UNIVERSITY OF LJUBLJANA
SCHOOL OF BUSINESS AND ECONOMICS

MASTER'S THESIS

A CONCEPTUAL STRATEGIC FRAMEWORK FOR IMPLEMENTING MACHINE LEARNING IN SMALL AND MEDIUM-SIZED ENTERPRISES

Ljubljana, September 2023

ELENA DAVKOVA

AUTHORSHIP STATEMENT

The undersigned Elena Davkova, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title A conceptual strategic framework for Implementing Machine Learning in Small and Medium-Sized Enterprises, prepared under supervision of Dr. Prof. Jurij Jaklič.

D E C L A R E

1. this written final work of studies to be based on the results of my own research;

2. the printed form of this written final work of studies to be identical to its electronic form;

3. the text of this written final work of studies to be language-edited and technically in adherence with the SEB LU's Technical Guidelines for Written Works, which means that I cited and / or quoted works and opinions of other authors in this written final work of studies in accordance with the SEB LU's Technical Guidelines for Written Works;

4. to be aware of the fact that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code of the Republic of Slovenia;

5. to be aware of the consequences a proven plagiarism charge based on the this written final work could have for my status at the SEB LU in accordance with the relevant SEB LU Rules;

6. to have obtained all the necessary permits to use the data and works of other authors which are (in written or graphical form) referred to in this written final work of studies and to have clearly marked them;

7. to have acted in accordance with ethical principles during the preparation of this written final work of studies and to have, where necessary, obtained permission of the Ethics Committee;

8. my consent to use the electronic form of this written final work of studies for the detection of content similarity with other written works, using similarity detection software that is connected with the SEB LU Study Information System;

9. to transfer to the University of Ljubljana free of charge, non-exclusively, geographically and time-wise unlimited the right of saving this written final work of studies in the electronic form, the right of its reproduction, as well as the right of making this written final work of studies available to the public on the World Wide Web via the Repository of the University of Ljubljana;

10. my consent to publication of my personal data that are included in this written final work of studies and in this declaration, when this written final work of studies is published.

11. that I have verified the authenticity of the information derived from the records using artificial intelligence tools.

Ljubljana, July/26/2023 Author's signature

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX

LIST OF ABBREVIATIONS

en. - English

AI - Artificial Intelligence

ASR - Automatic Speech Recognition

CEO - Chief Executive Officer

DL - Deep Learning

DSRPAI - Dartmouth Summer research Project on Artificial Intelligence

EU - European Union

GDPR - General Data protection Regulation

HR - Human Resources

ICT - Information and Communication Technologies

IoT - Internet of Things

IT - Information Technology

MIT - Massachusetts Institute of Technology

ML – Machine Learning

MSP – (en. Small and medium-sized enterprises); Majhna in srednje velika podjetja

R&D – Research and Development

ROI - Return on Investment

SMEs - Small and medium-sized enterprises

TAM - Technology Acceptance Model

TOE - Technology Organisation Environment Framework

UTAUT - Unified Theory of Acceptance and Use of Technology

1 INTRODUCTION

Micro, small and medium-sized enterprises (SMEs) account for 99% of companies in the European Union (EU). They constitute two thirds of the private sector jobs and make for more than half of the total added value created by businesses in the EU (European Parliament, 2023). In 2015 alone, just under 23 million SMEs generated EUR 3.9 trillion in value added, and employed around 90 million people (European Parliament, 2017). SMEs play a key role in the EU's competitive growth, creating jobs, manifesting innovation, and entrepreneurial spirit. According to the European Commission, "research and innovation are highly important for sustainable success and growth of SMEs in the European Union" (European Parliament, 2023). Moreover, "researchers agree in recognising innovation as a crucial factor for the success and long-term survival of companies" (Bigliardi & Galati, 2018). The main factors that determine whether or not an enterprise is an SME are number of employees, and annual turnaround or balance sheet total. In short, small and medium-sized enterprises are companies that have less than 250 employees, and less than 50 million euros of annual turnaround, or a balance sheet total that does not exceed 43 million euros.

Artificial intelligence (AI) and machine learning (ML) are new, promising technologies that can potentially enhance SMEs' performance and reveal new opportunities for business growth. Thanks to improvements in computing power and the rise of access to vast amounts of data, artificial intelligence has made important progress, particularly with the emergence of machine learning and a class of machine learning called deep learning (DL) (Wamba-Taguimdje, et al., 2020). Machine learning is a key subfield within the broader field of AI, playing a vital role by providing algorithms and models that can learn and adapt based on available information. Both AI and ML, have often been described by many as the catalysts of business model innovation. In essence, the term machine learning describes a set of techniques that are commonly used to solve a variety of real-world problems with the help of computer systems which can learn to solve a specific problem by leveraging existing data (Mahesh, 2019). Today, the term artificial intelligence, or just AI, is broadly and generally used to refer to any sort of a machine learning program (Wehle, 2017). With the rising popularity of AI, the term is often interchangeably used with machine learning, not just by the mainstream public but also across various theoretical and application-oriented contributions in recent literature (Kuhl et al., 2019).

According to an analysis by McKinsey covering 400 case studies across 19 sectors, advanced AI techniques such as machine learning have the potential to create an estimated value of \$3.5 trillion to \$5.8 trillion across 9 business functions in 19 industries (McKinsey, 2018). Furthermore, the European Parliament has projected that AI adoption will bring a vast range of positive impacts, for individual firms, and at societal and macroeconomic level, estimating the potential impact of AI to reach additional 294.9 billion euros in GDP, and creating additional 4.5 million jobs by 2023 in the European Union (European Parliament, 2021).

However, fostering AI adoption by SMEs remains a challenge. According to a study by the European Economic and Social Committee, small and medium-sized companies find it harder to capitalise on the technology. The research committee identified both internal (e.g. financial barriers, cultural resistance, lack of skills) and external (e.g. lack of venture capitalists) as barriers to adoption, with the financial aspect ranking as the number one barrier (European Economic and Social Committee, 2021). While in-house innovation is the usual ‘to-go’ for corporations who often possess the resources to invest in internal research and development, small and medium-sized enterprises mostly depend on external partners to help them foster innovation (Radziwon & Bogers, 2019).

A recent survey from McKinsey (McKinsey, 2018), reported that 43% of all organisations’ respondents cited “Lack of clear AI strategy” as the number one barrier to adoption of artificial intelligence technologies such as machine learning in their organisation. Having a clear strategy can help SMEs focus on their business goals and prioritise how machine learning technologies can help deliver those business goals. The lack of clear ML strategy can be explained by a recent empirical study showing that SMEs are still struggling to identify use cases which best fit their business needs, often have limited knowledge of the technology’s implications and terminology, fail to understand the quantity and format of data needed to train an algorithm, and possess too little knowledge and experience to assess a machine learning strategy and implementation plan (Bauer et al., 2020).

The purpose of this thesis is to provide SMEs necessary knowledge to help them better understand how to successfully implement machine learning in their organisation. Therefore, one of the goals of this thesis is to familiarise stakeholders with AI and ML terminology, its implications, and flag potential adoption challenges. Furthermore, we provide ideas, concepts, and methods to prepare SMEs for an easy start in their digitalisation journey and machine learning implementation. It is the goal to provide SMEs with a framework that will help executives better understand what is needed for successful machine learning implementation, **how** to assess the feasibility and risk of their particular use case, and **how** to scope their project for easy commercialisation. The outlook of this paper is how SMEs can use machine learning successfully, and leverage the technology to gain competitive advantage and growth in increasingly dynamic and competitive markets. Our insights are presented in a form of a conceptual strategic framework, aimed to be used by stakeholders who want to gain a better understanding of the potential challenges and opportunities that may arise on the road of ML implementation. The proposed framework suggests how SMEs can plan and prepare for a successful machine learning implementation journey, and it represents a guide that can further be utilized and personalised by the organisations. Finally, we provide recommendations for future research in the area.

Our research is focused on the current state of machine learning as a form of artificial intelligence. The main question of our research is how small and medium-sized enterprises can successfully implement ML technologies into their organisation, and do so while maximising the value of their particular business case.

The research is conducted in the form of a systematic literature study approach, multiple-case analysis, and a survey method. The methodology used in the literature study approach involved a literature review of technology acceptance theories and models from relevant books, journals, and academic papers. In the multiple case analysis, we analysed several case studies from the literature, and summarised the key findings. Moreover, we used the findings from our literature review and multiple case analysis to prepare questions related to the purpose of our thesis, for our survey with selected SMEs. The survey was conducted with real SMEs from different industries in Slovenia, covering both those with no experience with machine learning adoption and those that already have experience with implementing machine learning. Furthermore, we targeted employees that held managerial and/or decision-making positions in Slovenian SMEs. The survey questions provide information on the SMEs' experience with machine learning, how digitalised the companies are in terms of internal systems and data collection, what are their biggest challenges in terms of ML adoption, which departments could benefit the most from ML implementation, what is the overall employee attitude on machine learning adoption, and more. In order to analyse and better understand the data collected from our own survey, we leveraged the findings from the literature review and our multiple-case analysis. Our survey is an explorative study, conducted in order to gain a better understanding of the phenomenon we are observing, and later use those findings for our strategic framework.

2 DIGITAL TRANSFORMATION IN THE CONTEXT OF SMEs

Digital transformation can be defined as the integration of digital technology into all aspects and operations of an organisation, which in turn leads to changes in how the organisation is operated and how it delivers value to its customers (McGrath and Maiye, 2010; Vial, 2019). It encompasses both process digitalisation with a focus on efficiency, and digital innovation with a focus on enhancing existing physical products with digital capabilities (Berghaus & Back, 2016). In short, digital transformation is a process that integrates information, computer, communication, and networking technologies to improve an entity (Vial, 2019).

Existing research on digital transformation is mostly focused on bigger, established companies. Generally, there has been little research on how SMEs tackle digital transformation (Li, Su & Zhang, 2017). There are some notable outliers, such as the studies by Rassool and Dissanayake (2019) on digital transformation for small organisations and by Pelletier and Cloutier (2019) on digital transformation challenges in small and medium-sized enterprises. Like bigger corporations, smaller organisations operate under defined legal parameters and share the drive for profit. In order to ensure competitiveness, small and medium-sized enterprises must get ready for digital transformation (Trenkle, 2019).

Digital transformation can offer numerous benefits for SMEs, including improved efficiency, greater customer reach, and the potential for innovative new business models (Matt & Rauch, 2020). However, despite the great potential advantages, small and medium-sized enterprises have been slow to embark on digital transformation journeys. SMEs usually struggle with limited resources which decelerates them to innovate and foster competitiveness (Taneja, et al., 2016). However, the rise of digitalization has opened up a door for sustainable competitiveness and growth of SMEs (Wamba-Taguimdje, et al., 2020). Digital transformation technologies can help SMEs improve their capabilities for product differentiation and market segmentation. However, few SMEs have the resources to properly embrace this digital transformation.

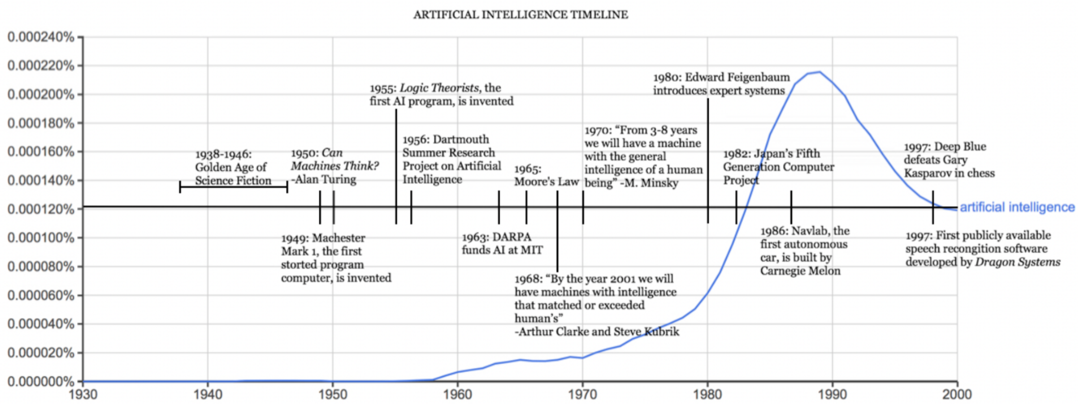
The rapid pace of technology development and innovation is increasing the gap between SMEs and large businesses, as more and more advanced tools enter the market (OECD, 2021). On the other side, small and medium-sized businesses need to be ready for the digital age. When it comes to digital technologies, timing is everything. Early adopters reap the greatest rewards, while those that arrive at the cutting edge later often reap fewer rewards, if any at all. The concept that late adoption of an invention leads to diminishing gains (in relation to market shares) after crossing a certain threshold was first presented by the Diffusion Theory in the early 1960s. Business practices that attempt to commercialize goods as rapidly as possible, often by exploiting beta versions of products, also demonstrate a first-mover advantage. This is especially the case in industries where network effects play a significant role, where first movers can increase their market share by establishing industry standards and accrediting their products as the gold standard, and where consumers will have a harder time switching to competing products (Lieberman & Montgomery, 1988). Because of the proliferation of digital technology, even modest improvements in efficiency, effectiveness, or quality may have a disproportionately huge impact on a business's bottom line (Matarazzo, et al., 2021). The stakes are high since SMEs are vital to the economies of most nations and regions. In addition, they are significant market players and can substantially impact an economy’s productivity and growth, competitiveness, and resilience.

