effects of each model or tool depend on both its technical abilities and the business situation in which it is used.

6.3.4 Implications and responsibility

The interviews showed that GenAI brings up a lot of complicated ethical, legal, and social issues (RQ4). Even though participants saw clear benefits, they always brought up worries about responsibility, transparency, data protection, intellectual property, and bigger social risks. To deal with these issues in a responsible way, they showed a tendency to subjectively find a balance between personal responsibility, organisational safeguards, and emerging regulation.

A dominant theme was user responsibility. B called it “some kind of self-responsibility” and said that without it, “you or your users will be harmed.” L said that responsibility is “always divided”, but that advanced tools should and will always put “a large part of responsibility on the users themselves.” This indicates that people think that using GenAI requires both self-control and group responsibility. It was also said that being open and transparent is an ethical duty. J said, “We try to be transparent and clear about when we use GenAI.” Participant A stressed the importance of being open in the EdTech field to keep students' and educators’ trust. As the research talked about in RQ2, transparency was considered important for keeping creative integrity; in RQ4, it was considered an ethical and possibly legal duty to clients, partners, and regulators (all stakeholders). DPO said, “The biggest issue, from my professional perspective, is who will control all this data that is being collected.” Data today is real power. That is why we need ethical approaches, transparency, and oversight. Trust is great, but oversight is better.”

There were many worries about following the GDPR. Participant D mentioned that “a lot of AI is not GDPR compliant, or at least not on its own, and one must be very careful,” especially regarding the handling of other people’s personal information, such as CVs, which contain very private details. P said, “We don't put business secrets into ChatGPT.” DPO was even clearer as she stated, “For me, there is an absolute red line – no personal data or business secrets go into these tools.” As explained in RQ1 and RQ3, business owners often change the tools they use as well as pseudo-anonymise the data to keep personal or sensitive information private. RQ4 makes it clear that these actions are legal and moral protections. Another issue that wasn't resolved was intellectual property (IP). For example, B said that it is “the bigger problem,” especially when AI-generated images use copyrighted works without giving credit. To further complicate the matter, A also mentioned that in a startup

environment, “it's almost expected that you use AI tools, but no one says this,” which shows a conflict between what is common and what is expected by law and ethics.

Uncertainty about new rules made it harder to make decisions. J said, “The law isn't completely clear yet, but the EU AI Act is going into effect.” The DPO expert also stated, “Currently, the situation is chaotic. Europe is trying to set rules through legislation, which is good and necessary, but in reality, it remains at the level of paper and principles. We don’t really know what we got, how to control it, or whether it is effectively enforced. We are still a toothless tiger.” The interviews suggest that variations in compliance not only influenced adoption but also reflected entrepreneurs' perception of legal accountability. All participants were also worried about data leaks and did not trust outside platforms. P expressed, “We are really afraid of our data leaking or being sent forward,” while D discussed the potential for handling leaks on a case-by-case basis, emphasising the need for a protocol that is enacted and well understood by all employees. B also said that outside companies like Google keep metadata longer than expected, which is why he doesn't upload client data to AI platforms at all.

There was also anxiety about job retention. No interviewee experienced it directly, but many said that they know of some workers/friends who think along the lines of “I might lose my job now that AI is here.” P especially made clear to her employees that layoffs were not planned and that AI-related fear is not grounded. She also referenced a more widely discussed international case, e.g., teenagers being exposed to disturbing suicide-related GenAI conversations, which could be and are harmful for people's mental health and social wellbeing. These worries go beyond just following the rules and have to do with the health of workers and the safety of society as a whole.

Therefore, the analysis can say three main interconnected challenges shaped entrepreneurs' perceptions of GenAI's implications: responsibility vs. freedom, transparency and legal uncertainty. Participants talked about a few different ways to deal with these risks. Internally, organisations made attempts with guidelines and rules: A kept shared folders with rules; D already had many established procedures that also applied to GenAI, e.g., how to deal with leaks; and B insisted on case-by-case reviews. Collectively, they all wanted to promote innovation while also upholding ethical standards like transparency. They thought that regulation, especially the EU AI Act, would make things clearer from the outside, but they stressed the need for proactive responsibility instead of waiting for regulators. Overall results indicate that the ethical, legal, and social ramifications of GenAI are complex. Entrepreneurs always stressed the importance of user responsibility, openness, and being careful with data, knowing that misuse could hurt both businesses and stakeholders. Entrepreneurs therefore positioned themselves as both adopters and stewards of GenAI, recognising that long-term legitimacy hinges on the anticipation and mitigation of ethical, legal, and social risks.

6.3.5 Adoption strategies

When looking at what strategies and best practices enable effective adoption and use of GenAI across entrepreneurial processes and workflows (QR5), the interviews showed a variety of ways that businesses and entrepreneurs use GenAI effectively. These practices include individual experimentation, organisational training, community learning, formalisation and evaluation mechanisms, and context adaptation. There are some overlaps with earlier findings, like prompting skills (RQ2) or evaluating setup costs (RQ3), but the main point here is how these things come together to make structured or new strategies for adoption.

Prompt engineering was repeatedly called a core skill at the individual level. D contended that "prompting will become almost a core function or knowledge you need," whereas J emphasised the significance of "meta-prompting" and proposed the creation of an internal "prompt library" for employees. This shows a change from casual use to intentional skill-building, which is similar to what RQ2 found about creativity but goes further into a strategic adoption practice. Entrepreneurs also said that trial and error was an important part of the process. A said that adoption was "really trial and error and some mix of my own experience while working," and similarly, L talked about trying things out with free trials. These accounts show that best practices come from learning by doing over theorising or following some formula or set of rules.

Training and education were key parts of the organisation's strategy. D said, "We have annual education for everyone," while P said that the upcoming training sessions would be "a good thing, because by now everyone who would benefit from the tool is probably already using it," and they must all actively and collectively work on it. DPO saw training and education (a prerequisite for employee awareness) as non-negotiable. She stated three things she won't compromise on: "Tools must be reviewed by experts, companies must provide enterprise accounts, and users must be educated and made aware. Without critical users, you will always risk misuse or inappropriate results." Training was therefore often thought of as the first planned step after trying things out on the fly (after the experimental and decision period). Unfortunately, the entrepreneurs' informal approach also included verbal onboarding guidelines and best practices. Participants A, D, and P said that currently, onboarding for GenAI tools is mostly done in person and not systematically written (yet), but it is still important to make sure employees know what their role is in the workflows.

Making communities of/for users was another important theme (inside the company as well as outside/public). B talked about how important LinkedIn groups and AI-focused influencers are, calling them "the most credible, responsive, and up to date with new features." He also said that communities helped people in his field learn more about brands and share information. These communities served as informal yet highly effective knowledge networks, enhancing internal learning. Participants also discussed the importance of external resources such as webinars, podcasts, and online tutorials. D said, "We all go to

different AI webinars," and P and J said that sites like YouTube, LinkedIn, and TikTok are always providing them with new information. These outside channels worked with internal strategies to keep businesses flexible and up to date on changes that happened quickly. The CISO's more regulated organisation, in contrast, has a much more structured process; he stated that "Once a year, everyone must attend mandatory training on information security, AI, and social engineering, concluding with a test that requires at least 80–85% to pass. Fail, and you repeat."

Several entrepreneurs talked about how hard it is to measure AI's effects. P said, "We haven't set any KPIs yet," which shows that formal metrics don't always keep up with how things are really used. ROI again kept coming up, though only one large corporation had it defined (mentioned in chapter 5.3.3 Factors and comparative impact, in a CISO's quote). Entrepreneurs mainly referenced tool evaluation and cost-benefit analysis. D said, "If you think AI can do it, try it." A and J told their coworkers to "test before making bigger investments in AI," while P said they used tools "right away if they bring clear benefits and costs are not too high." These strategies show that while formal KPIs are not very common, continuous and practical evaluation practices are very common (e.g., ad hoc ROI checks, small-scale pilots, etc.).

Different levels of knowledge within teams also affected how they adopted new ideas. Participant A mentioned that any coworker/employee could try out a new GenAI tool first, report their findings and leave the final decision up to the whole group (based on what everyone thinks). This flexible, peer-driven method made sure that everyone in the group could use the new technology at their own level of skill and comfort.

These practices show three main and somewhat contradictory things that are true across the board: (free) experimentation as strategy, individual skill-building as best practice, and evaluation without metrics. The results show that the best ways to get people to use GenAI are to encourage them to take the initiative, create structures within organisations, and learn from each other. Finally, adapting to the different levels of knowledge in a team and using outside resources keeps organisations flexible and responsive. RQ5 shows that successful adoption is more than just using GenAI (RQ1), using it for creativity (RQ2), choosing between tools (RQ3), or dealing with risks (RQ4). Rather, it entails formulating strategies and practices that amalgamate all these dimensions into enduring frameworks. Entrepreneurs don't think of best practices as set rules; instead, they see them as changing, iterative methods based on trying things out, learning, and adapting.