3 INTRODUCTION TO AI AND MACHINE LEARNING

3.1 Brief history of artificial intelligence

In essence, artificial intelligence is a field which combines computer science and robust datasets to enable problem-solving. The roots of artificial intelligence can be traced back to the 1940s, when the American Science Fiction writer Isaac Asimov published his short story *Runaround* (Haenlein & Kaplan, 2019). Around 10 years later, a young British mathematician, logician, and cryptographer, named Alan Turing started exploring the mathematical possibility of artificial intelligence. In his paper from the 1950s named Computing Machinery and Intelligence, Alan discussed how to use available information and reason to build intelligent machines and test their knowledge (A.M. Turing, 1950). The term artificial intelligence was officially coined six years later in 1956, by Marvin Minsky and John McCarthy (computer scientists at Stanford) who hosted the *Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI)* at Dartmouth College in New Hampshire (Haenlein & Kaplan, 2019). The following 20 years after the Dartmouth Conference, the field of artificial intelligence saw significant successes such as the famous ELIZA computer program created by Joseph Weizenbaum at the Massachusetts Institute of Technology (MIT). ELIZA was the first natural processing tool able to simulate a conversation between a human and a computer (Weizenbaum, 1966). The success of the project was largely thanks to computers becoming faster, cheaper, more accessible, and being able to store more information.

Figure 1: Artificial intelligence timeline



Source: Harvard University (2017).

In the 1980s, John Hopfield and David Rumelhard popularised "deep learning" techniques which allow for computers to learn from experience. In addition, during this period Edward Feigenbaum introduced a piece of software called "expert systems", which mimicked the decision-making process made by a human expert. In the following period of the 1990s, artificial intelligence continued to thrive, with one specific event winning everyone's attention. In 1997, then world grand master champion in chess, Gary Kasparov, was defeated by a chess computer program by IBM's Deep Blue. This progression of AI can be attributed to the increasing capabilities of computer storage and processing speed. According to Moore's Law, the memory and speed of computers doubles every year, and as shown on the y axis in Figure 1, this trend had finally caught up.

Today, the majority of applications that go by the term of artificial intelligence are built using machine learning, as a main subset of AI. Machine learning serves as the foundation of the Facebook image recognition algorithms, the voice recognition algorithms powering smart speakers, and self-driving cars. Since ML can improve the automation and prediction capabilities of businesses and organisations, as well as take natural language processing and computer vision to the next level, it is finding increasingly widespread use in many areas of today's industries and societies.

3.2 Introduction to machine learning technologies as part of AI

Artificial intelligence was described by its founder, a Stanford Professor John McCarthy in 1995, as "the science and engineering of making intelligent machines". In essence, AI is comprised of cutting-edge technologies made to study and understand information from vast amounts of data, gathered from variety of sources, too intricate for human beings to make sense with basic analytics. In short, artificial intelligence includes a machine's capacity to observe, understand, learn, and solve problems using available data and by emulating human behaviour. Therefore, AI can automate routine and difficult tasks so humans may concentrate on strategic tasks.

Machine learning as part of AI, is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without being explicitly programmed. Primarily, there are four types of machine learning algorithms, called supervised, semi-supervised, unsupervised, and reinforcement learning algorithms. Supervised learning is defined by its use of labelled datasets to train algorithms to classify data or predict outcomes accurately. Semi-supervised learning uses labelled data to ground predictions, and unlabeled data to learn the shape of the larger data distribution. Unsupervised learning analyses and clusters unlabeled datasets to discover hidden patterns or data groupings without the need for human intervention. Whereas reinforcement learning enables the machine to learn in an interactive environment by trial and error setting, based on rewarding desired behaviours and/or punishing undesired ones.

The main applications of ML technologies include computer vision, natural language processing, speech recognition, and recommendation systems. Natural language processing is a subset of ML that enables computers to understand, generate, and manipulate human languages. Some of the most common techniques in natural language processing are sentiment analysis, summarization, keyword extraction, and tokenization. Computer vision is a subset of ML that enables computers to accurately identify, understand, and extract meaningful information of objects from digital images, videos, and other visual inputs. Speech recognition as a subset of ML, also known as automatic speech recognition (ASR), computer speech recognition, or speech-to-text, is the process of capturing, digitizing, and understanding sound waves, thus transforming them to correct linguistics units or phonemes while ensuring correct spelling. Recommendation systems are a subset of ML that aim to provide personalised suggestions and recommendations to users based on their preferences, behaviours, and historical data. Overall, these systems leverage ML to analyse large datasets to identify patterns and predict user preferences or interests.

3.3 The role of machine learning in business

Machine learning is one of the most commonly utilised AI subfields for business purposes, primarily used to quickly and accurately process large amounts of data. Processing and understanding massive volumes of data in real-time are two of ML's most valued business advantages. What's more, ML can be leveraged in almost all aspects of an organisation including human resources (HR), sales, marketing, manufacturing, finance, supply chain, customer support, etc. Businesses integrate machine learning into their essential processes for number of tactical reasons, such as operational costs reduction, increase in efficiency, revenue growth, improvement in customer experience, and more. Machine learning can also assist businesses by helping them find patterns and relations in data, enhance customer segmentation and targeting, and eventually expand their revenue, market share, and profitability. What's more, businesses can achieve significant time and efficiency benefits by machine learning applications to cut down on costs and shift human resources to higher value activities (Deloitte Access Economics, 2017).

ML models can be trained to recognise certain types of patterns and use these patterns to learn in a self-referential fashion from the available data. At a business level, some of the ML benefits include quick unveiling of patterns in big data, speedy and advanced analytics, improved product design, delivering diligent insights, and many more. These benefits introduce a new level of service in business, as well as profit increases, business expansions, general competitive advantage, and improved cost and efficiency structures (Soni, et al., 2020). Machine learning can also help businesses discover non-trivial insights from their data without having to be specifically programmed to know where to seek for them.

In the past years, companies have started to increase the implementation of ML into their research and development of commercial products and services, as well as how they structure their internal organisation and manage communication. Today, businesses can offer their clients smart programs similar to Amazon's product recommendation engine and Apple's virtual assistant Siri. At the same time, these models are becoming more and more a standard fare for the modern consumer and offer helpful advice whenever they ask for it (Baabdullah et al., 2021).

The commercial presence of AI-driven products and services demonstrates the role of the technology and its ability of transforming businesses and thus, the global economy. The impact of AI in research and development on the global market is clearly shown in the analysis of 200 AI start-ups by Soni, et al., in the 2020 paper Artificial Intelligence in Business: From Research and Innovation to Market Deployment. Nowadays, we can see AI and ML impacting many industries including automobiles, healthcare, finance, telecommunications, retail, consumer goods, security, gaming, and logistics. It is continuing to affect how businesses build products and services and place themselves on the global competitive market. Some of the primary benefits the technology has on these industries encompasses an increase in productivity, reduction in human error, better and faster business decisions, customer preference prediction, and sales maximization.

3.4 Implementation of machine learning in businesses

The rapid growth and development of machine learning has had a significant impact on businesses of all sizes and industries. Machine learning algorithms are commonly for tasks that include data analysis, pattern identification, and predictive analytics. For example, in the field of finance, machine learning algorithms can be utilised to examine large volumes of financial data in order to discover patterns and make predictions regarding market trends. Moreover, ML can help financial businesses identify potential risks and make investment decisions based on data analytics. In healthcare, on the other hand, machine learning algorithms are commonly applied in patient data analytics, identifying potential patient health risks, recommending best treatment options, or analysing insights from clinical trials. Another way that businesses can implement ML is through chatbots and virtual assistants. Chatbots can be utilized to automate customer support tasks, such as responding to requests and resolving customer issues. Virtual assistants can be used to automate administrative tasks, like scheduling appointments or managing emails. Businesses benefit from these ML technologies by enhancing customer services and increasing employee’s productivity.

Another implementation of machine learning in business is commonly seen in the field of marketing, through predictive analytics. For example, predictive analytics can be used by marketing departments to identify which customers are most likely to make a purchase, and act accordingly by personalizing the marketing approach and messages based on the customer’s interest and behaviour.

The implementation of ML in businesses offers several advantages, and increased efficiency and productivity are one of the main benefits businesses gain by deploying these technologies into their organisation. Furthermore, by automating tedious processes, businesses can reduce the time and resources required to complete tasks. This can lead to cost savings and increase efficiency and productivity. Another major benefit is improved and data-driven decision-making. ML technologies can offer comprehensive reports with real-time insights and recommendations that will help businesses make better-informed decisions.

Despite the advantageous impact of ML on businesses, there are a few challenges associated with ML implementation on a company level. One of the main challenges can be the cost of implementation. ML technologies can be expensive, and not all businesses are on an even playing field when it comes to having the resources for necessary IT infrastructure and technical expertise. Additionally, there may be internal concerns about job displacements, as ML has the potential to automate mundane tasks that are currently performed by human employees. Moreover, because ML technologies require access to large amounts of data, small and medium-sized enterprises may also face challenges around data privacy and security. However, businesses can partner with specialised ML service providers in their industry or other complementary businesses in their sector, and share resources and expertise around security and infrastructure.

Overall, implementing ML can provide several benefits for businesses, including increased efficiency, improved decision-making, improved customer service, better risk management, increased innovation, product or service differentiation, and competitive advantage in global markets. However, the process of implementing ML may seem challenging for some small and medium-sized enterprises due to financial constraints, lack of internal expertise, and concerns around data privacy and security.

Machine learning implementation requires a strategic approach that will take into account both the benefits and the risks associated with adopting the technology into the business. To maximise the benefits of ML while minimising its risks, SMEs must develop a comprehensive implementation plan that will take into account the organisation's unique needs, goals, and available resources. The plan can involve collaboration with ML service providers, investing in employee training and education, and implementing robust data protection policies and procedures. For first-time adopters, the road to ML implementation may seem challenging at first, but with the right approach, SMEs can embrace machine learning as a tool for innovation, growth, product and service differentiation, and competitive edge in today's dynamic international markets.

4 TECHNOLOGY ACCEPTANCE THEORIES AND MODELS

In order to better understand the various factors that can impact technology adoption, in this chapter, we analyse different technology acceptance theories and models. The theories and models that were considered relevant to our research are: 1) The Technology Acceptance Model (TAM), 2) The Unified Theory of Acceptance and Use of Technology (UTAUT), and 3) The Technology-Organisation-Environment Framework (TOE).

The Technology Acceptance Model was created by Fred D. Davis, in 1985, who aimed at explaining how users accept and use new technology. The model is based on the idea that perceived usefulness and perceived ease of use are the primary factors that determine an individual's intention to use a technology. The model focuses on how individual perceptions of the system's usefulness and ease of use are directly influenced by the technology's design features. TAM has been widely used in economics research as a way to predict the acceptance of information technology in various domains. According to TAM, there are five key drivers of technology acceptance and five barriers to technology acceptance. The five drivers of technology acceptance are: 1) perceived usefulness, 2) perceived ease of use, 3) perceived compatibility, 4) perceived enjoyment, and 5) social influence. Davis defined perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her job performance", and perceived easy of use as "the degree to which a person believes that using a particular system would free the effort" (Davis, 1985). Perceived usefulness as a driver for technology adoption argues that users are more likely to accept a technology when they perceive it as useful and believe it will improve their effectiveness, efficiency, or productivity. Perceived ease of use signifies that users are more likely to accept a technology when they perceive it as easy to use and believe that learning and operating it will not require excessive effort. Perceived compatibility refers that users are more likely to accept a technology when they perceive it as compatible with their existing values, experiences, and needs. Perceived enjoyment implies that users are more likely to accept a technology when they find it enjoyable, engaging, and satisfying to use. And social influence indicates that external influences such as recommendations, opinions of others, and social norms can positively impact technology acceptance. According to Davis, the barriers to technology acceptance are: 1) perceived complexity, 2) lack of technical skills, 3) perceived risk, 4) lack of awareness or familiarity, and 5) resistance to change. Perceived complexity refers to users showing resistance to accepting a technology if they perceive it as overly complex or difficult to understand and use. Lack of technical skills implies that users who lack the necessary technical skills or knowledge required to use the technology may face barriers to acceptance. Perceived risk encapsulates concerns related to security, privacy, data protection, or potential negative consequences, which may make users uncertain about technology acceptance. Lack of awareness or familiarity embodies that users who are not aware or have limited exposure to a technology may be hesitant to accept it. And finally, resistance to change suggests that individuals may exhibit resistance to change and prefer to stick with familiar technologies or established routines, and therefore impeding acceptance. However, the limitation of TAM is that the model pertains to the behaviour of the users, which cannot be reliably quantified in an empirical investigation due to a variety of subjective factors, like social norms, personal values, individual characteristics, and personality traits (Ajibade, 2018). Furthermore, a user's IT proficiency and experience can promote the ease of use of new technologies, while the perceived usefulness can be dictated by the company's policy, rules, and IT guidelines. As a conclusion, TAM may produce falsifiable arguments when used in a study as theoretical underpinnings (Ajibade, 2018).

Unified Theory of Acceptance and Use of Technology was introduced by Venkatesh and others in *Unified theory of acceptance and use of technology: Toward a unified view*, in 2003. UTAUT is an acceptance model that was built on the foundations of TAM, and it introduces four core drivers of technology acceptance: 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions. In addition, the model proposes two new barriers to technology adoption, such as: 1) inertia, and 2) cost. Performance expectancy suggests that users are more likely to accept and use a technology if they believe it will enhance their performance and help them achieve their goals. Effort expectancy embodies that users are more likely to accept and use a technology if they perceive it as easy to use and if it requires minimal effort to learn and operate. Social influence suggests that external influences, such as opinions and recommendations of others can positively impact technology acceptance. Facilitating conditions points that the availability of necessary resources such technical support and infrastructure can facilitate technology acceptance. However, UTAUT insinuates that users may resist adopting a new technology due to inertia of perceived need for change, and that high costs associated with the technology such as financial expenses or resource requirements may act as barriers to acceptance. UTAUT is built on top of TAM, in an effort to fill in the gaps, by trying to assess the likelihood of success for new technologies adoption by individual users who are less likely to adopt new systems. Ever since its introduction, the theory has been widely used in technology adoption and diffusion research as a theoretical lens by researchers undergoing empirical studies of user intention and behaviour. However, the model has a limitation in assessing the technology adoption by company decision-makers as it is solely focused on the individual user.

The Technology-Organisation-Environment Framework was first described in 1990, by Tornatzky and Fleischer, in their book titled *The Processes of Technological Innovation* where the authors describe the entire process of company innovation, from development to implementation. In short, TOE is an organisation-level theory that explains how technology adoption decisions are conducted on a company level. According to the theory, there are three factors that influence technology acceptance within a company: 1) technological factor, 2) organisational factor, and 3) environmental factor. The technological factor refers to all technologies that an organisation uses, and those technologies that are not yet implemented in the company but are available in the marketplace. According to the framework, a company's existing technologies are important to the acceptance process as they can restrain the scope and pace of technological change that an organisation can undertake (Collins, et al., 1988). If current innovative technologies that exist in the market are not being used by the organisation, they can become a barrier for digital innovation. According to Tushman and Nadler (1986), innovations that exist outside a company can create incremental, synthetic, or discontinuous changes. Innovations that produce incremental changes introduce new features or new versions to existing technologies (Baker, 2011). Innovations that produce synthetic change represent a middle point of moderate change, where existing ideas or technologies are being combined in a novel fashion. And finally, innovations that produce discontinuous change, often referred to as “radical” innovations, represent significant departures from current technology or processes. The second context, being the organisational one, covers the company’s attributes, resources, connecting structures between employees, and internal communication processes. According to TOE’s organisational factor, a company’s organisational structure can impact its relationship to the innovation adoption process. Good internal communication processes can also promote company innovation, as well as having top management that is open to embrace technological changes that complement the company’s vision and mission. The last factor introduced by TOE is the environmental factor, which covers industry regulations, structure of the industry, and presence of technology service providers. Government regulations, if not beneficial, can have a detrimental impact on innovation. For example, unclear or inconsistent regulations can create legal uncertainty which can impede innovation, especially for exploratory projects or investments with higher default risk. Regarding industry structure, it is argued that companies from fast-growing industries tend to innovate more quickly than companies in mature or declining industries (Tornatzky et al., 1990). Some companies leverage the decline of the industry to expand into new lines of business, while others may avoid investment altogether in an effort to reduce costs (Baker, 2011). Finally, the presence of technology service providers can give companies more flexibility, and offer specialised expertise around technology development and implementation. In addition, technology service providers can help in bringing new external expertise and skills to the company through collaboration, where companies can continue to focus on their main goals and activities without needing to free up internal resources for technological development. To summarise, according to TOE, all three elements described as technological, organisational, and environmental factors influence a company’s level of technological innovation. However, the framework has been criticised as being more of a “generic” theory, and it has seen relatively little further development since its inception in the 1990s.

While general technology acceptance models such as TAM, UTAUT, or TOE can be used to assess AI and ML acceptance, there are some unique aspects of these technologies that are worth considering. We list some characteristics of machine learning that make its acceptance different from other technologies: 1) complexity and understandability, 2) explainability, 3) data considerations, 4) ethical and societal concerns. AI systems such as machine learning, which are based on deep learning and neural networks can be highly complex and difficult to understand as they often operate as a “black box”. The term “black box” represents the un-understandability and unexplainability of machine learning’s internal logic in achieving the desired outputs of results (Hussain, 2019). This can make it challenging for users to understand ML decision-making processes, and that is something that acceptance models for ML need to account for. Related to its complexity as a “black box”, ML models often lack transparency in their decision-making, resulting in a need for explainability. The need for explainability arises due to a discrepancy between what a ML model can explain and what a decision maker wants to know (Burkart & Huber, 2021). While machine learning technologies can generate impressively accurate predictions, they struggle to provide explanations for those predictions. Hence why, acceptance models for ML technology need to address the importance of explainability to ensure users trust the underlying process of the technology. In addition, machine learning models rely heavily on data, as data quality and availability can significantly impact the performance of the technology (Sesssions & Valtorta, 2006). Finally, AI and ML technologies raise unique ethical concerns due to their nature of opacity, unpredictability, and the need for big training dataset (Stahl, 2021). Some of the primal ethical questions related to AI and ML are that of data privacy and protection, transparency, bias, and discrimination (Stahl, 2021). These aspects can be particularly relevant for acceptance, as they go beyond the former technical aspects and concern the broader impact of ML systems on individuals and society.

5 LITERATURE CASE STUDIES

The literature case study review in this chapter constitutes the most relevant case studies that were chosen in order to better understand the implications of our research problem and its represented research available in the literature. Our literature review constitutes Rowe’s first dimension of literature review typologies, where one is aiming at “understanding a new phenomenon or problem through related concept(s) that have been proposed in former research” (Rowe, 2014). Our approach constituted: 1) finding literature case studies that are directly or indirectly related to what is known or unknown about ML and AI adoption in SMEs, and 2) analysing the key findings and implications related to ML and AI adoption in SMEs from these studies. We searched for academic publications involving keywords such as “ML”, “AI”, “adoption”, “implementation”, “transformation”, and “SMEs” in Google Scholar, Science Direct, and CORE. The research resulted in us selecting three case studies that were considered relevant to our research goal and hypothesis. The selected case studies are titled 1) Adoption of artificial intelligence technologies in German SMEs – Results from an empirical study, 2) Initiating transformation towards AI in SMEs, and 3) How Artificial Intelligence will transform Nordic businesses.

5.1 Case studies review

A study by Ulrich, Frank and Kratt (2021) titled *Adoption of artificial intelligence technologies in German SMEs - Results from an empirical study* examines the adoption and usage of artificial intelligence technologies in small and medium-sized enterprises in Germany. The study was conducted through a survey of 248 SMEs across different sectors, including medical technology, healthcare, logistics, service sector, mechanical and analogue engineering, logistics, energy sector, and more. The results of the study found that AI adoption is still low amongst SMEs in Germany, where only 22% of the surveyed SMEs had adopted AI technologies, and 49% of the SMEs had no plans to adopt AI. When the SMEs were given multiple answer questions on where they see the greatest opportunities of AI for their organisation, 77% responded in automation of processes, 72% saw great opportunities in the efficient use of data, 66% answered acceleration of processes, 55% answered potential cost saving through AI, and 53% of the respondents answered better decision making. Furthermore, the surveyed SMEs were asked what are the barriers to implementing AI in their organisation. The question offered the option for multiple answers by the respondents. The highest-ranking barriers to implementing AI were lack of competence (65%), obstacles at implementation (52%), and data problems (52%). The rest of the barriers that were put forward by the SMEs were IT infrastructure (46%), financial barriers (39%), lack of commitment from top management (32%), not having a defined business case (28%), and fear of cyber attacks (13%). Only 7% of the 248 SMEs that participated in this survey said they don't see a value-added through AI. In addition, when asked which technologies are seen as of the highest relevance for their company, SMEs mentioned rule-based systems and machine learning as technologies of high relevance. However, the companies attributed low relevance to deep learning technologies, process mining, chatbots, computer vision, and collaborative robotics. The study further analyses the SMEs' perception of AI importance per company sector. The most popular answers were information technology (IT), logistics, materials and production management, finance, marketing and sales, research and development (R&D), and controlling. The authors conclude that from the initial empirical results, German SMEs are not yet fully aware of the relevance and potential of AI technologies. This could be changed by introducing adequate AI training and education, addressing data protection and privacy concerns, as well as increasing the collaboration between SMEs with larger enterprises which can help promote AI adoption and implementation. Overall, the study provides valuable insights into how German SMEs perceive the challenges and opportunities in the adoption of AI technologies.

Another study carried out by Ronnberg and Areback (2020), titled *Initiating transformation towards AI in SMEs*, explores the challenges and opportunities that arise from AI transformation in small and medium-sized enterprises. The study was carried out as a qualitative literature research, and a single case study with an SME through interview questions. The single case study was conducted on a mass-producing SME from Sweden, which sees the potential of AI technologies and has started to slowly work on implementing AI in its business. The study's findings reveal AI's potential benefits for the company, the challenges that can occur, and the requirements necessary to overcome them. The results of the study identified four main opportunities for AI implementation in the SMEs. The opportunities included improved forecasting, maintenance and repair of assets, self-optimizations, and tracing and tracking of inventory. The challenges of implementing AI were related to cultural difficulties, lack of external and internal communication, lack of internal processes, and lack of sufficient resources. Furthermore, the authors identified the requirements which were lacking for a successful implementation of AI, such as automation, data, strategy, and capabilities. The study also emphasises the importance of involving employees in the AI transformation process and investing in their knowledge and skills as a way to overcome cultural resistance to change. Furthermore, the authors provide a framework that can guide SMEs in initiating AI adoption, including improved internal communication to all employees, fostering a culture for innovation, establishing partnerships and collaborations with external partners such as universities, research institutions, or technology providers, as well as developing a clear and realistic strategy for AI implementation.

Finally, a case study conducted by McKinsey (2019), titled *How Artificial Intelligence will transform Nordic businesses* analyses the strategic and business implications of AI on organisations in the Nordic region. The study was conducted in a form of a survey of over 75 executive directors of Nordic companies. The survey shows that while most companies in the region already have some experience with using AI to some degree, there was still significant room for growth and innovation. When asked if they believe they have a good understanding of how AI can benefit their current business model, only 17% of the interviewed directors answered yes. Nonetheless, most respondents (78%) reported they are already experimenting with AI, but only 30% managed to implement at least one technology across their organisation. In addition, most of the AI projects were not focused on fixing actual business problems and improving core organisation activities, leading to only 40% of executives expecting AI to have a significant financial impact. Still, when asked about the future of AI in their organisations, nine in ten executives responded that they would like to increase AI implementation over the next three to five years, and foresee AI playing an important role in their organisations. The main barriers to AI adoption in the Nordics region, reported by the study, are a lack of clear AI strategy, insufficient IT infrastructure, and a lack of internal talent. The implications to a better AI implementation could be a clearer AI vision, better understanding of possible business cases for AI in the organisation, as well as improving IT capabilities for successful production of AI pilot projects. The authors estimate that AI can bring value to the region by advancing sectors such as transport and logistics, retail, travel, high-tech, automotive and assembly, banking and insurance, telecommunications, consumer packaged goods, agriculture, and more. The summary of the key findings from the case studies review is shown in Table 1.

Table 1: Summary of literature case studies review

Author	Title of Paper	Key Findings
Ulrich, Frank, and Kratt, (2021)	Adoption of artificial intelligence technologies in German SMEs - Results from an empirical study	German SMEs are not yet fully aware of the relevance and applicability of different AI technologies.
Ronnberg and Areback, (2020)	Initiating transformation towards AI in SMEs	The main challenges faced in the adoption of AI by SMEs are cultural resistance to change, poor communication, insufficient resources, and lack of internal processes.
McKinsey, (2019)	How Artificial Intelligence will transform Nordic businesses	The main barriers to AI adoption are lack of clear AI strategy, insufficient IT infrastructure, and lack of internal talent.

Source: Own work.

By observing our key findings from the literature case study review, we can draw a connection with some of the technology acceptance barriers from TAM, UTAUT, and TOE. In our first case study review, the authors observed that German SMEs are not yet fully aware of the relevance and potential of AI technologies, which according to TAM, this lack of awareness or familiarity with the technology can lead to a potential barrier to acceptance. The second case study by Ronnberg and Areback (2020), suggests implication of several technology acceptance barriers from TAM, UTAUT, and TOE. Their study found that challenges of AI adoption are related to cultural resistance to change, poor communication, insufficient resources, and lack of internal processes. Namely, TAM's fifth acceptance barrier, resistance to change, suggests that individuals may impede technology acceptance by exhibiting opposition to change and preferring to stick with familiar technologies or already established routines. UTAUT states cost as a technology acceptance barrier, where high costs and insufficient resources associated with the technology such as financial expenses or resource requirements, may act as barriers to acceptance. TOE brings up the importance of the organisational factor in technology acceptance, highlighting the importance of good internal communication processes that can promote company innovation.

Finally, the case study by McKinsey on AI in Nordic businesses reveals that the main barriers to adoption are lack of clear AI strategy, insufficient IT infrastructure, and lack of internal talent. According to TOE's technological factor, a company's already existing technologies are important for the acceptance process as they can limit the scope and pace of new technology acceptance that an organisation can undertake. Lastly, TAM highlights the importance of technical skills, and flags its lack as a barrier to technology acceptance. According to TAM, lack of technical skills limits the users from accepting the technology as they lack the necessary knowledge required in order to use it.