7 CONCLUSION

Mixing, integrating and triangulating findings from both research approaches and supporting it with theory, the analysis' conclusion can state that GenAI has indeed become integrated into entrepreneurial processes (with survey findings indicating extensive adoption: 84.3% of

entrepreneurs as long-term users and 52.9% engaging in daily use, while interviewed entrepreneurs state they are already expected to use them and have many plans to adopt, implement and integrate them further into their workflows). The most common uses are writing texts, making content, transcribing meetings, and analysing data, which align closely with interview results, wherein participants highlighted transcription tools and writing aids. This focus on knowledge work and cognitive enhancement is backed up by research (Potts, 2023; Alavi et al., 2024). The significant overlap indicates that entrepreneurs mainly appreciate GenAI for its efficiency and cognitive alleviation, rather than as a means of profound process automation (at least for now). This is in line with other research (Chatterji et al., 2025) that found that text and knowledge tasks are the most common ways people use ChatGPT (GenAI).

The survey showed a strong positive link between GenAI and entrepreneurial creativity: 72.9% said they had new ideas, and 77.1% said they had made meaningful changes to their creative approaches. However, the interviews showed that people had more complex opinions. Some people thought GenAI was a "co-creator" that helped people come up with new ideas, while others thought its results were too generic and needed to be improved by a human. This ambivalence reflects theoretical discussions (e.g., Gomez et al. (2025)), which contend that GenAI fosters individual creativity while not yet fully facilitating collective/group innovation. Importantly, survey data indicated that overall collaboration gains were limited (M=2.5); however, entrepreneurs reported significantly greater improvements compared to non-entrepreneurs (30% vs. 0%, p=0.004). So, this triangulation shows that GenAI boosts creative productivity, but its ability to help with collaborative innovation is different in different situations.

Survey data also indicated that entrepreneurs extensively utilise various GenAI tools, with 78.6% employing more than one. Interviews added depth by comparing generalist LLMs (which are flexible but need advanced prompting) to specialised tools that derived immediate, low-friction value. This differentiation resonates with the literature on affordances (Byrne, 2022), wherein usability and skill prerequisites influence outcomes. The results indicate that adoption patterns represent a trade-off: generalist tools require proficiency and yield inconsistent results, whereas specialised tools integrate more seamlessly but may be a bit limited in scope. This is why entrepreneurs try out different combinations of tools, which is inline to survey data that shows that selection factors are balanced across groups.

The survey results showed real but moderate concerns: 54.3% of entrepreneurs faced ethical or legal concerns, with statistical significance exclusively for legal preparedness. Interviews showed that this was true, as entrepreneurs focused on how things worked in the real world, while corporate stakeholders (DPO, CISO) unsurprisingly focused on regulatory risks (GDPR, AI Act, intellectual property). This difference shows how people in different roles see things: entrepreneurs are more risk-pragmatic, while corporate experts are more focused on compliance and governance. Theory (Bouschery et al., 2023) underscores that sustainable

adoption necessitates the integration of these logics. Consequently, the integration shows both a gap and a complementarity: entrepreneurs focus on opportunities, while bigger companies focus on safety.

Survey evidence indicated that organisational adoption can exclusively depend on organic individual initiatives as experienced users become advocates and share their knowledge. But for broader integration to work, strategy, training, and leadership support were needed (insights from the interview). Interviewees indicated that they provided testimonials about their experiences using trial-and-error methods, sharing prompts, and utilising only certain tools. Stakeholders, on the other hand, stressed the need for structured onboarding, awareness training, and governance frameworks. This is further supported by the literature (Creswell & Plano Clark, 2011; Malterud et al., 2016), which emphasises the interaction between individual agency and organisational structures. These findings therefore raise the broader question of whether GenAI adoption should be approached as a conventional IT initiative or whether its organisation-wide implications necessitate a more holistic, cross-functional transformation perspective. The findings also support research on digital transformation, which states that leadership and culture in an organisation are what make it possible to grow (Korzyński et al., 2023).

In general, the breadth of the survey and the depth of the interview come together to form four integrative insights. First, GenAI adoption is common and widespread among entrepreneurs, mostly to improve cognitive efficiency in tasks related to text and knowledge (Alavi et al., 2024; Ganuthula, 2025). Second, GenAI greatly enhances individual creativity, yet its collaborative capabilities are still insufficiently utilised, a deficiency reflected in both empirical evidence and contemporary literature (Gomez et al., 2025). Third, various tools offer various benefits, which is why entrepreneurs use a variety of tools (specialised ones for quick wins and generalist GenAI tools for flexibility). Fourth, the dynamics of adoption reveal a tension: entrepreneurs prioritise opportunity and improvisation, while institutional stakeholders prioritise risk mitigation and regulation. Sustainable adoption necessitates the amalgamation of entrepreneurial agility with organisational governance.

The master's thesis, therefore, shows that GenAI is not a single thing but a set of tools, a toolkit, that can be used in different ways. Its present influence is in enhancing individual productivity and creativity, while its enduring transformative function is contingent upon strategic implementation, technology's limitations and regulatory frameworks. The results both back up and add to what theory already suggested: they show that GenAI can help people learn and be creative and stress the need to make sure that entrepreneurial experimentation fits with organisational strategy and compliance. Table 5 captures key data relevant for a brief recap and overview of the study hypotheses.

Table 5: Summary of supported hypotheses

Code	Type	Statement	Outcome
H1a	Alternative	The application of GenAI tools is a regular practice among entrepreneurs.	Supported
H1b	Alternative	Entrepreneurs with substantial GenAI experience have higher mean creativity scores than entrepreneurs with no/minimal GenAI experience.	Supported
H1c	Alternative	Many different GenAI tools are used by entrepreneurs.	Supported
H0d	Null	Entrepreneurs encounter ethical and legal misgivings about GenAI use.	Partially supported
H0e	Null	Widespread organisational-level adoption of GenAI can be achieved through individual initiatives.	Supported

Source: Own work.

7.1 Relevance of the topic

The quick growth of GenAI has made it essential for entrepreneurs to know it, use it and implement it into their work. Entrepreneurs operate in situations where they do not know what will happen (VUCA world), and there's always a lack of resources, meaning GenAI tools that help with efficiency, creativity, and make better decisions are even more valuable. This study adds to current discussions by placing GenAI at the crossroads of entrepreneurship, digital transformation, and responsible innovation. The literature emphasises both opportunities and risks (Dwivedi et al., 2023; Korzyński et al., 2023); however, empirical evidence regarding the actual deployment of GenAI by entrepreneurs is limited but growing. This study offers insights into how adoption patterns, perceived benefits, and ethical tensions are influencing entrepreneurial work by integrating survey data with comprehensive interviews.

7.2 Study limitations and further research

At the end, the author has to again point out that this thesis research is subject to several limitations. The survey sample, though substantial, was still on the smaller side (especially for deeper analysis than some descriptive statistics), was biased towards digitally literate participants, and possibly exaggerates adoption rates. The interviews were concentrated on a limited cohort of entrepreneurs and two corporate specialists, thereby constraining generalisability across various industries and regions. Self-reported metrics may also introduce bias in assessing creativity or productivity improvements. Future research should investigate longitudinal adoption trajectories, showing the evolution of usage as GenAI tools advance and regulatory frameworks solidify. Comparative studies across various industries and organisational sizes would also help clarify contextual disparities. Additionally, empirical studies on team-level collaboration, ethical decision-making, and integration with

other emerging technologies could enhance understanding of GenAI's transformative potential within the entrepreneur's new toolkit.