5.2 Discussion on case study literature

Artificial intelligence can have a significant impact on small and medium-sized enterprises in a variety of ways. However, the adoption of AI among SMEs has been slower than in large enterprises due to factors such as lack of sufficient knowledge of AI benefits, lack of IT expertise, data quality, and organisational resistance to change and innovation. In addition, the price tag associated with implementing artificial intelligence and big data systems, as well as the need for trained personnel, can be major roadblocks for SMEs. Despite these challenges, a study by Bauer, et al. (2020), suggests that about 30% of SME CEOs support using AI in some form in their organisation. The executives understand that AI can bring in substantial benefits and help companies save money, reduce risks, maximise the effectiveness of completing a certain job, and streamline internal operations (Hamal & Senvar, 2021). As more and more organisations will implement AI technologies, SMEs will have to employ solutions based on machine learning and artificial intelligence in order to stay competitive.

There is plenty of available literature on AI, digital transformation, and Industry 4.0, however, there is little published research on the potential impact of these technologies in the context of SMEs. Most literature focuses on large corporations, but SMEs differ from large corporations in several ways, such as their resources, company structure, operational dynamics, and business processes. In addition, SMEs are typically more agile, flexible, and their structures are often more streamlined. Therefore, it's important to study how SMEs can benefit from AI and successfully take advantage of the technology, especially if taking into account that SMEs have less employees than large organisations and could significantly benefit from AI automation and analytics. SMEs are the drivers of our economy, accounted for 99% of companies in the European Union. As we march towards AI innovation and digitalisation, it is crucial for SMEs not to be left behind during this transformation journey. Moreover, by studying the implications of AI for SMEs, managers of small and medium-sized enterprises can get the valuable insights, which can guide them on how to start their AI journey, what considerations to keep in mind, and how to mitigate any potential risks of project failure. Finally, such insights can help SMEs harness the potential of AI more effectively and confidently, reducing the uncertainty that often surrounds the adoption of AI and new technologies.

6 SURVEY

6.1 Survey design

According to the European Commission, the category of SME applies to organisations that have less than 250 employees, with annual turnover that does not exceed 50 million euros, or annual balance sheet that does not exceed 43 million euros in total. Table 2 displays the enterprise categories based on the mentioned requirements (European Commission, 2003).

Table 2: SMEs criteria according to the European Commission

Enterprise category	Definition
Micro	Less than 10 employees, not exceeding 2 million euros in annual turnover or in balance sheet total
Small	Less than 50 employees, not exceeding 10 million euros in annual turnover or in balance sheet total
Medium-sized	Less than 250 employees, not exceeding 50 million euros in annual turnover or 43 million euros in balance sheet total

Adapted from the European Commission (2003).

We used the criteria provided by the European Commission to target small and medium-sized companies in Slovenia and carry out our online survey. Our poll sample includes decision-makers holding somewhat of a managerial position such as C-level executives, senior management, directors, middle management, or team leaders. The survey containes 15 questions, grouped into seven categories, and aimed at understanding the SMEs company profile, digitalisation and data state, ML implementation and adoption, timeline and budget, perceived ML benefits, risk mitigation and attitude towards ML collaboration, and implementation confidence. Furthermore, the questions were inspired and guided by findings from the literature analysis, including the literature case analysis, and drivers and barriers from technology acceptance theories and models. The survey respondents could select their answers from already offered choices, often having an option to select Other and specify their answer. Like the questions, the proposed answers were derived from literature findings, and other, similar case studies. In total, we managed to compile responses from 50 individuals from our target group, which included decision-makers from small and medium-sized enterprises from all regions of Slovenia. The full list of questions used in the survey are shown in Table 3.

Table 3: List of questions used in the survey

Question No.	**Question Statement**	**Categories**
Q1	What is the size of your company?	Company information
Q2	In which industry does your company operate?	
Q3	How do you currently analyse and collect data in your business?	Digitalisation and data
Q4	How would you rate the digitalisation level of your company's internal systems?	
Q5	Have you tried implementing machine learning in your company before?	Machine learning implementation and adoption
Q6	What are the biggest challenges that your company is facing when it comes to adopting machine learning?	
Q7	What is the overall attitude of your employees towards implementing machine learning in your company?	
Q8	What is your timeline for implementing machine learning?	Timeline and budget
Q9	What is the budget that your company is willing to dedicate to machine learning adoption and development?	
Q10	Which company departments do you think can benefit the most from machine learning adoption?	Perceived ML benefits
Q11	How do you think machine learning can benefit your organisation?	
Q12	Have you considered the potential risks and challenges associated with implementing machine learning?	Risk mitigation and attitude towards ML collaboration
Q13	Have you considered using third-party vendor to help with machine learning implementation?	
Q14	On a scale from 0-5, how confident are you in your company's ability to successfully implement machine learning into your internal company system and processes?	Implementation confidence
Q15	How confident are you in your ability to start a machine learning project for your department or organisation?	

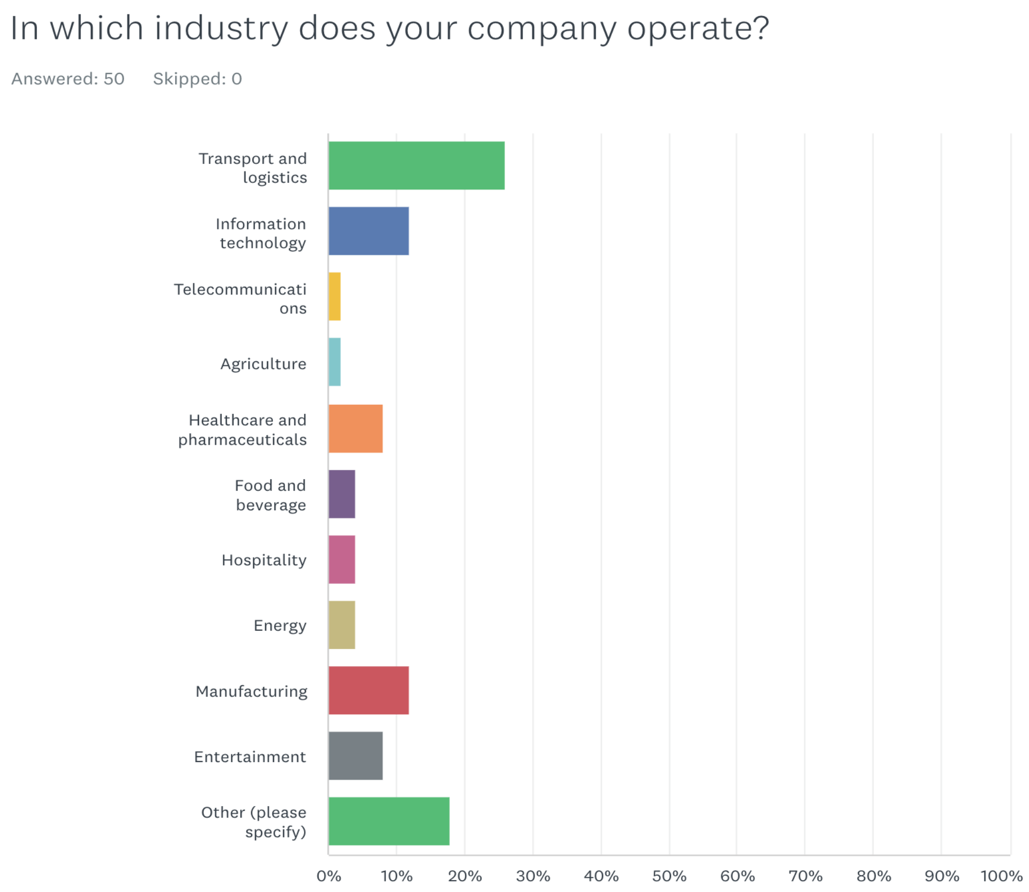
Source: Own work.

6.2 Survey results

Respondents were evenly distributed across company sizes, with 32% of respondents working for microenterprises (0-9 employees), 34% working for small enterprises (10-49 employees), and 34% working for medium-sized enterprises (50-249 employees). Most of our respondents were age 30-44 (58%), 28% of the respondents were aged 45-60, and 12% of our respondents were aged 20-29. Furthermore, we achieved a gender-balanced study, with 50% of respondents being male and 50% of respondents being female.

We surveyed companies working in transport and logistics (26%), information technology (12%), manufacturing (12%), entertainment (8%), healthcare and pharmaceuticals (8%), and Other (18%) consisting of retail, real estate management, recycling, construction, and finance industry. The rest were companies working in telecommunication, food and beverage industry, hospitality, energy, and agriculture. The distribution of companies across different industries is shown in Figure 2.

Figure 2: Distribution of SMEs by industry



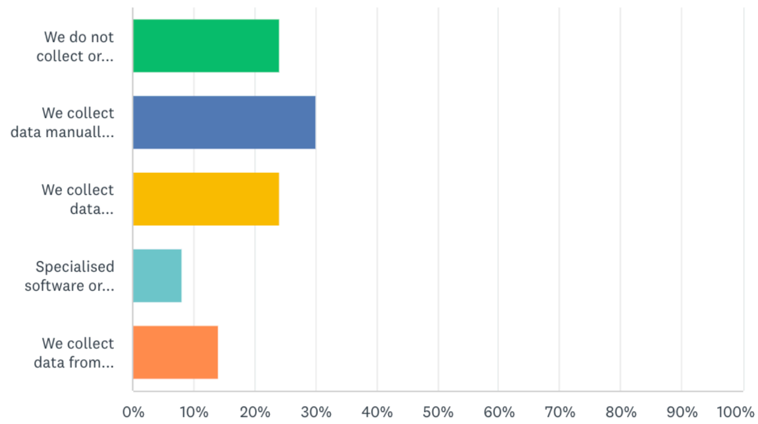
Source: Own work.

We asked the respondents how they currently collect and analyse data in their business, as a way to assess the facilitating conditions by UTAUT. Of all our respondents, only 24% answered they do not collect or analyse data in their company. The rest (76%), of the companies reported having established processes for data collection and analysis, however, to a different degree. 30% of the respondents reported their companies collect data manually using spreadsheets or other basic software or tools, and analyse it using simple statistical methods. 24% reported they collect data automatically using advanced software or tools, and analyse it using advanced statistical methods. Moreover, 14% of the respondents reported they collect data from multiple sources using a variety of tools and software, and analyse it using advanced statistical and machine learning methods. Whereas, 8% of our respondents reported they use specialised software or Cloud-based data analytics tools. The full results are shown in Figure 3.

Figure 3: Data collection and analysis in SMEs

How do you currently collect and analyse data in your business?

Answered: 50 Skipped: 0

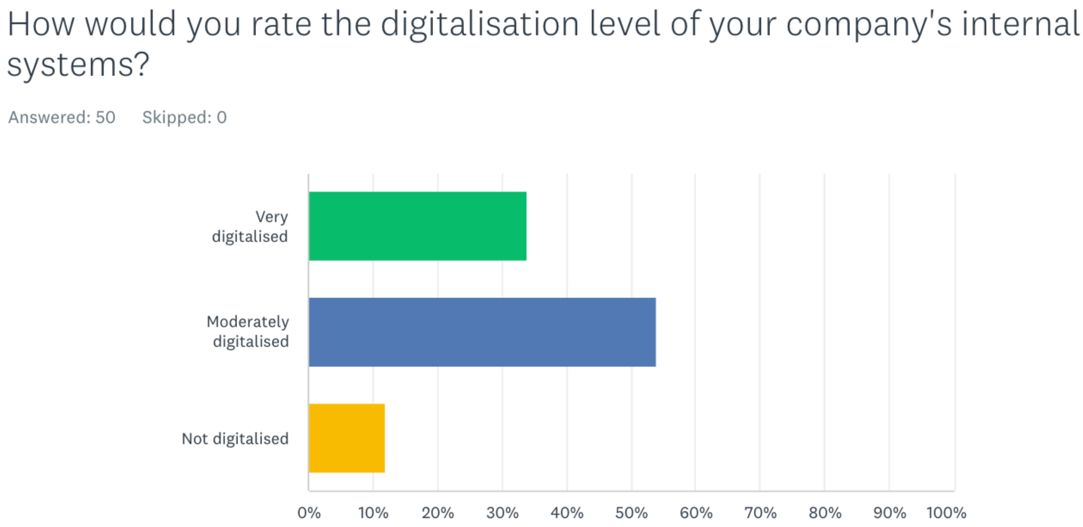


ANSWER CHOICES	RESPONSES	
We do not collect or analyse data in our company	24.00%	12
We collect data manually using spreadsheets or other basic software or tools, and analyse it using simple statistical methods	30.00%	15
We collect data automatically using advanced software or tools, and analyse it using advanced statistical methods	24.00%	12
Specialised software or Cloud-based data analytics tools	8.00%	4
We collect data from multiple sources using a variety of tools and software, and analyse it using advanced statistical and machine learning techniques	14.00%	7
TOTAL		50

Source: Own work.

Our next question is aimed to assess the digitalisation level of SMEs internal systems, as a way to assess TOE's technological factor within the SMEs. According to the TOE framework, a company's existing technologies can play an important role in the acceptance process of new technologies, as they can restrain the scope and pace of technological change within an organisation. Conversely, if the new technology significantly deviates or is not compatible with a company's existing infrastructure of internal systems, the adoption rate can be lower. This is because the new technology may require more significant changes in internal technologies and systems, and hence companies would likely face more resistance from employees and potentially have higher costs in terms of money, time, and resources. Therefore, by assessing the current level of digitalisation of SMEs' internal systems, we can get a better understanding on how prepared SMEs are for adoption of new technologies. The full results from this question are shown in Figure 4.