LIST OF KEY LITERATURE

1. Abendroth-Dias, K., Cabarcos, P. A., Bacco, M., Bassani, E., Bertoletti, A., Bertolini, L., Van Bavel, R., Bertoletti, A., Bertolini, L., Bertrand, A., Bili, D., Boucher, P., Cachia, R., Ceresa, M., Chaslot, G., Chaudron, S., Comte, V., Consonni, C., Cosgrove, J., … Sellitto, A. (2025). *Generative AI outlook report: Exploring the intersection of technology, society, and policy.* Publications Office of the European Union. https://data.europa.eu/doi/10.2760/1109679
2. Bahrini, A., Khamoshifar, M., Abbasimehr, H., Riggs, R. J., Esmaeili, M., Majdabadkohne, R. M. & Pasehvar, M. (2023). ChatGPT: Applications, opportunities, and threats. In *Proceedings of the Systems and Information Engineering Design Symposium (SIEDS)* (pp. 274–279). IEEE. https://doi.org/10.1109/SIEDS58326.2023.10137850
3. 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. https://doi.org/10.1111/jpim.12656
4. Feuerriegel, S., Hartmann, J., Janiesch, C. & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering, 66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7
5. Ganuthula, V. R. (2025). The Solo Revolution: A Theory of AI-Enabled Individual Entrepreneurship. *arXiv.* https://doi.org/10.48550/arXiv.2502.00009
6. Korzyński, P., Mazurek, G., Altmann, A., Ejdys, J., Kazlauskaite, R., Paliszkiewicz, J., Wach, K. & Ziemba, E. (2023). Generative artificial intelligence as a new context for management theories: Analysis of ChatGPT. *Central European Management Journal, 31*(1), 3–13. https://doi.org/10.1108/CEMJ-02-2023-0091
7. Vu, H., Klievtsova, N., Leopold, H., Rinderle-Ma, S. & Kampik, T. (2025, March). Agentic business process management: Practitioner perspectives on agent governance in business processes. *arXiv.* https://doi.org/10.48550/arXiv.2504.03693

REFERENCE LIST

1. Abendroth-Dias, K., Cabarcos, P. A., Bacco, M., Bassani, E., Bertoletti, A., Bertolini, L., Van Bavel, R., Bertoletti, A., Bertolini, L., Bertrand, A., Bili, D., Boucher, P., Cachia, R., Ceresa, M., Chaslot, G., Chaudron, S., Comte, V., Consonni, C., Cosgrove, J., … Sellitto, A. (2025). *Generative AI outlook report: Exploring the intersection of technology, society, and policy.* Publications Office of the European Union. https://data.europa.eu/doi/10.2760/1109679

2. AdviceScout. (2025, February 21). *Top 10 AI Tools for Entrepreneurs and Business Owners.* https://www.advicescout.com/10-ai-tools-for-entrepreneurs/?utm_source=chatgpt.com
3. Alavi, M., Leidner, D. & Mousavi, R. (2024). Knowledge Management Perspective of Generative Artificial Intelligence (GenAI*). Journal of the Association for Information Systems, 25*(1), 1–12. https://doi.org/10.17705/1jais.00859
4. Albashrawi, M. (2025). Generative AI for decision-making: A multidisciplinary perspective. *Journal of Innovation & Knowledge*, 10, 100751. https://doi.org/10.1016/j.jik.2025.100751
5. Allen, D. W., Berg, C., Ilyushina, N. & Potts, J. (2023, May 4*). Large language models reduce agency costs.* Blockchain Innovation Hub. https://dx.doi.org/10.2139/ssrn.4437679
6. Ameen, N., Sharma, G. D., Tarba, S., Rao, A. & Chopra, R. (2022). Toward advancing theory on creativity in marketing and artificial intelligence. *Psychology & Marketing, 39*(9), 1802–1825. https://doi.org/10.1002/mar.21699
7. Arrigo, L. (2025, July 6). *H&M Unveils AI Digital Twins and Generative AI in Groundbreaking Fashion Campaign*. https://aimodelagency.com/hm-unveils-ai-digital-twins-and-generative-ai-in-groundbreaking-fashion-campaign/
8. Ashby, C. (2025, May 9). *10 Must-Try AI Tools For Startups & Entrepreneurs (2025)* [YouTube]. https://www.youtube.com/watch?v=vHpMJOhQCKw
9. Bahrini, A., Khamoshifar, M., Abbasimehr, H., Riggs, R. J., Esmaeili, M., Majdabadkohne, R. M. & Pasehvar, M. (2023). ChatGPT: Applications, opportunities, and threats. In *Proceedings of the Systems and Information Engineering Design Symposium (SIEDS)* (pp. 274–279). IEEE. https://doi.org/10.1109/SIEDS58326.2023.10137850
10. Bashir, N., Donti, P., Cuff, J., Sroka, S., Ilic, M., Sze, V., . . . Olivetti, E. (2024, Mar 27). The Climate and Sustainability Implications of Generative AI. *An MIT Exploration of Generative AI.* Retrieved August 28, 2025, from https://mit-genai.pubpub.org/pub/8ulgrckc/release/2
11. Batra, G., Queirolo, A. & Santhanam, N. (2018). *Artificial intelligence: The time to act is now.* McKinsey & Company. Retrieved from https://www.mckinsey.com/industries/industrials-and-electronics/our-insights/artificial-intelligence-the-time-to-act-is-now
12. Bender, S. M. (2023). Coexistence and creativity: screen media education in the age of artificial intelligence content generators. *Media Practice and Education, 24*(4), 351–366. https://doi.org/10.1080/25741136.2023.2204203
13. Birkinshaw, J. & Cohen, J. (2013, September). *Make Time for the Work That Matters.* Harvard Business Review. https://hbr.org/2013/09/make-time-for-the-work-that-matters
14. Bollinger, S. R. (2020). Creativity and forms of managerial control in innovation processes: tools, viewpoints and practices. *European Journal of Innovation Management, 23*(2), 214–229. https://doi.org/10.1108/EJIM-07-2018-0153

15. 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. https://doi.org/10.1111/jpim.12656
16. Bransten, S. (2025, September 9). *Ask Ralph: Where style meets AI—a new era of conversational commerce.* Retrieved September 10, 2025, from https://www.microsoft.com/en-us/industry/blog/retail/2025/09/09/ask-ralph-where-style-meets-ai-a-new-era-of-conversational-commerce/
17. Braun, V. & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology, 3*(2), 77–101. http://dx.doi.org/10.1191/1478088706qp063oa
18. BSG Global. (n.d.). *Generative AI.* Retrieved June 25, 2025, from https://www.bcg.com/capabilities/artificial-intelligence/generative-ai
19. Burger, B., Kanbach, D. K., Kraus, S., Breier, M. & Corvello, V. (2023). On the use of AI-based tools like ChatGPT to support management research. *European Journal of Innovation Management, 26*(7), 233–241. https://doi.org/10.1108/EJIM-02-2023-0156
20. Byrne, D. (2022, June 26). A worked example of Braun and Clarke's approach to reflexive thematic analysis. *Quality & Quantity, 56,* 1391–1412. https://doi.org/10.1007/s11135-021-01182-y
21. Cavale, S. (2025, July 24). *Walmart bets on AI super agents to boost e-commerce growth.* Retrieved August 27, 2025, from https://www.reuters.com/business/retail-consumer/walmart-bets-ai-super-agents-boost-e-commerce-growth-2025-07-24/
22. Chatterji, A., Cunningham, T., Deming, D. J., Hitzig, Z., Ong, C., Yan Shan, C. & Wadman, K. (2025, September). *How People Use ChatGPT* (NBER Working Paper No. 34255). National Bureau of Economic Research. https://www.nber.org/papers/w34255
23. Cloud, A., Le, M., Chua, J., Betley, J., Sztyber-Betley, A., Hilton, J., Marks, S. & Evans, O. (2025). Subliminal Learning: Language models transmit behavioral traits via hidden signals in data. *arXiv.* https://doi.org/10.48550/arXiv.2507.14805
24. Creswell, J. W. & Plano Clark, V. L. (2011). *Designing and conducting mixed methods research* (2nd ed.). SAGE.
25. Dhoni, P. (2023, August 29). Exploring the Synergy between Generative AI, Data and Analytics in the Modern Age. *TechRxiv.* https://doi.org/10.36227/techrxiv.24045792.v1
26. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges, and implications of generative conversational AI for research, practice, and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642
27. Eisfeldt, A. L., Schubert, G. & Zhang, M. B. (2023). *Generative AI and Firm Values* (NBER Working Paper No. 31222) National Bureau of Economic Research. https://www.nber.org/papers/w31222

28. Eloundou, T., Manning, S., Mishkin, P. & Rock, D. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. *arXiv.* https://doi.org/10.48550/arXiv.2303.10130
29. Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data (General Data Protection Regulation), OJ L 119/1, 4.5.2016
30. Regulation (EU) 2023/2854 of the European Parliament and of the Council of 13 December 2023 on harmonised rules on fair access to and use of data (Data Act), OJ L 2023/2854, 22.12.2023.
31. Feuerriegel, S., Hartmann, J., Janiesch, C. & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering, 66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7
32. Financial Times. (2025, September 29). *The graduate "jobpocalypse": Where have all the entry-level jobs gone? | FT Working It* [Youtube]. https://www.youtube.com/watch?v=IeTFpsuCor8
33. Fountaine, T., McCarthy, B. & Saleh, T. (2021, May–June). *Getting AI to Scale.* Harvard Business Review. https://hbr.org/2021/05/getting-ai-to-scale
34. Frare, A. B. & Beuren, I. M. (2021). Fostering individual creativity in startups: comprehensive performance measurement systems, role clarity and strategic flexibility. *European Business Review, 33*(6), 869–891. https://doi.org/10.1108/EBR-11-2020-0262
35. Futurepedia. (2025, January 30). *These 13 AI Tools Will Save You 1,000 Hours in 2025*. [YouTube]. https://www.youtube.com/watch?v=upDOltxNRqQ
36. Ganuthula, V. R. (2025). The Solo Revolution: A Theory of AI-Enabled Individual Entrepreneurship. *arXiv.* https://doi.org/10.48550/arXiv.2502.00009
37. Gao, L., Schulman, J. & Hilton, J. (2023). Scaling laws for reward model overoptimization. In A. Krause, E. Yang, & A. van der Schaar (Eds.), *Proceedings of the 40th International Conference on Machine Learning (ICML 2023)* (Vol. 202, pp. 10835–10866). Proceedings of Machine Learning Research. https://proceedings.mlr.press/v202/gao23h.html
38. Geng, B. & Varshney, P. K. (2022). Human-Machine Collaboration for Smart Decision Making: Current Trends and Future Opportunities. In *Proceedings of the International Conference on Computational Science and Engineering* (pp. 61–67). IEEE. https://doi.org/10.1109/CIC56439.2022.00019
39. Goldman Sachs. (2023, April 5). *Generative AI could raise global GDP by 7%*. Goldman Sachs. Retrived March 17, 2025, from https://www.goldmansachs.com/insights/articles/generative-ai-could-raise-global-gdp-by-7-percent
40. Goldstein, J. A., Sastry, G., Musser, M., DiResta, R., Gentzel, M. & Sedova, K. (2023). Generative language models and automated influence operations: Emerging threats and potential mitigations. *arXiv*. https://doi.org/10.48550/arXiv.2301.04246

41. Gomez, C., Cho, S. M., Ke, S., Huang, C.-M. & Unberath, M. (2025). Human-AI collaboration is not very collaborative yet: a taxonomy of interaction patterns in AI-assisted decision making from a systematic review. *Frontiers in Computer Science, 6,* 1521066. https://doi.org/10.3389/fcomp.2024.1521066
42. Gupta, V. (2024, March 18). An empirical evaluation of a generative artificial intelligence technology adoption model from entrepreneurs' perspectives. *Systems, 12*(3), 103. https://doi.org/10.3390/systems12030103
43. Haefner, N., Wincent, J., Parida, V. & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting & Social Change, 162,* 120392. https://doi.org/10.1016/j.techfore.2020.120392
44. He, R., Cao, J. & Tan, T. (2025). Generative artificial intelligence: a historical perspective. *National Science Review, 12*(5). https://doi.org/10.1093/nsr/nwaf050
45. Hernandez, D., Kaplan, J., Henighan, T. & McCandlish, S. (2021). Scaling Laws for Transfer. *arXiv*. https://doi.org/10.48550/arXiv.2102.01293
46. Hightower, S. S. (2025a, March 3). Daily Harvest's AI strategy is giving customers what they want. *Business Insider.* Retrieved August 28, 2025, from https://www.businessinsider.com/daily-harvest-implements-ai-to-improve-meal-delivery-customer-care-2025-2
47. Hightower, S. S. (2025b, March 12). This eco-friendly brand offers compostable alternatives to household items. AI has been key to scaling its operations. *Business Insider*. Retrieved August 28, 2025, from https://www.businessinsider.com/compostable-tableware-business-is-using-ai-to-stay-competitive-2025-3
48. Hightower, S. S. (2025c, March 7). A global dress distributor gave AI a chance. Now it makes creative content faster, and overstock is down 40%. *Business Insider*. Retrieved August 28, 2025, from https://www.businessinsider.com/wholesale-formal-gown-distributor-using-ai-for-ecommerce-operations
49. Kamboj, A. (n.d.). Top 10 generative ai tools for starups in 2025. *Binmile*. Retrived August 25, 2025, from https://binmile.com/blog/generative-ai-tools/
50. Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., Gray, S., Radford, A., Wu, J. & Amodei, D. (2020). Scaling Laws for Neural Language Models. *arXiv*. https://doi.org/10.48550/arXiv.2001.08361
51. Korzyński, P., Mazurek, G., Altmann, A., Ejdys, J., Kazlauskaite, R., Paliszkiewicz, J., Wach, K. & Ziemba, E. (2023). Generative artificial intelligence as a new context for management theories: Analysis of ChatGPT. *Central European Management Journal, 31*(1), 3–13. https://doi.org/10.1108/CEMJ-02-2023-0091
52. Kshetri, N. (2023). ChatGPT in Developing Economies. *IT Professional, 25*(2), 16–19. https://doi.org/10.1109/MITP.2023.3254639
53. Kwa, T., West, B., Becker, J., Deng, A., Garcia, K., Hasin, M., Jawhar, S., Kinniment, M., Rush, N., Von Arx, S., Bloom, R., Broadley, T., Du, H., Goodrich, B., Jurkovic, N.,

Miles, L. H., Nix, S., Lin, T., Parikh, N., … Chan, L. (2025). Measuring AI Ability to Complete Long Tasks. *arXiv*. https://doi.org/10.48550/arXiv.2503.14499

54. Malterud, K., Siersma, V. D. & Guassora, A. D. (2016). Sample size in qualitative interview studies. *Qualitative health research, 26*(13), 1753–1760. https://doi.org/10.1177/1049732315617444
55. Mariani, M. M., Machado, I., Magrelli, V. & Dwivedi, Y. K. (2022). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation, 122,* 102623. https://doi.org/10.1016/j.technovation.2022.102623
56. Marr, B. (2024a, April 11). Instacart harnesses generative ai to revolutionize grocery delivery experience. *Forbes.* Retrieved August 27, 2025, from https://www.forbes.com/sites/bernardmarr/2024/04/11/instacart-harnesses-generative-ai-to-revolutionize-grocery-delivery-experience/
57. Marr, B. (2024b, April 5). The amazing ways IKEA is using generative AI. *Forbes.* Retrieved August 29, 2025, from https://www.forbes.com/sites/bernardmarr/2024/04/05/the-amazing-ways-ikea-is-using-generative-ai/
58. McKinsey & Company. (2024, April 30). What is machine learning? *McKinsey & Company*. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-machine-learning
59. McLean, S., Read, G. J., Thompson, J., Baber, C., Stanton, N. A. & Salmon, P. M. (2023). The risks associated with Artificial General Intelligence: A systematic review. *Journal of Experimental and Theoretical Artificial Intelligence, 35*(5), 649–663. https://doi.org/10.1080/0952813X.2021.1964003
60. Merali, S. & Merali, A. (2023). The Generative AI Revolution: Opportunities, Shocks, and Risks. *Onward.* https://coilink.org/20.500.12592/tckn3g
61. Milanez, A. (2023). *The impact of AI on the workplace: Evidence from OECD case studies of AI implementation* (OECD Social, Employment and Migration Working Papers, No. 289). OECD Publishing. https://doi.org/10.1787/2247ce58-en
62. Mueller, M. (2024). *The myth of AGI: How the illusion of artificial general intelligence distorts and distracts digital governance* (IGP White Paper No. 11). Internet Governance Project. https://www.internetgovernance.org/research/the-myth-of-agi-how-the-illusion-of-artificial-general-intelligence-distorts-and-distracts-digital-governance/
63. Noguchi, T., Hashizume, Y., Moriyama, H., Gauthier, L., Ishikawa, Y., Matsuno, T. & Suganuma, A. (2018). A practical use of expert system “AI-Q” focused on creating training data. In *Proceedings of the 5th International Conference on Business and Industrial Research (ICBIR)* (pp. 73–76). IEEE. https://doi.org/10.1109/ICBIR.2018.8391169
64. OpenAI. (n.d.). *Trust Portal.* Retrieved September 3, 2025, from https://trust.openai.com/