Figure 4: SMEs digitalization level of internal systems



Source: Own work.

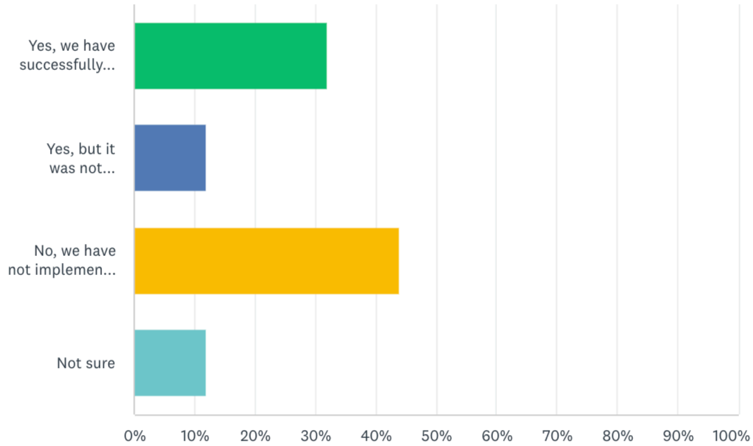
The survey results shown in Figure 4, paint a promising picture of the current state of digitalisation of SMEs' internal systems. Overall, 88% of our respondents indicate that their companies are at least moderately, if not very, digitalised. This demonstrates that a large portion of the surveyed SMEs have already embraced digitalisation and have made substantial efforts towards establishing very or moderately digitalized internal systems.

After assessing the digitalisation level of SMEs' internal systems, we moved on to a specific domain of digital technology – machine learning. We inquired if the SMEs have made any attempts to implement machine learning before. Out of the 50 surveyed SMEs, just under half, 44%, answered they have not yet implemented machine learning. This reveals a substantial portion of businesses that, despite their digitalisation, may still be missing out on strategic advantages that machine learning technology can offer. Furthermore, 32% reported they have successfully implemented machine learning in their company, 12% answered they have but it was not successful, and the remaining 12% were uncertain about their machine learning implementation status. Overall, the results reveal an interesting mix of machine learning experience among the SMEs. The full results are shown in Figure 5.

Figure 5: Machine learning implementation in SMEs

Have you tried implementing machine learning in your company before?

Answered: 50 Skipped: 0



ANSWER CHOICES	RESPONSES	
Yes, we have successfully implemented machine learning	32.00%	16
Yes, but it was not successful	12.00%	6
No, we have not implemented machine learning yet	44.00%	22
Not sure	12.00%	6
TOTAL		50

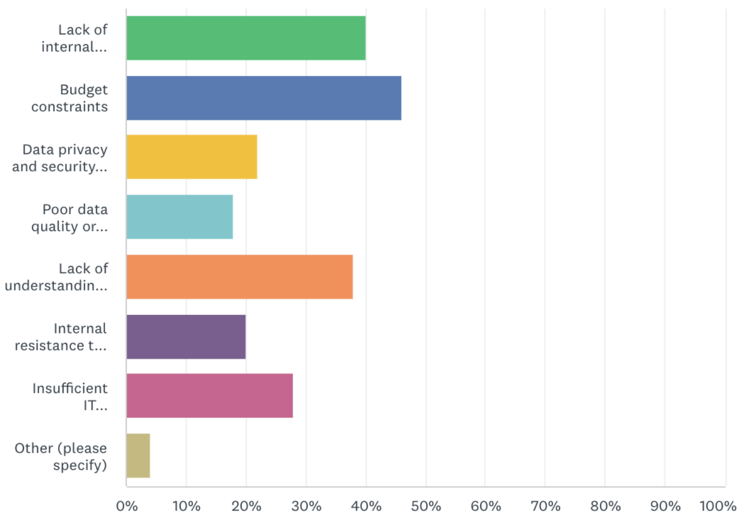
Source: Own work.

To gain an understand on the acceptance barriers that Slovenian SMEs face in adopting machine learning, and to comprehend why only 32% of our respondents have an experience with successful machine learning implementation, we went on to explore their biggest hurdles and asked what are the biggest challenges when it comes to machine learning adoption. Our question was guided and inspired by the insights of a previously conducted empirical case study by Ulrich, et al. (2021) that focused on AI adoption in German SMEs. We used this research to help frame our question and understand the context of the responses. The full data of the responses is shown in Figure 6.

Figure 6: Challenges of machine learning adoption in SMEs

What are the biggest challenges that your company is facing when it comes to adopting machine learning? (select all that apply)

Answered: 50   Skipped: 0



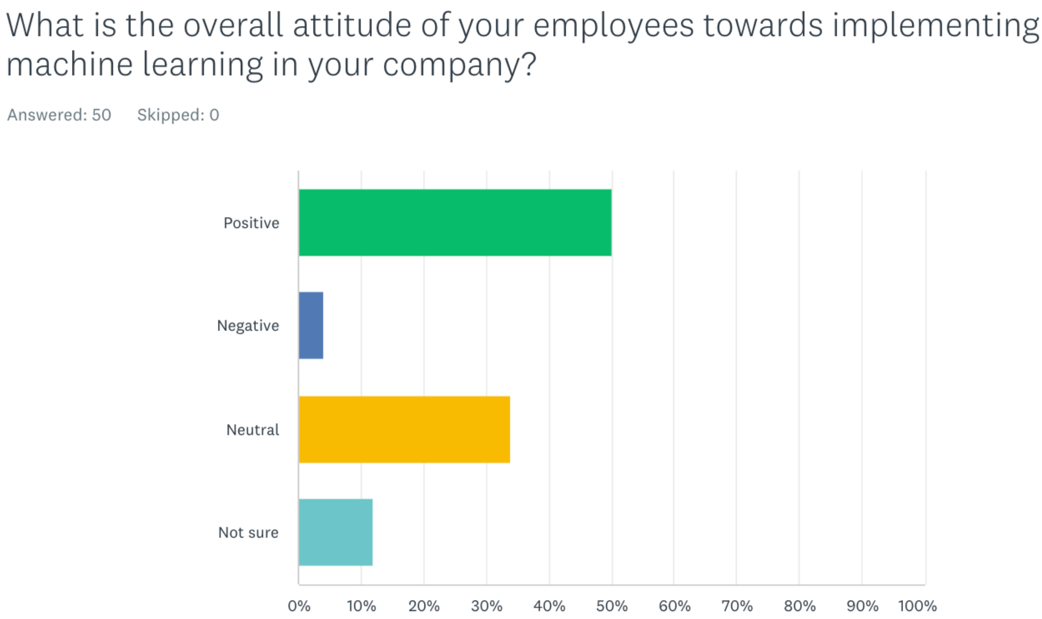
ANSWER CHOICES		RESPONSES	
Lack of internal expertise		40.00%	20
Budget constraints		46.00%	23
Data privacy and security concerns		22.00%	11
Poor data quality or insufficient data		18.00%	9
Lack of understanding for machine learning applications and relevant use cases		38.00%	19
Internal resistance to change		20.00%	10
Insufficient IT infrastructure		28.00%	14
Other (please specify)	Responses	4.00%	2
Total Respondents: 50			

Source: Own work.

The respondents could select all challenges that may apply for their company and name other, if any. The most frequently named challenges were budget constraints (46%), lack of internal expertise (40%), lack of understanding for machine learning applications and relevant use cases (38%), and lack of sufficient IT infrastructure (28%). The less frequently reported challenges were data privacy and security concerns (22%), internal resistance to change (20%), and poor data quality or lack of data (18%). Only two respondents reported lack of business alignment as other challenges for machine learning adoption (4%).

In an effort to evaluate the social influence as TAM's driver for technology acceptance, we asked the SMEs about the general employee attitude towards machine learning implementation. According to TAM, external opinions, especially those coming from employees, can contribute and positively impact the acceptance of new technologies. Half of the interviewed managers and decision makers responded that their employees showcase a positive attitude towards machine learning implementation, while 34% responded their employees hold a neutral stance for machine learning implementation in the company. The remaining participants were not sure (12%), and only 4% reported having employees with negative attitude towards machine learning implementation. The results indicate a general willingness to embrace machine learning as a technology, but they also highlight a need for better communication and education to address the employee's uncertainties and enhance the understanding of the technology. Full results are shown in Figure 7.

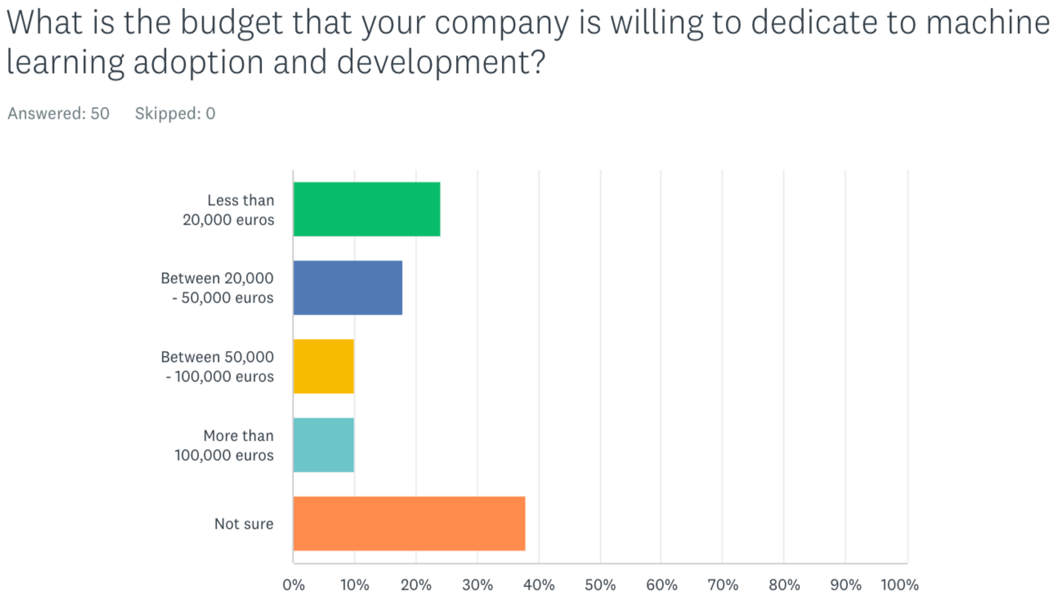
Figure 7: Employee attitude towards machine learning implementation



Source: Own work.

According to UTAUT, financial cost is recognised as one of the main barriers of technology acceptance. Often, the cost of acquiring, developing, and maintaining new technology can be significant, which may serve as a deterrent for many companies, particularly SMEs. As such, we felt it was important to gain an insight on the financial commitment that SMEs are willing to allocate to machine learning adoption and development. With the widespread recognition of machine learning's ability to drive innovation and business growth, the allocated budget can be a telling sign of an organisation's readiness to embrace the technology. Hence, we sought to understand the budget range the SMEs are willing to allocate for machine learning, and use that information to later analyse if there is any link between the size of the SMEs and their budget for machine learning. The full results are shown in Figure 8.

Figure 8: SMEs' budget allocation for machine learning

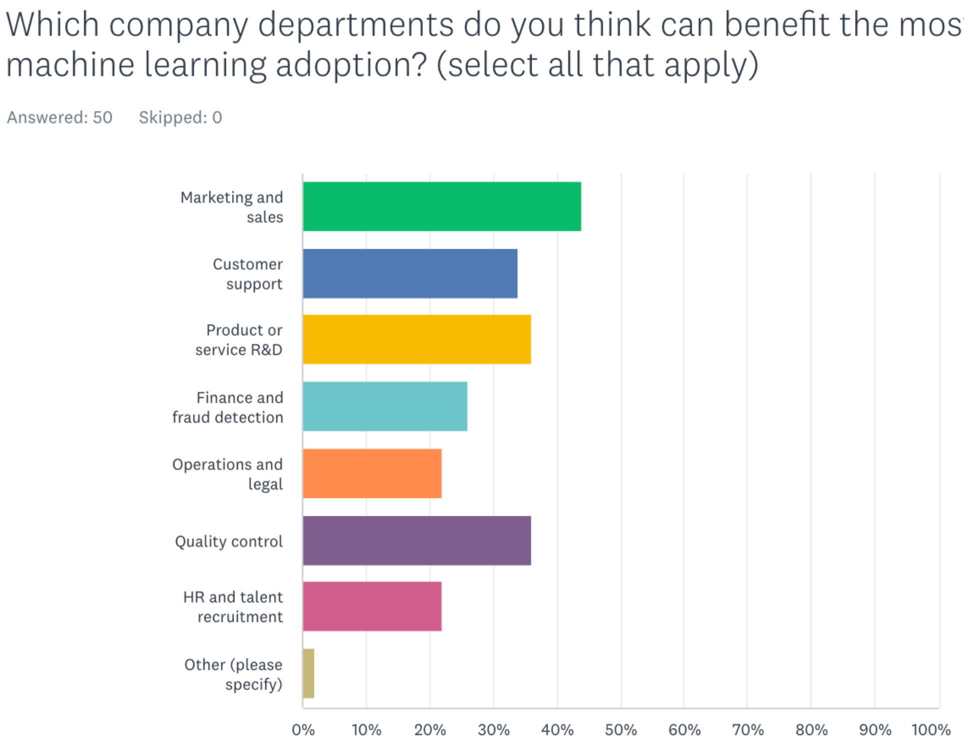


Source: Own work.