65. Peres, R., Schreier, M., Schweidel, D. & Sorescu, A. (2023). On ChatGPT and beyond: How generative artificial intelligence may affect research, teaching, and practice. *International Journal of Research in Marketing, 40*(2), 269–275. https://doi.org/10.1016/j.ijresmar.2023.03.001
66. Phillips-Wren, G. & Virvou, M. (2025). Issues and trends in generative AI technologies for decision making. *Intelligent Decision Technologies, 19*(2), 574–584. https://doi.org/10.1177/18724981251320551
67. Pietkiewicz, I. & Smith, J. A. (2014, January). A practical guide to using interpretative phenomenological analysis in qualitative research psychology. *Psychological journal, 20*(1), 7–14. http://dx.doi.org/10.14691/CPPJ.20.1.7
68. 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. https://doi.org/10.1016/j.techfore.2022.121828
69. Potts, J. (2023). The use of knowledge in a digital economy. *King's College conference.* SSRN. http://dx.doi.org/10.2139/ssrn.4440771
70. Pushkarska, Y. & Danielkievych, A. (2024, December 3). Top 8 generative ai tools to consider for your business in 2025. *Forbytes.* Retrieved September 2, 2025, from https://forbytes.com/blog/generative-ai-tools/
71. Rai, D. H. (2024). *Artificial intelligence through time: A comprehensive historical review.* https://doi.org/10.13140/RG.2.2.22835.03364
72. Ren, M., Chen, N. & Qui, H. (2023). Human-machine collaborative decision-making: An evolutionary roadmap based on cognitive intelligence. *International Journal of Social Robotics, 15*(7), 1101–1114. https://doi.org/10.1007/s12369-023-01020-1
73. Russell, S. J. & Norvig, P. (2022). *Artificial intelligence: a modern approach* (4th ed., Global ed.). Pearson Education.
74. Sahoo, P., Singh, A. K., Saha, S., Jain, V., Mondal, S. & Chadha, A. (2024). A systematic survey of prompt engineering in large language models: Techniques and applications. *arXiv.* https://doi.org/10.48550/arXiv.2402.07927
75. Sastry, G., Heim, L., Belfield, H., Anderljung, M., Brundage, M., Hazell, J., O'Keefe, C., Hadfield, G. K., Ngo, R., Pilz, K., Gor, G., Bluemke, E., Shoker, S., Egan, J., Trager, R. F., Avin, S., Weller, A., Bengio, Y. & Coyle, D. (2024). Computing power and the governance of artificial intelligence. *arXiv*. https://doi.org/10.48550/arXiv.2402.08797
76. Sawers, P. (2025, February 1). AI agents could birth the first one-person unicorn — but at what societal cost? *TechCrunch.* Retrieved June 30, 2025, from https://techcrunch.com/2025/02/01/ai-agents-could-birth-the-first-one-person-unicorn-but-at-what-societal-cost/
77. Schleidgen, S., Friedrich, O., Gerlek, S., Assadi, G. & Seifert, J. (2023). The concept of "interaction" in debates on human–machine interaction. *Humanities and Social Sciences Communications, 10*(1), Article 551. https://doi.org/10.1057/s41599-023-02060-8
78. Seeber, I., Bittner, E., Briggs, R. O., de Vreede, G.-J., de Vreede, T., Druckenmiller, D. A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G. & Söllner, M.

(2018). Machines as teammates: A collaboration research agenda. In T. X. Bui (Ed.), *Proceedings of the 51st Hawaii International Conference on System Sciences (HICSS 2018)* (pp. 420-429). IEEE. https://doi.org/10.24251/HICSS.2018.055

79. Shepherd, D. A. & Majchrzak, A. (2022). Machines augmenting entrepreneurs: Opportunities (and threats). *Journal of Business Venturing, 37*(4), 106227. https://doi.org/10.1016/j.jbusvent.2022.106227
80. Short, C. E. & Short, J. C. (2023, June). The artificially intelligent entrepreneur: ChatGPT, prompt engineering, and entrepreneurial rhetoric creation. *Journal of Business Venturing Insights, 19,* e00388. https://doi.org/10.1016/j.jbvi.2023.e00388
81. Simonton, D. K. (2001). Talent development as a multidimensional, multiplicative, and dynamic process. *Current Directions in Psychological Science, 10*(2), 39–43. https://doi.org/10.1111/1467-8721.00110
82. Singh, R., Singh, S. & Singh, A. (2024). Landmark events, major trends, and the future of AI research: history, promise, hype. In *Proceedings of the 2nd International Conference on Artificial Intelligence and Machine Learning Applications (AIMLA 2024)* (pp. 1–5). IEEE. https://doi.org/10.1109/AIMLA59606.2024.10531477
83. Smith, T. (2024, February 21). *Make way for one-person unicorns: AI startups say their software will replace thousands of jobs.* Retrieved June 30, 2025, from https://sifted.eu/articles/ai-one-person-unicorns
84. Soniox. (n.d.). *Security.* Soniox. Retrieved September 3, 2025, from https://sonix.ai/security
85. Statista. (2025, March). *Generative AI - Worldwide.* Retrieved April 10, 2025, from https://www.statista.com/outlook/tmo/artificial-intelligence/generative-ai/worldwide
86. Stratvert, K. (2025, March 5). 7 best ai tools you need to try in 2025 (free & powerful!) [YouTube]. https://www.youtube.com/watch?v=TZe5UqlUg0c
87. Su, Z., Togay, G. & Côté, A. M. (2020). Artificial intelligence: a destructive and yet creative force in the skilled labour market. *Human Resource Development International, 24*(3), 341–352. https://doi.org/10.1080/13678868.2020.1818513
88. Sullivan, M. (2025, May 23). 9 of the most out-there things Anthropic CEO Dario Amodei just said about AI. *Fast Company*. Retrieved June 30, 2025, from https://www.fastcompany.com/91350535/thanks-to-ai-the-one-person-unicorn-is-closer-than-you-think
89. The Associated Press. (2023, July 13). AP, OpenAI agree to share select news content and technology in new collaboration. Retrieved August 27, 2025, from https://www.ap.org/media-center/press-releases/2023/ap-open-ai-agree-to-share-select-news-content-and-technology-in-new-collaboration/
90. Toosi, A., Bottino, A., Saboury, B. & Siegel, E. (2021). A brief history of AI: How to prevent another winter. *PET Clinics, 16*(4), 449–469. https://doi.org/10.48550/arXiv.2109.01517
91. Viswanathan, P. S. (2025). Prompt engineering for conversational AI systems: A systematic review of techniques and applications. *International Journal of Scientific*

Research in Computer Science, Engineering and Information Technology, 11(1), 733–741. https://doi.org/10.32628/CSEIT25111276

92. Von Hippel, E. (2016). *Free innovation.* The MIT Press.
93. Vu, H., Klievtsova, N., Leopold, H., Rinderle-Ma, S. & Kampik, T. (2025). Agentic business process management: Practitioner perspectives on agent governance in business processes. *arXiv.* https://doi.org/10.48550/arXiv.2504.03693
94. Walkowiak, E. (2023). Task-interdependencies between Generative AI and Workers. *Economics Letters, 231,* 111315. https://doi.org/10.1016/j.econlet.2023.111315
95. Walmart. (2025, April 9). *In an ever-changing environment, Walmart uses GenAI to create cool for customers.* Retrieved August 27, 2025, from https://corporate.walmart.com/news/2025/04/09/in-an-ever-changing-environment-walmart-uses-genai-to-create-cool-for-customers
96. Y Combinator. (2025, July 30). *Scaling and road to human-level AI | Anthropic co-founder Jared Kaplan* [YouTube]. https://www.youtube.com/watch?v=p8Jx4qvDoSo
97. Yopko, N. (2025, August 6). *Spinnin' Records and Endel partner to produce 50 AI-powered sleep and wellness albums.* Retrieved August 28, 2025, from https://edm.com/lifestyle/spinnin-records-endel-50-ai-powered-sleep-wellness-albums/
98. Zha, D., Bhat, Z. P., Lai, K., Yang, F., Jiang, Z., Zhong, S. & Hu, X. (2025). Data-centric artificial intelligence: A survey. *ACM Computing Surveys, 57*(5), 1–42. https://doi.org/10.1145/3711118
99. Zhang, C., Zhang, C., Zheng, S., Qiao, Y., Li, C., Zhang, M., Dam, S. K., Thwal, C. M., Tun, Y. L., Huy, L. L., Kim, D., Bae, S.-H., Lee, L.-H., Yang, Y., Shen, H. T., Kweon, I. S. & Hong, C. S. (2023). A complete survey on generative AI (AIGC): Is ChatGPT from GPT-4 to GPT-5 all you need? *arXiv.* https://doi.org/10.48550/arXiv.2303.11717

APPENDICES

Appendix 1: Prompt engineering

The evolution of AI systems from rule-based chatbots to advanced neural networks capable of comprehending and producing human-like responses with contextual understanding, memory mechanisms, and adaptive learning capabilities has fundamentally transformed human-AI interaction. Underscoring the necessity for more nuanced and context-aware communication strategies and thus bringing forth a discipline called prompt engineering. Prompt engineering can be defined as "the systematic methodology of crafting and optimising input queries to elicit desired responses from AI systems, particularly in conversational contexts" and goes beyond simple input-output relationships, as it represents the primary interface between human intent and machine comprehension (Viswanathan, 2025, p. 734).

It is an emerging task that seeks to design and develop high-quality prompts to optimise performance on downstream tasks (Zha et al., 2025, p. 129:20), facilitating a complete translation process that bridges natural language understanding with computational processing (Viswanathan, 2025, p. 735). Prompts can be natural language directions that give the model context to follow or learnt vector representations that bring up relevant information (Sahoo et al., 2024, p. 1). With the introduction of LLMs, it became feasible to accomplish a task solely by fine-tuning the input in real-time and probing the model (its knowledge base) while keeping the model itself fixed (Zha et al., 2025, p. 129:20). Prompt engineering as a discipline is addressing and helping address challenges the current AI field is grappling with, including ensuring consistency in AI responses, maintaining contextual relevance across extended conversation, mitigating inherent biases, and adapting to domain-specific requirements, all in real-time and while balancing the performance, specificity, and generalisation of outputs (Viswanathan, 2025, p. 734).

The key original challenge in prompt engineering is the lack of a single, effective template. Different templates can cause different model behaviours, so the desired answers are not guaranteed (Zha et al., 2025, p. 129:20). Further research is thus needed to understand the model's response to prompts and guide prompt engineering as well as define and provide a more systematic structure and comprehension of the diverse prompt engineering methods and procedures (Sahoo et al., 2024, pp. 1–2). Nevertheless, the discipline did develop its own theoretical principles, practical methodologies, and core concepts (Viswanathan, 2025, pp. 734–735).

Understanding language model behaviours, regulating cognitive demands, and applying information retrieval theory underpin prompt engineering. These concepts and techniques outline how to structure, contextualise, and optimise AI prompts for optimal efficacy. Well-designed prompts improve AI output, optimise computational load, and improve response efficiency. This methodology covers everything from simple query-response systems to complex multi-turn dialogues. The core components of prompt engineering are clarity, context, structure, and validation. Clarity in prompts depends on precise instruction

construction, employing plain language and detailed commands. The context includes background information integration and must be rated on relevance, completeness, and conciseness. Logical flow and hierarchical order are key to prompt structure. On the other hand, consistency checks and error detection are crucial to validation in quality assurance (Viswanathan, 2025, p. 735).

An effective prompt will therefore utilise precise language, provide unambiguous instructions, and outline clear outcome expectations. While creating, the user must thoughtfully reflect on the intended purpose and uphold linguistic accuracy to reduce the chances of misinterpretation by the model used. The prompt must include all pertinent background information, specialised knowledge, and situational context to ensure that the AI system can provide an accurate and relevant response. The entire process should consistently strike a balance between providing complete information and maintaining conciseness, ensuring that the AI system is not inundated while still having sufficient context for precise interpretation. The phrasing strategies focus on the careful selection of appropriate command words, structural patterns, and linguistic frameworks that direct AI through the intended process, considering the model's training paradigms and response tendencies. Every choice of phrasing can significantly impact the quality and relevance of generated output. Finding the ideal prompt length involves striking a balance between comprehensive instructions and efficient communication. While longer prompts can offer more context and specificity, they may also introduce complexity that hinders the model's performance. When determining the length of the prompt, the user must consider the complexity, necessary context, and the model's processing capabilities (Viswanathan, 2025, p. 735).

Appendix 2: Survey questionnaire used in data collection

INTRODUCTION:

Dear participant,

My name is Val Kuret, and I am a master's student at the School of Economics and Business, University of Ljubljana. As part of my master's thesis, entitled *"*The entrepreneur's new toolkit: Potential benefits, limitations, and implications of the use of generative artificial intelligence*"*, I am researching the use of generative artificial intelligence (GenAI) in business processes, with a particular focus on its impact on entrepreneurship. The aim of the research is to understand how GenAI tools are being used in practice, what benefits and challenges they bring, and what impact they may have on entrepreneurial processes.

I kindly invite all those who use GenAI tools in their work to participate in this survey – especially entrepreneurs and employees who operate with a more pronounced entrepreneurial mindset. Your responses will make an important contribution to shaping a broader understanding of GenAI use in business environments and to identifying potential candidates for in-depth interviews.

The survey is anonymous and will take approximately 10 minutes (5 research topics) to complete. At the end of the questionnaire, you will have the opportunity to leave your contact e-mail address if you are willing to participate in a follow-up interview. This information will be used exclusively for the purpose of contacting you regarding the interview.

All collected data will be treated with strict confidentiality and used solely for the purpose of this master's thesis. The results will not be published or shared with third parties. *You may complete the questionnaire in either Slovenian or English, according to your preference.*

Thank you very much in advance for your time and valuable contribution.
Val Kuret

DEMOGRAPHIC AND PROFESSIONAL BACKGROUND:

1. Age group (by years):
- 18–24
- 25–34
- 35–44
- 45–54
- 55–64
- 65+
- Prefer not to say

2. Gender:
- Male
- Female
- Prefer not to say

3. Highest level of education completed:
- Primary education (ISCED 1–2)
- Secondary education (ISCED 3–4)
- Post-secondary non-tertiary education (ISCED 4)
- Undergraduate degree – Bachelor's (ISCED 6)
- Postgraduate degree – Master's (ISCED 7)
- Doctoral degree – Doctorate (ISCED 8)

4. Current employment status:
- Full-time employment
- Part-time employment
- Self-employed
- Student
- Unemployed

5. Industry or sector:
- Information and communication technologies (ICT)
- Marketing, advertising, and media
- Professional, technical, or scientific services
- Consulting or business services
- Education and research
- Finance, banking, and insurance
- Healthcare, social services, and pharmaceuticals
- Trade (retail, wholesale, e-commerce)
- Manufacturing and industrial production
- Transport, logistics, and warehousing
- Government and public administration
- Tourism, hospitality, and entertainment
- Agriculture, forestry, and rural industry
- Non-profit sector and NGOs
- Other

6. Type of organisation:
- Public sector
- Private sector
- NGO

7. Organisational size (number of employees):
- Sole proprietor/individual
- 1–10
- 11–50

- 51–250
- 250+

8. Primary function/department:
- Marketing and sales
- Finance and accounting
- Human resources (HR)
- Research, development, and innovation (R&D)
- Information technology (IT) and digital services
- Operations and logistics
- Customer support/client support
- Executive/senior management
- Education/research/academic work
- Other

9. Level of responsibility/decision-making:
- Individual contributor
- Team leader/middle management
- Senior management
- Executive leadership

10. Entrepreneurial experience:
- No experience
- Limited experience
- Regular experience
- Extensive experience

11. Duration of GenAI tool use:
- Less than 1 year
- 1–3 years
- More than 3 years

12. Frequency of GenAI tool use at work:
- Never
- Rarely
- Occasionally
- Regularly
- Very frequently

RQ1 - APPLICATIONS OF GENAI TOOLS:

13. Primary factors encouraging first use of GenAI tools (max 3):
- Idea generation & creativity
- Productivity & efficiency
- Support in decision-making

- Automation of routine tasks
- Recommendations from colleagues
- Maintaining competitiveness
- Curiosity
- Overcoming skill limitations
- Improving customer experience
- Cost/resource optimisation

14. GenAI tools used regularly:
ChatGPT, Claude, Copilot, Gemini, DeepSeek, Perplexity, GitHub Copilot, Notion AI, Otter AI, Midjourney, Gamma, Canva AI, Jasper AI, Descript, Opus Clip, Synthesia, NotebookLM, Make

15. Proficiency using GenAI tools (1–5)

16. Business processes with the strongest GenAI impact (max 3):
- Idea generation
- Text creation/editing
- Data analysis
- Decision-making & strategy
- Visual content & presentations
- Automation
- Collaboration & communication

17. Frequency of use in work tasks (1–5)

18. Integration into daily work processes (1–5)

19. Business functions with greatest GenAI impact (max 3):
- Marketing & sales
- Finance & accounting
- HR
- R&D
- IT & digitalisation
- Operations & logistics
- Customer support
- Management & leadership

RQ2 - CREATIVITY AND INNOVATION:

20. Has GenAI led to new ideas, solutions, or improvements?
- Yes / No / Unsure

21. Extent GenAI changed approach to creative tasks (1–5)

22. Frequency of GenAI use for idea generation (1–5)

23. Extent GenAI improved collaboration (1–5)

24. Most frequent GenAI tasks (max 3):
- Research
- Drafting text
- Messages/emails
- Data analysis
- Decision-making
- Visual content
- Automation
- Collaboration

RQ3 - COMPARISON OF GENAI TOOLS:

25. Factors influencing choice of GenAI tools (max 3):
- Experience
- Peer influence
- Ease of use
- Licensing/access
- Integration
- Training availability
- Features
- Reputation
- Accuracy
- Reliability
- Language quality
- Security
- Compliance
- Cost
- User adoption

26. Most useful type of GenAI tools:
- Text / Image / Audio / Video / Code / Multimodal

27. GenAI tools regularly used:
(Full extended list including ChatGPT, Claude, Gemini, DeepSeek, Perplexity, GitHub Copilot, Notion, Bard, Canva AI, Runway, etc.)