In McKinsey's (2019) study on AI in Nordic businesses, the authors analysed what their respondents think of the future of AI in their organisation. As an inspiration, we asked our SMEs if they plan to implement machine learning, and if yes, what is the foreseen timeline. From all our respondents, 30% of businesses reported they have no plans to implement machine learning in the near future, 28% were currently in the planning stages but do not have a defined timeline for implementation yet, 22% plan on implementing machine learning within the next 6-12 months, 18% foresee implementing machine learning in the next 2 years, and only one company (2%) responded foreseeing machine learning implementation in the next 7 years.

Furthermore, as an effort to understand the perceived usefulness as a TAM driver for technology acceptance, we asked the SMEs which departments they think will benefit the most from machine learning adoption. Perceived usefulness is defined as a degree to which an individual believes that using a particular technology would be beneficial in the context of increasing their productivity, effectiveness, or goals. When asked about which departments SMEs believe would mostly benefit from machine learning, the highest ranking answers were marketing and sales (44%), quality control (36%), product or service research and development (36%), and customer support (34%). The rest of the responses included finance and fraud detection (26%), operations and legal (22%), and human resources and talent recruitment (22%). Only one company (2%) responded with "I don't know", demonstrating that most of the SMEs have a good understanding on where machine learning can be beneficial in their organisation. These results show high presence of perceived usefulness within Slovenian SMEs, which is a driver for technology acceptance according to TAM. The full results are shown in Figure 9.

Figure 9: Perceived machine learning benefits across departments



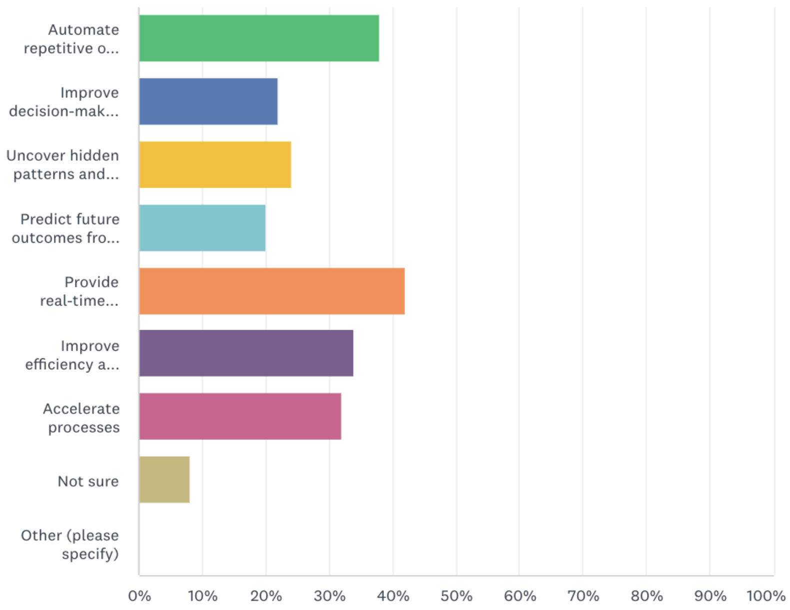
Source: Own work.

Building on our previous inquiry, we asked the SMEs to elaborate how machine learning could benefit their organisation as a whole. We took inspiration from Ulrich, et al. (2021) empirical case study on AI adoption in German SMEs, where the authors had asked their respondents to identify the areas of their business where they perceived greatest opportunities for AI. Similarly, our respondents were also given the freedom to indicate more than one potential benefit from machine learning. The respondents highlighted a range of ways SMEs perceive machine learning having a benefit to their organisation. The highest ranking benefits were providing real-time analysis (42%), automating repetitive or mundane processes (38%), and improving efficiency and cost saving (34%). Other, less named benefits were uncovering hidden patterns and trends in data (24%), improving decision-making (22%), and predicting future outcomes from data insights (20%). Interestingly, a small portion of our respondents (8%) were not sure of the specific benefits machine learning could bring to their organisation. The full results are shown in Figure 10.

Figure 10: Perceived machine learning benefits across organisations

How do you think machine learning can benefit your organisation? (select all that apply)

Answered: 50 Skipped: 0

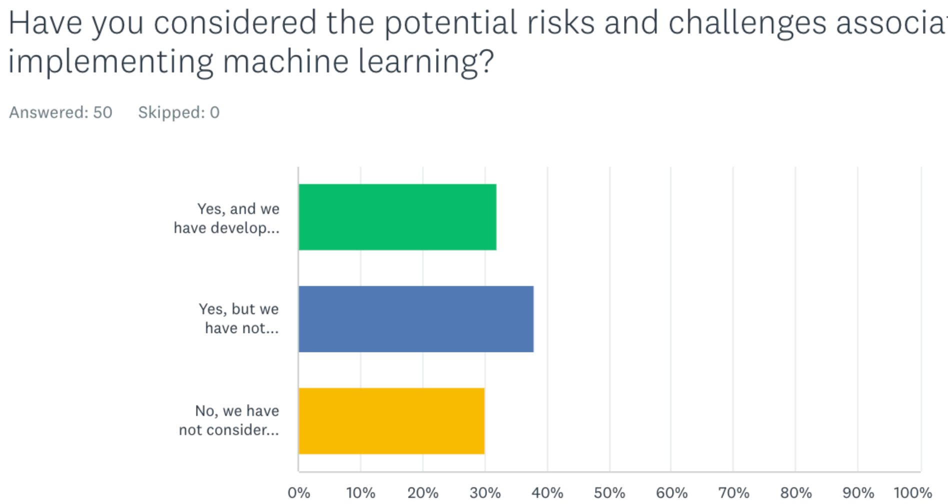


ANSWER CHOICES		RESPONSES	
Automate repetitive or mundane processes		38.00%	19
Improve decision-making		22.00%	11
Uncover hidden patterns and trends in data		24.00%	12
Predict future outcomes from data insights		20.00%	10
Provide real-time analytics		42.00%	21
Improve efficiency and cost saving		34.00%	17
Accelerate processes		32.00%	16
Not sure		8.00%	4
Other (please specify)	Responses	0.00%	0
Total Respondents: 50			

Source: Own work.

With the attention to analyse any perceived risk, as TAM driver for technology acceptance, we posed the question to the SMEs if they have considered any potential risks and challenges associated with implementing machine learning in their organisation. We were interested in gauging their risk and challenge awareness, and the level of planning that has been undertaken to mitigate such risks. The responses were quite evenly spread across different stages of consideration for potential risks and challenges associated with machine learning implementation. About 38% of the SMEs acknowledged their consideration of potential risks and challenges, but admitted they do not yet have a developed plan to address them. A slightly smaller portion, 32%, reported being aware of potential risks and challenges and also having a defined plan in place to address them. However, a substantial 30% of the respondents revealed that they have not yet considered any potential risks or challenges associated with machine learning implementation. The full results are shown in Figure 11.

Figure 11: Risk and challenges of machine learning implementation

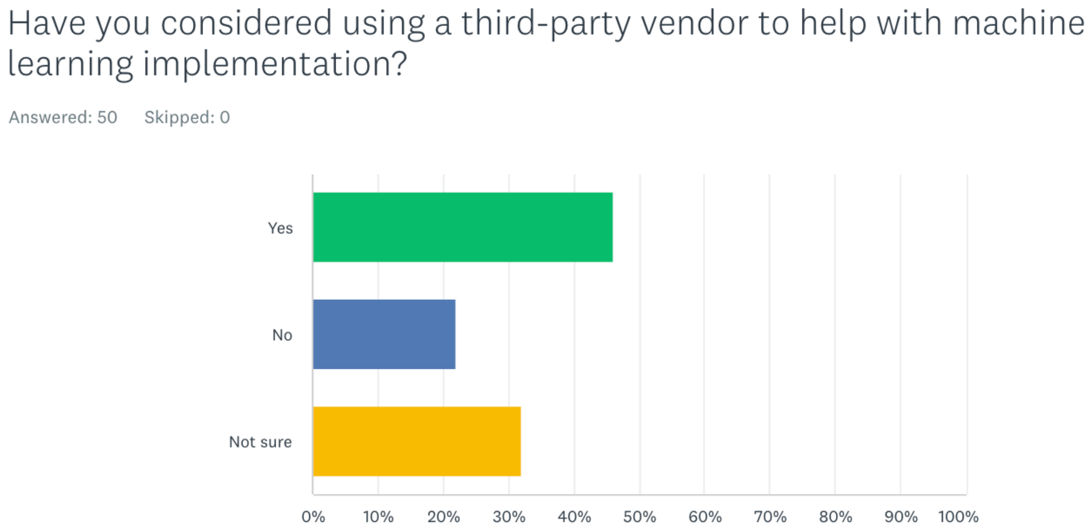


ANSWER CHOICES	RESPONSES	
Yes, and we have developed a plan in place to address them	32.00%	16
Yes, but we have not developed a plan to address them yet	38.00%	19
No, we have not considered the potential risks and challenges	30.00%	15
TOTAL		50

Source: Own work.

The empirical case study by Ulrich, et al. (2021) on AI adoption in German SMEs reveled the majority of the surveyed SMEs depended on third-party partners and collaborations. This strategy of the German SMEs helped them navigate the complexities associated with AI technology, by leveraging the expertise of specialised vendors, reducing the burden of in-house development and management of AI systems. Inspired by these findings, we aimed to investigate whether Slovenian SMEs harbored a similar mindset when it comes to machine learning. Our next question centered around the SMEs openness to collaborate with third-party vendors which can help with machine learning implementation. The responses show nearly half of the SMEs (46%) have considered machine learning collaboration as a way for better and more effective implementation. This group viewed the expertise and resources of specialised vendors as a valuable asset that could accelerate their machine learning journey, making the implementation process smoother and more successful. However, a notable portion of the respondents, 32%, were unsure about this approach, and 22% answered negatively to the idea of collaboration with specialised machine learning vendors. The mixed responses show a diversity of attitude among Slovenian SMEs when it comes to strategic collaborations around machine learning implementation. We show the full results in Figure 12.

Figure 12: SMEs attitude towards machine learning collaboration

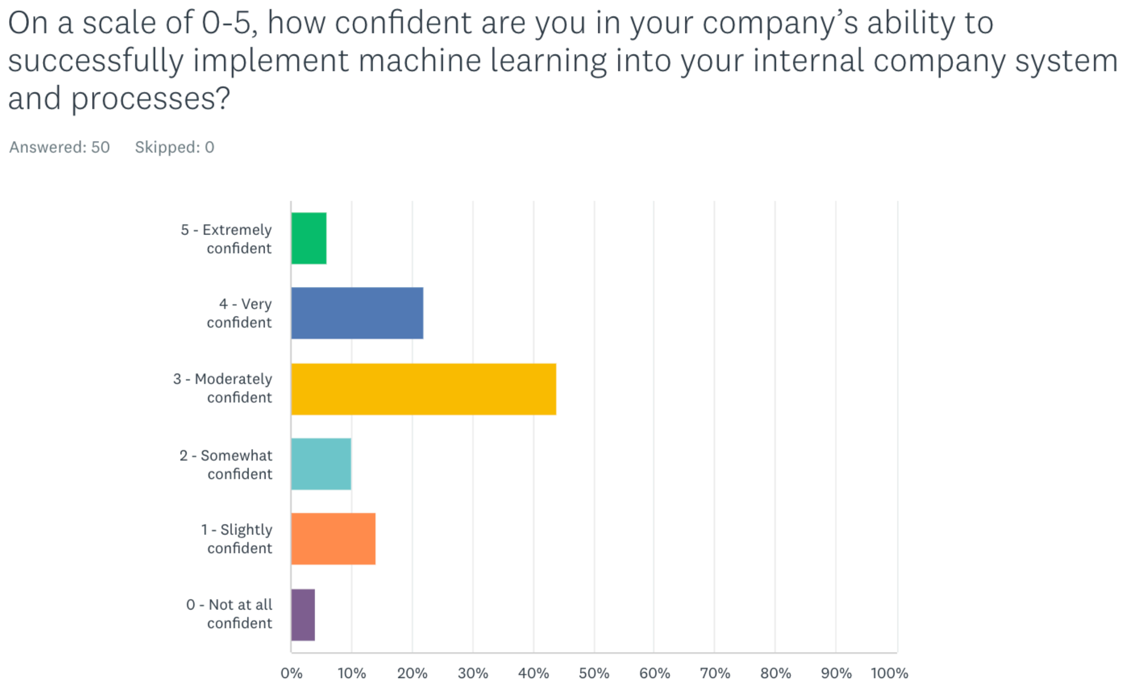


Source: Own work.

The final two questions from our survey were aimed at assessing the technical skill gap in SMEs. Based on the principles of the TAM, the lack of technical skills in an organisation can play a role as a barrier to technology acceptance. We asked the SMEs to evaluate their company's ability to successfully implement machine learning into their existing system and processes, and if the interviewed decision makers and managers felt confident in their ability to start a machine learning project for their department or organisation.