28. Agreement statements (1–5):
- Differences in tool quality
- Better performance for creative tasks
- Cost influences choice
- Switching between tools

- Satisfaction with tools
- Tools meet expectations

29. Frequency of switching GenAI tools (1–5)

RQ4: ETHICAL, LEGAL, AND SOCIAL ISSUES

30. Is GenAI changing your work?
- Yes / No / Uncertain

31. Ethical or legal concerns encountered?
- Yes / No / Uncertain

32. Importance of clear GenAI labelling (1–5)

33. Preparedness for legal challenges (1–5)

34. Need for more regulatory oversight?
- Yes / No / Uncertain

RQ5 - BEST PRACTICES AND STRATEGIES:

35. Organisation has GenAI procedures?
- Yes / No / In preparation

36. Organisation provides training?
- Yes / No / In preparation

37. Organisation allocates resources/budget?
- Yes / No / In preparation

38. Organisation measures GenAI value?
- Yes / No / In preparation

39. Organisation measures GenAI efficiency?
- Yes / No / In preparation

40. Recommendation of GenAI integration (1–5)

41. Obstacles to best practices (1–5):
- Lack of knowledge
- Costs
- Lack of time
- Lack of management support
- No policies

42. Sharing work-related GenAI insights frequency (1–5)

INTERVIEW PARTICIPATION:

43. Email for follow-up interview (open-ended)

THANK-YOU MESSAGE:

Thank you for your time and participation in completing this survey.

Your responses have been successfully submitted and will make a valuable contribution to the research on the use of generative artificial intelligence in the business environment.

Appendix 3: Consent form for interview participants

UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

INFORMED CONSENT FORM FOR PARTICIPATION IN RESEARCH

This informed consent form is a legal document designed to ensure compliance with ethical research standards and the General Data Protection Regulation (GDPR). By signing this form, the participant acknowledges understanding of the study and voluntarily agrees to participate.

PROJECT DETAILS
Project Title: The Entrepreneur's New Toolkit: Potential Benefits, Limitations, and Implications of Generative Artificial Intelligence
Researcher: Val Kuret, master's student, School of Economics and Business, University of Ljubljana
Supervisor: Assoc. Prof. Dr. Anja Svetina Nabergoj

The purpose of this study is to investigate how entrepreneurs and entrepreneurial employees use generative artificial intelligence (GenAI) tools in their work. The study examines potential benefits, drawbacks, limitations, implications, and best practices of GenAI adoption.

PARTICIPATION AND PROCEDURES
a) Completion of a short online survey (approx. 10–12 minutes).
b) If selected, participation in a semi-structured interview (45–70 minutes).
c) The interview will be audio-recorded and transcribed with your consent using GenAI tool called Soniox (paid and GDPR compliant).

Participation is voluntary. The participant may refuse to answer any question or withdraw at any time without penalty. Withdrawal will not affect any rights or legal entitlements.

RISKS AND BENEFITS
There are no anticipated risks. The potential benefit is contributing to knowledge about the use of GenAI in entrepreneurship.

CONFIDENTIALITY AND DATA PROTECTION
a) All personal data will be anonymised or pseudonymised.
b) Data will be securely stored (encrypted, password-protected).
c) Data will be deleted upon completion of the master's thesis.
d) GDPR compliance principles observed: consent, confidentiality, data minimisation, and secure storage (Regulation (EU) 2016/679, Article 5).

e) Use of AI tools (e.g., Soniox for transcription, ChatGPT for coding assistance) will be limited to anonymised data, and outputs will be manually verified.

CONSENT STATEMENT

By signing this document, I declare that I have read and understood the above information. I voluntarily agree to participate in this study, and I consent to the interview being audio-recorded, transcribed, and anonymised. I acknowledge my right to withdraw at any stage without consequences.

Participant's Name:

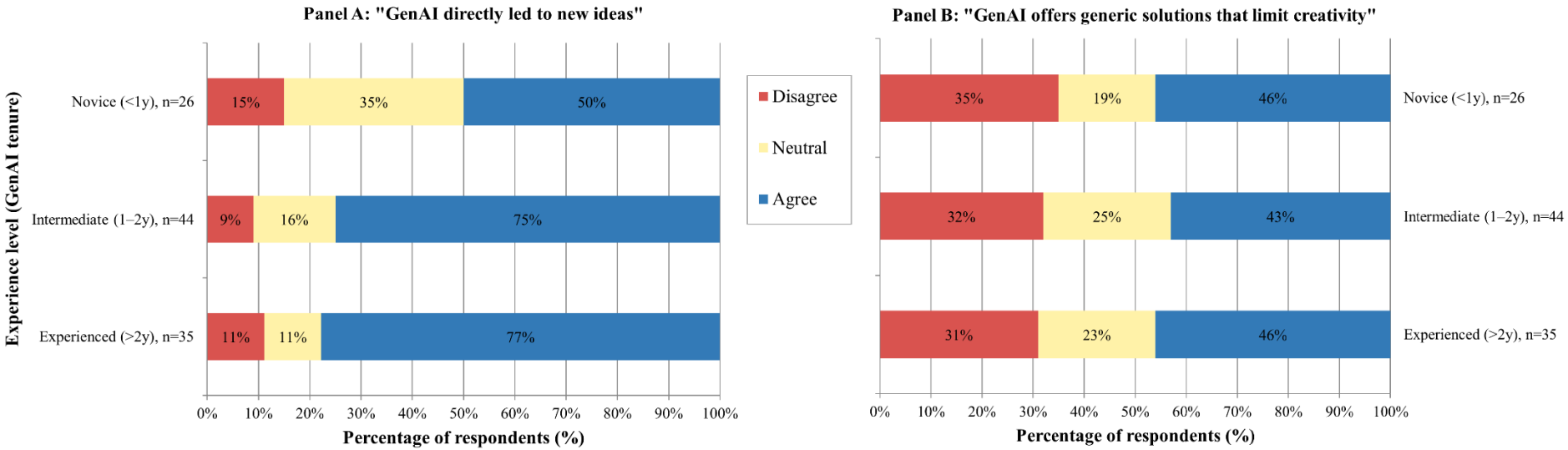
Signature: _____ Date: _____

Researcher's Name: Val Kuret

Signature: _____ Date: _____

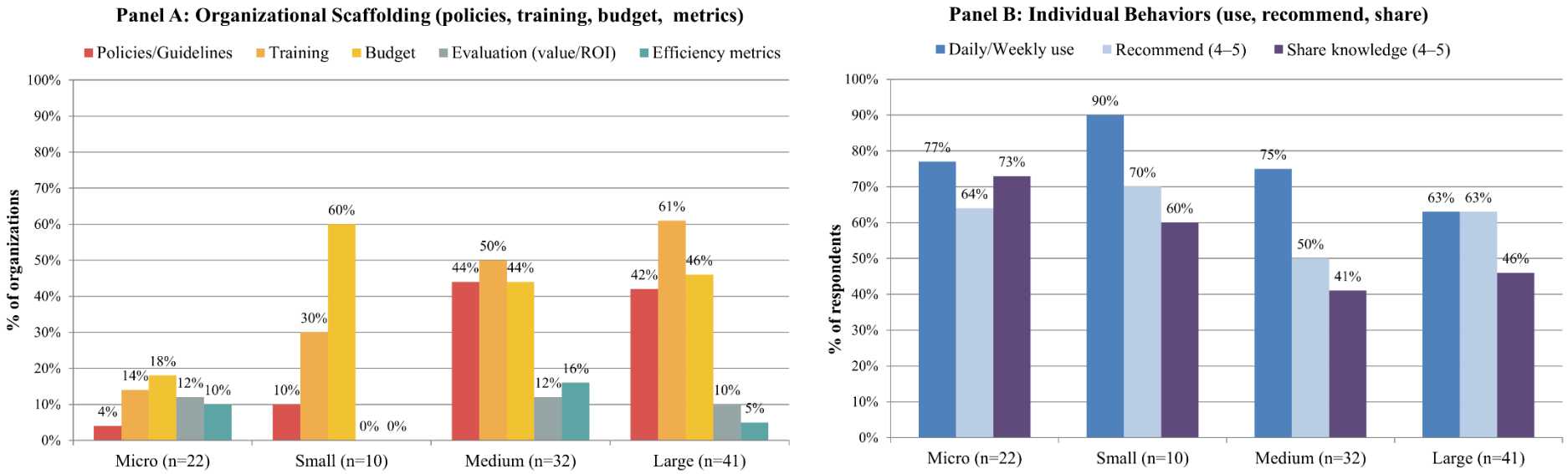
Appendix 4: Additional key figures

Figure 9: Results of creativity related questions by experience group (panel A, B)



Source: Own work.

Figure 10: Organisational scaffolding vs. individual behaviours by org. size (panel A, B)



Source: Own work.

Appendix 5: Interview transcripts sample (Interviewee J by Soniox)

Val Kuret:

Ok. Za začete bi te prosil, da mi malo poveš, katera so tvoja najljubša orodja, oziroma katera orodja poznaš, katera uporabljaš, katera raje nisi uporabljal zaradi nekih razlogov, oziroma katera raje uporabljaš bolj redno.

Anonymous J:

Torej, v teh general purpose najbolj znanih LLM-ih največ uporabljam definitivno ChatGPT in Gemini. ChatGPT za neke vrste jack of all trades. Gemini je, torej pa bom rekel, celoten Google Workspace in vsi tool-i, ki pridejo zraven. Ima zelo dobre vizualizacije, image generation, video generation, integrira se direktno v Google Workspace, to pomeni, da imam asistenta v Google Drive-u, v mailih, torej Gmail in vse to. Zelo prav pride. Vse, kar je nek deep research ali pa deep analysis, je Perplexity na prvem mestu, trenutno še zmeraj najboljši. Z vsemi viri in citiranjem in tako. Uporabljamo tudi nekaj malega pač za image in video generation, največkrat Midjourney. Gamma, prezentacije smo tudi že delali. Kaj so še kakšna orodja? Consensus, mislim, da smo tudi že nekaj pogledali, ki je za akademske zadeve. To bi bilo to. Izogibam se Groku, vsaj zaenkrat nisem dobil dobrih razlogov or priporočil, mislim, jaz še ne vidim nekih praktičnih zase osebno, ampak še zmeraj ima zelo kreativne zadeve, kako lahko te personal GPT-je ali pa te avatarje kreiraš. Pa tudi Claude, torej od Anthropica, Claude sem gledal in testiral, ampak se mi zdi, da trenutno mojim potrebam vse zadovolji Gemini in pa ChatGPT.

Val Kuret:

Super. Kako pa se odločiš, katero orodje uporabiti, oziroma kdaj sploh uporabljati GenAI orodje, kdaj pa je boljše, da ti sam pristopiš do naloge, oziroma jo rešiš sam in zakaj?

Anonymous J:

Zase zelo hitro ocenim, ali je to neka naloga, ki bo zelo repetitive, torej, da se bo veliko ponavljala in da se bo mogoče spreminjal samo kontekst in vsebina, ampak sam proces se bo ponavljal. Tam probam, če se le da, izkoristiti AI. Veliko je še trial and error, to pomeni, ali lahko v vsakodnevnem življenju, pač tem poslovnem, si izboljšam procese in ga uporabljam. Ni vedno uspešno, čisto po pravici. Včasih hočeš ti še zmeraj na nek svoj specifičen način nekaj narediti, da mogoče ti on samo pomaga break it down korake, pa strateško se pripraviti, pa da ti v bistvu začne brainstormati vsebine. Ja, to je pa to, približno. Malo intuicija predvsem.

Val Kuret:

… (the interview carries on)

Appendix 6: Interview coding matrix

Interview quote	Codes	Category	Theme
	meeting transcription automation	Process applications	General application information (RQ1)
	employee onboarding		
	translations		
	Security testing/monitoring		
	project applications		
	email drafting	Communication applications	
	language simplification		
	pitches		
	meeting summaries		
	market analysis	Strategic applications	
	SWOT analysis		
	business model development		
	legal clauses		
	B2B marketing	Industry-specific applications	
	legal services		
	robotics		
	Recruitment/ATS		
	HR compliance (GDPR-sensitive data)		
	Sales prospecting		
	AI-generated marketing content		
	Creative applications (music/art)		
	academic research		
	brainstorming	Creativity stimulation	Creativity & Innovation (RQ2)
	idea generation		
	content planning		
	Skeleton drafts/structural templates		
	Music/creative prototyping		
	visualizations		
	R&D acceleration	Innovation processes	
	product design		
	iterations		
	market opportunity canvas		
	complacency	Creativity limitations	
	reduced critical thinking		

	Over-standardised outputs		
	generic output		
	human as main creator	Perceptions of thehuman role	
	AI as facilitator		
	AI draft + human polish		
	critical evaluation		
	time savings	Micro-level impact (individual)	Factors and comparative impact (RQ3)
	increased productivity		
	prompting frustrations		
	Environmental concerns		
	Delegation of admin tasks		
	learning new skills		
	cost optimization	Macro-level impact (organisation)	
	reduced hiring needs		
	task distribution		
	KPI-linked adoption		
	Awareness culture/organisational training impact		
	Cultural acceptance trajectory		
	knowledge access		
	IT	Industry differences	
	law		
	marketing		
	traditional industries		
	startup	Differences by organisation size	
	SME		
	corporation		
	user responsibility	Ethics	Implications and responsibility (RQ4)
	AI use disclosure		
	transparency		
	model bias		
	GDPR	Legal aspects	
	intellectual property		
	trade secrets		
	Data anonymisation/maskin g		
	Third-party vendor risk		
	AI Act regulation		
	trust	Social aspects	
	digital divide		
	job displacement		

	Awareness campaigns & phishing simulations		
	impact on communication		
	user–developer–state	Trust vs. control	
	enterprise licenses		
	Zero-trust frameworks		
	Transparency of AI use not required		
	Human accountability for AI outputs		
	data control		
	prompt engineering	Individual strategies	Adoption strategies (RQ5)
	selective use		
	tool combination		
	trial & error		
	training & education	Organizational practices	
	enterprise licenses		
	onboarding guidelines		
	Zero-trust & RBAC		
	Awareness/phishing training		
	Benchmarking external best practices		
	Communities of practice / knowledge sharing groups		
	internal playbooks		
	KPIs	Formalisation and measurement	
	ROI		
	process documentation		
	tool evaluation		
	department-specific guidelines	Context adaptation	
	Setup cost vs. time saved evaluation		
	AI as skeleton, human refinement		
	different team knowledge levels		

Appendix 7: Example of interview coding (interview J sample)

Interview quote	Codes	Category	Theme
"največ uporabljam definitivno ChatGPT in Gemini. ChatGPT za neke vrste jack of all trades. Gemini … celoten Google Workspace … image generation, video generation, integrira se direktno v Google Workspace …"	tool combination; visualizations; image generation; video generation; integration with productivity suite	Individual strategies; Creative applications; Process applications	(RQ5); (RQ2); (RQ1)
"Vse, kar je nek deep research ali pa deep analysis, je Perplexity na prvem mestu, … z vsemi viri in citiranjem …"	academic research; knowledge access	Creative applications; Macro-level impact (organization)	RQ2; (RQ3)
"uporabljamo tudi nekaj malega pač za image in video generation, največkrat Midjourney."	image generation; video generation	Creative applications	(RQ2)
"Gamma, prezentacije smo tudi že delali."	presentations (structural templates)	Creativity stimulation	(RQ2)
"Consensus … za akademske zadeve."	academic research	Creative applications	(RQ2)
"Izogibam se Groku … ima zelo kreativne zadeve, kako lahko te personal GPT-je ali pa te avatarje kreiraš."	creative prototyping; selective use	Creative applications; Individual strategies	(RQ2); (RQ5)
"Claude … sem gledal in testiral, ampak se mi zdi, da trenutno mojim potrebam vse zadovolji Gemini in pa ChatGPT."	trial & error; selective use	Individual strategies	(RQ5)
"… zelo hitro ocenim, ali je to neka naloga, ki bo zelo repetitive … sam proces se bo ponavljal. Tam probam … izkoristiti AI."	repetitive tasks; increased productivity	Process applications; Micro-level impact (individual)	(RQ1); (RQ3)
"Veliko je še trial and error … si izboljšam procese …"	trial & error; process improvement	Individual strategies; Process applications	(RQ5); (RQ1)
"mogoče ti on samo pomaga break it down korake, pa strateško se pripraviti, pa da ti v bistvu začne brainstormati vsebine."	brainstorming; strategic preparation; idea generation	Creativity stimulation; Strategic applications	(RQ2); (RQ1)
"Malo intuicija predvsem."	intuition-driven adoption	Individual strategies	(RQ5)