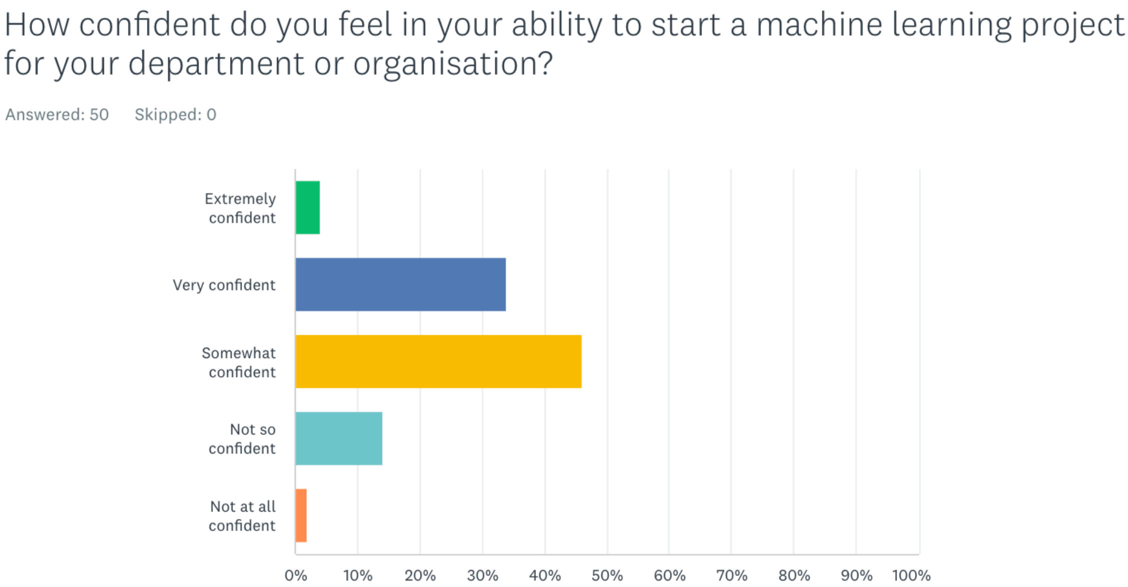
The first question was aimed to uncover the perceived level of technological preparedness, and to offer an overview into decision maker's confidence in dealing with potential complexities of machine learning implementation. The second question was aimed to understand the confidence level of the decision makers in their ability to initiate and oversee a successful machine learning implementation in their company. In essence, we sought to understand if the decision makers driving the future of these SMEs felt equipped and ready to navigate the machine learning landscape, a factor that can significantly influence the degree and success of machine learning implementation. The responses provide valuable insight into the perceived technical preparedness of SMEs, and the results are shown in Figure 13 and Figure 14.

Figure 13: SMEs ability to successfully implement ML in their system and processes



Source: Own work.

Figure 14: Decision maker confidence to start an ML project for their department or organisation



Source: Own work.

6.3 Analysis and findings

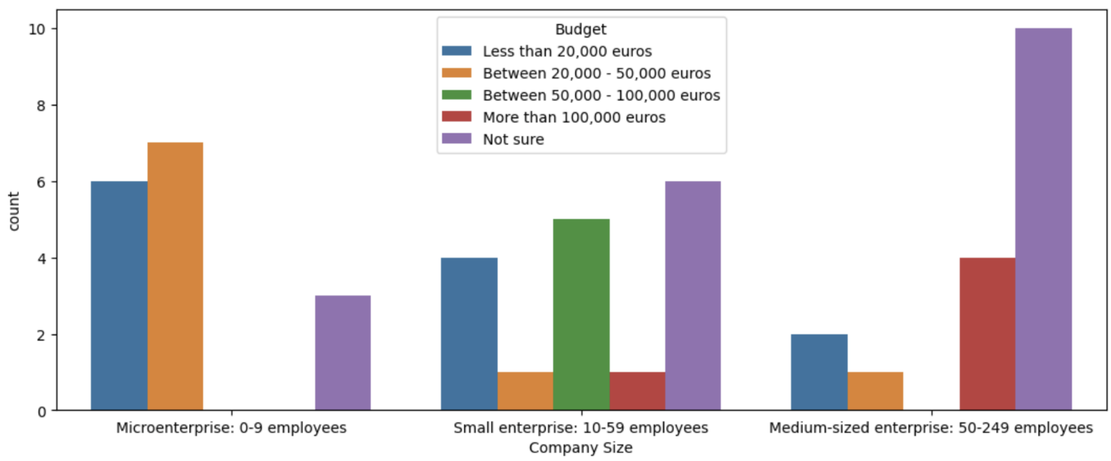
In order to further analyse the gathered observations from all our individual respondents and compare variables from different questions, we used two approaches: 1) Python as a programming language to create contingency tables, and further visualise the distributions in grouped bar charts, and 2) multiple-case approach, analysing literature findings and our own survey results. The main findings of our survey on Slovenian SMEs and machine learning are summarised in five propositions.

6.3.1 SMEs size has an impact on their budget for machine learning

From the 50 small and medium-sized enterprises that we surveyed, 16 companies were microenterprises, 17 were small companies, and 17 were medium-sized companies. When we analysed the three groups and the budget their company is willing to allocate to machine learning adoption and development, we observed a connection between the size of the SMEs and their stance on machine learning budget.

For microenterprises, the two most prevalent answers were that they are willing to allocate less than 20,000 euros, or between 20,000 to 50,000 euros for machine learning adoption and development. Small enterprises were mostly not sure or willing to allocate between 50,000 to 100,000 euros for machine learning adoption. Whereas medium-sized enterprises were for the most part not sure of the exact budget or willing to allocate more than 100,000 euros for machine learning adoption. The data is shown in Figure 15.

Figure 15: Relationship between SMEs' size and their budget for ML



Source: Own work.

This is not surprising, as larger SMEs often benefit from economies of scale. They have a larger customer base than smaller SMEs, and a greater purchasing power. As a result, larger SMEs can allocate a larger portion of their budget towards strategic initiatives such as technology investments and machine learning implementation. On the flip side, smaller SMEs typically face resource constraints because of limited financial capabilities. Consequently, they are more cautious about how and where they spend their budget and may prioritise expenses related to core business functions over technology investments such as machine learning.

6.3.2 Cost and lack of technical skills are key barriers for ML adoption

During our survey of Slovenian SMEs, we asked the respondents to name all challenges that the company is facing when it comes to machine learning adoption. Almost all 50 companies named more than one challenge, resulting in 108 submitted answers. Nearly half of the companies reported budget constraints (46%), lack of internal expertise (40%), and lack of understanding for machine learning applications and relevant use cases (38%), as main challenges when it comes to machine learning adoption. In the Unified Theory of Acceptance and Use of Technology, cost is considered a significant barrier to technology acceptance and adoption. It refers to the financial budget required to acquire, implement, and maintain the technology. UTAUT suggests that when users perceive the cost of adopting and using a technology to be high, they are more likely to resist its acceptance. Moreover, cost considerations can lead to concerns about budgetary constraints, especially for individuals or organisations with limited financial resources. As such, understanding the financial implications related to the cost of technology is essential in order to increase its acceptance and promote successful implementation.

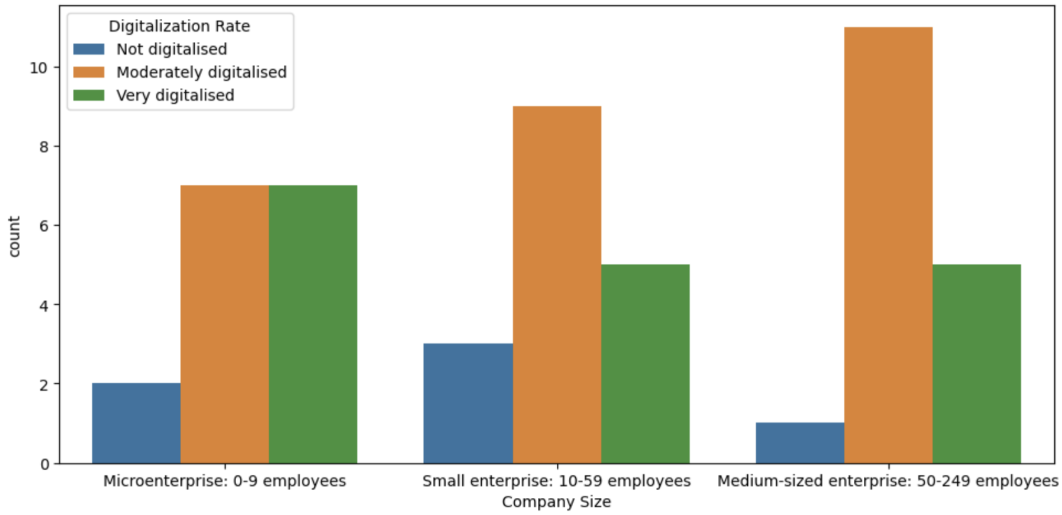
The Technology Acceptance Model suggests lack of technical skills as one of the main barriers to technology acceptance. When individuals or organisations lack the necessary technical skills, they may perceive the technology as difficult to use and may doubt their ability to effectively use it. This can be especially pronounced when dealing with new technologies or complex systems. To address the lack of technical skills as a barrier to technology acceptance, it is crucial for organisations to provide appropriate training and support. Comprehensive training programs, workshops, or online resources can help individuals get familiarised with the technology, grow their competence and confidence in using the technology, ultimately promoting its acceptance and successful adoption.

While it is important for companies to consider the financial implications and skill gaps associated with machine learning implementation, the potential benefits often outweigh the initial challenges. Companies can explore various strategies such as seeking external funding, engaging in strategic partnerships, or leveraging pre-built machine learning solutions to overcome these barriers.

6.3.3 SMEs size does not influence the level of internal system digitalisation

Digitalisation refers to the development and implementation of information and communication technology to streamline and enhance business processes. In our survey of Slovenian SMEs, the size of the enterprise did not play a role in the level of digitalisation the company has attained. There was a widespread digitalization across the board, with almost all microenterprises, small enterprises, and medium-sized enterprises reporting that their company's internal systems are either moderately digitalised or very digitalised. Only a handful of companies across all size categories, two microenterprises, three small enterprises, and one medium-sized company, reported that their internal systems have not yet been digitalised. It indicated that the vast majority of the surveyed SMEs have already integrated technology into their operation to some extent. The data is shown in Figure 16.

Figure 16: Relationship between SMEs size and their digitalisation level



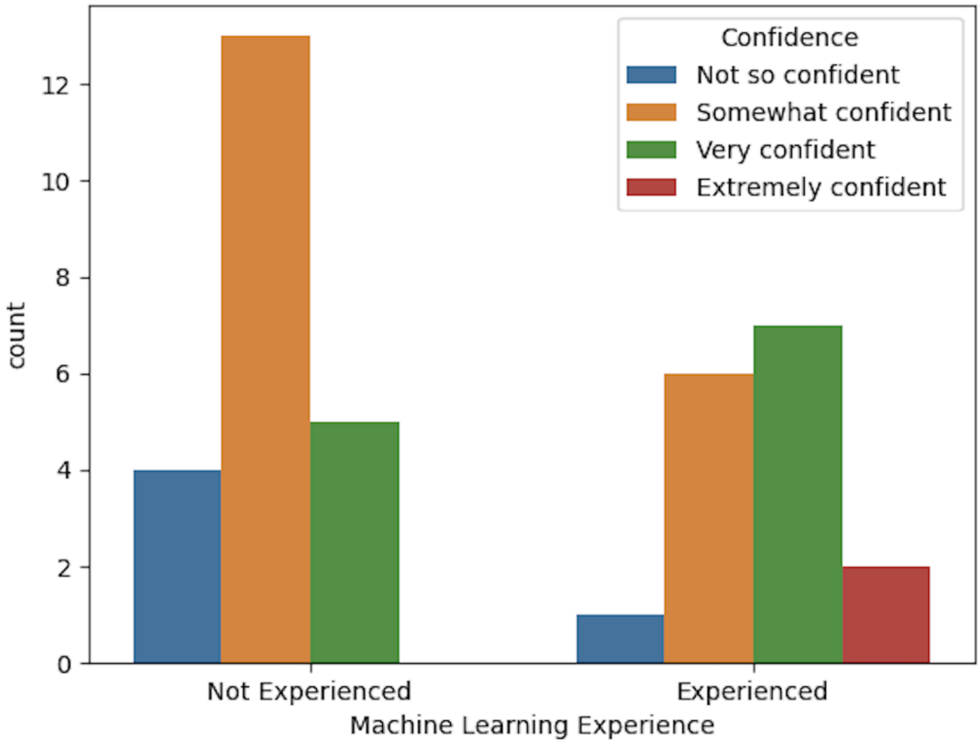
Source: Own work.

In today's digital age, a wide range of digital tools and solutions are available for often affordable prices, or even free of charge. The affordability and accessibility of digital solutions makes digitalisation viable for companies of all sizes. Furthermore, regardless of their size, SMEs realise the importance of digitalisation as a means to gain competitive advantage and be more efficient. Finally, digitalisation offers flexibility and scalability, making it easier for SMEs to start small and gradually expand their digital capabilities and initiatives as the business grows.

6.3.4 Prior ML experience does not guarantee ML implementation confidence

Internal systems are all technology products and systems operated or controlled inside an organisation, including but not limited to computers, communication networks, application services, and more. Internal processes are considered all business processes that are performed inside an organisation without involvement of any external partners. We observed that having prior experience with machine learning does not guarantee having confidence in implementing machine learning in internal systems and processes. Both the experienced, and inexperienced machine learning respondents, predominantly answered being moderately confident in implementing machine learning into their company's systems. The data is shown in Figure 17.

Figure 17: Relationship between ML experience and implementation confidence



Source: Own work.

This can be due to a complex IT infrastructure, lack of technical expertise, lack of implementation knowledge, and change management. Machine learning projects need to work seamlessly with existing internal systems and processes, which can be challenging for companies with complex IT infrastructures. In addition, it may require high-performance computing and storage infrastructure, or large amount of memory or processing power which can be seen as a fearsome undertaking for companies with limited computing resources. Also, implementing machine learning into internal processes can require technical expertise, such as engineers, software developers, or IT architects. Lastly, certain machine learning implementations may require an organisational change, including upgrade in processes and skills.

7 STRATEGIC FRAMEWORK FOR ML IMPLEMENTATION

In this chapter, we propose a conceptual strategic framework for implementing machine learning in small and medium-sized enterprises. The proposed framework is based on technology acceptance theories and models, literature case studies, and SMEs' survey results. The framework is aimed to guide SMEs through the essential steps and considerations that are needed for successful implementation of machine learning technology. The purpose of the framework is to provide SMEs with necessary knowledge to help them better understand how to successfully implement machine learning in their organisation. We provide ideas, concepts, and methods to prepare SMEs for an easy start to machine learning implementation. Furthermore, we explore various components of the strategic framework, discuss challenges and opportunities associated with machine learning implementation, and provide guidance on how SMEs can overcome potential barriers and risks. The results of our survey showed that 68% of the SMEs have not considered potential challenges or risks associated to ML adoption, or have considered the potential risks or challenges associated with ML adoption but have not yet developed a plan to address them. The goal of the proposed framework is to help SMEs better understand what is needed for successful machine learning implementation, how to assess the feasibility and risk of their particular use case, and how to scope their project for easy implementation and commercialisation. The proposed framework is divided into five steps, each addressing a specific aspect of a successful machine learning implementation.

The framework begins by emphasising the importance of defining a machine learning use case and application, and aligning it with the organisation's business problems and objectives. This step is crucial in ensuring that the ML initiative directly addresses the organisation's needs and provides value. Next, we emphasise the significance of assessing the existing internal technical expertise and securing stakeholder engagement for successful ML implementation. Subsequently, the framework highlights the importance of assessing technical feasibility and data availability, followed by the importance of defining a timeline and budget for ML implementation. Lastly, the framework highlights the significance of promoting internal communication and fostering innovation culture as a way to promote acceptance and successful commercialisation of the ML technology.

7.1 Define ML use cases by aligning ML benefits with business needs

Our survey on Slovenian SMEs revealed that only 4% of the surveyed SMEs are not sure on how ML can benefit their organisation. The most reported benefits of machine learning were providing real-time analytics, automating repetitive or mundane tasks, and improving efficiency and cost saving. Furthermore, the results of the survey reveal that only one SME was not aware of which company departments can benefit the most from machine learning adoption. The departments most commonly considered to benefit the most from ML adoption were marketing and sales, product or service research and development, quality control, and customer support. However, even though our survey results show that almost all of the SMEs had an understanding of the potential ML benefits to their business and company departments, 38% of them had a challenge in understanding machine learning applications and relevant use cases for their organisation. Therefore, as a first step in our strategic framework, we propose a guideline to help SMEs define machine learning use cases and applications for their organisation. In order to understand ML applications and use cases within an organisation, it is important for SMEs to first assess their business problems and objectives, and later align them with the ML benefits. The alignment helps create a pathway for focused and successful implementation, ensuring that the technology directly addresses business needs, and is perceived as useful to their effectiveness, efficiency, or productivity.

The first step in the process is identifying and understanding the business problems an organisation would like to solve. Without well-defined business problems, organisations risk implementing irrelevant or ineffective ML applications, wasting time and resources, and leading to poor return on investment (ROI). The case study by McKinsey (2019) on AI in Nordic businesses, shows that most of the AI projects reported by the respondents were not focused on fixing actual business problems or improving core organisation activities, which according to the authors, can explain Nordic businesses' low implementation rate and the low expectancy of any significant financial impact. According to TAM, users are more likely to accept a technology when they perceive it as useful and believe it will impact their effectiveness, efficiency, or productivity (Davis, 1985). Clearly defined business problems can provide a sense of direction and purpose, and hence play a role in shaping technology perceived usefulness. Therefore, if the ML initiative doesn't align with a clear business problem, the end users may not see value in using it, which can lead to low user adoption. To define clear business problems, SMEs need to have a good understanding of the current state of their organisation and its specific needs. This can involve a business problem statement, conducting a SWOT analysis of existing strengths, weaknesses, opportunities, and threats of the organisation, or creating focused group discussions with key stakeholders and employees. Engaging with key stakeholders, including business leaders and employees, can provide valuable insights into business problems where machine learning implementation can have a significant impact (Peppard et al., 2007).

In the second step, organisations should define their objectives, so that they reflect the defined business problems. When defining objectives, it is important they are actionable and measurable, which can allow for clear evaluation of the impact of the machine learning application and use case. The SMART criteria (Specific, Measurable, Assignable, Realistic, and Time-related) can serve as a useful framework for defining clear objectives. The SMART criteria was firstly introduced by George T. Doran, in his 1981 paper called *There is a S.M.A.R.T way to write management's goals and objectives*. According to Doran, a meaningful objective needs to be specific, measurable, assignable, realistic, and time-related. A specific objective means that it has to target a specific area of improvement. Measurable means it has to quantify or at least be able to suggest an indicator of progress, and assignable means it has to specify who will do it. Realistic states that the objectives have to state results that can be realistically achieved, given the available resources. And lastly, time-related refers to the fact that the objectives should specify when the result(s) can be achieved. Today, the SMART method is widely used as the standard for developing effective, measurable goals and objectives within management, and within program planning and evaluation (Bjerke & Renger, 2017).

After assessing the organisation's business problems and objectives, SMEs should aim to align them with the perceived benefits of machine learning, as a way to define ML applications and use cases. This way, SMEs can evaluate the perceived compatibility of the technology with their needs, values, and work processes, which according to TAM, is a driver for technology acceptance. Some of the machine learning benefits from our survey results include automating repetitive and mundane processes, improving decision-making, providing real-time analytics, improving efficiency and cost saving, uncovering hidden patterns and trends in data, and more. To align the perceived ML benefits with the business problems and objectives, SMEs must ask questions such as 'How could the perceived benefits address our existing business challenges or needs?', and 'How could the perceived benefits help us achieve our strategic goals and objectives?'. According to TOE, good communication can promote company innovation, as well as having management that is open to embracing technology changes that complement the company's vision and mission can be a driver for technology acceptance. By understanding the organisation's business problems and objectives, and aligning them with perceived ML benefits, organisations can select a ML use case that reflects the organisation's needs and goals, and by that, set the stage for effective and successful machine learning implementation. Once an organisation has defined ML use cases and applications that reflect their business problems, objectives, and expected ML benefits, the company can embark the journey towards successful machine learning implementation and leverage the technology to drive growth and innovation.

7.2 Evaluate internal technical expertise and get key stakeholders on board

After defining machine learning applications and use cases, the next step to a successful implementation of machine learning within an organisation is evaluating its internal expertise and securing stakeholders' support. In this part, we focus on the importance of assessing the internal expertise and getting key stakeholders on board for successful machine learning implementation.

Evaluating the internal technical expertise and talent within an organisation can prevent future acceptance barriers. Our survey results revealed that the second biggest challenge for ML adoption for Slovenian SMEs is lack of internal expertise. Furthermore, the case study by Ulrich, Frank and Kratt revealed that 65% of German SMEs listed lack of competence as the highest barrier to AI implementation. As such, lack of internal expertise can lead to lack of awareness or familiarity and, therefore, resistance to change, which are TAM barriers to technology acceptance. Internal expertise involves the skill sets of the existing employees in areas such as data science, machine learning, software engineering, and related fields. By assessing the internal expertise, SMEs can identify any gaps in technical knowledge or skills, and can determine if additional training or hiring is required. Even Ronnberg and Areback (2020) emphasised the importance of involving employees in the process, and investing in their knowledge and skills as a way to overcome cultural resistance to change. Through strategic hiring, training, and talent retention, organisations can optimise their investment in human capital, ensuring the team possesses the necessary skills to deliver successful machine learning projects. In addition, the assessment of internal technical skills can help determine if an organisation would like to do the ML development in-house, or partner with complementary organisations, such as companies specialised in ML development or consultants, and supplement their in-house expertise. Almost half of the surveyed SMEs reported they have considered using a third-party vendor to help with machine learning implementation, and 32% were not sure. Ronnberg and Areback (2020) suggested establishing partnerships and collaborations with external partners such as universities, research institutions, or technology providers in their framework for AI adoption in SMEs. An analysis on the internal technical skills can help determine if the best approach for ML implementation includes investing in in-house development, or outsourcing with third-party vendors.

Another acceptance barrier revealed by the case study of AI in German SMEs was the lack of commitment from top management. Getting key stakeholders on board can facilitate resource allocation, support, and user-centric design and acceptance. The right stakeholders have the authority and ability to allocate necessary resources to the machine learning initiative. That includes securing financial resources, necessary technical infrastructure, access to data sources, and personnel support. Their involvement can help ensure the ML project receives the required resources and support for successful implementation. Moreover, having key stakeholders on board can increase the likelihood of securing necessary approvals and overcoming potential implementation barriers. In addition, key stakeholders often well understand the end-users and the clients, which can provide insights into user requirements, expectations, and preferences, which can drive acceptance. Furthermore, having key stakeholders on board can promote user acceptance, minimise resistance, and increase the likelihood of successful adoption and utilisation of the machine learning technology.

Evaluating the internal expertise and getting key stakeholders on board can be of paramount importance for the success of the machine learning implementation. By understanding the existing technical skills and engaging the right stakeholders, organisations can maximise the potential of machine learning initiatives and drive valuable outcomes. Evaluating internal expertise can help uncover a need for any necessary training and hiring, as well as lead to a culture for innovation, and partnerships. In addition, stakeholders can play a vital role in overcoming cultural difficulties, establishing internal processes, and providing necessary resources for successful ML implementation.

7.3 Access technical feasibility, data availability and quality

The successful implementation of machine learning projects relies heavily on properly assessing its technical feasibility, data availability, and data quality. If these three factors are not assessed prior to the machine learning implementation, they can later cause perceived complexity, and perceived risk, which are TAM barriers to technology acceptance. Therefore, assessing these factors lays the foundation of a successful machine learning implementation and can help mitigate potential adoption risks or challenges further down the road.

One of the primary steps in assessing technical feasibility of machine learning is evaluating the organisation's internal IT infrastructure, existing technologies, and scalability capabilities. Our survey results on the digitalisation level of Slovenian SMEs showed that most of the companies had moderately or very digitalised internal systems. However, 28% of the SMEs reported insufficient IT infrastructure as a ML adoption challenge. Furthermore, the case study on German SMEs and AI adoption revealed that 46% of German SMEs reported that insufficient IT infrastructure can be a barrier to technology adoption. Moreover, one of the main barriers to AI adoption in the Nordics region, as reported by McKinsey (2019) was insufficient IT infrastructure. Evaluating the organisation's current IT infrastructure can determine if the company has the necessary systems in place to handle machine learning technologies. This can include establishing necessary storage capacities, processing, or network capabilities. If the IT infrastructure is not robust enough to support machine learning implementation, the company should consider investing in upgrades or exploring cloud-based solutions which can help ensure a successful implementation of the technology. Secondly, accessing technical feasibility also includes analysis of existing software systems, and their compatibility with the machine learning technology the company would like to implement. According to TOE's technological factor, a company's existing technologies are important to the acceptance process as they can impact the scope and pace of technological changes that an organisation can undertake. For a seamless implementation, ideally, the ML systems need to be integratable with the company's existing software and operations. Furthermore, TOE's technological factor, suggests that current innovative technologies that exist on the market but are not being used by the organisation, can become a barrier to innovation. Lastly, an SME's scalability capabilities can play in ML technical feasibility. Organisations need to evaluate their infrastructure's ability to handle growing data volume and increasing computational requirements. Our survey results show that most of the respondents feel moderately confident in their company's ability to successfully implement ML into their internal systems and processes. It is important to consider the future scalability needs of the machine learning implementation and ensure that the internal systems and processes can accommodate these requirements. Scalability considerations may include hardware upgrades, cloud-based solutions, or distributed computing frameworks.

Data availability is a fundamental aspect of any machine learning project. Our survey results show that around 42% of the Slovenian SMEs collect data automatically, using advanced software or tools, cloud-based tools, or by leveraging a variety of sources, tools and software. However, 24% reported not collecting or analysing data, and 30% reported collecting data manually using spreadsheets or other basic software or tools. Before starting any ML project, organisations should evaluate their ability to collect and store data. If a company does not collect data but considers implementing machine learning, it should consider implementing data collection mechanisms and evaluate its capacity to handle data collection processes efficiently and ethically, while adhering to data privacy regulations. Data accessibility is another critical factor in data availability, which includes the accessibility of data for machine learning purposes. This involves understanding data storage, data sharing, and any legal considerations surrounding the use of the data, such as the General Data Protection Regulation (GDPR).

Finally, data quality can be detrimental to the effectiveness and reliability of machine learning models, and by such, significantly impact the success of the machine learning implementation. The case study by Ulrich, Frank and Kratt reveals that 52% of German SMEs reported data problems as a barrier to AI implementation. Therefore, ensuring accuracy and completeness of available data is essential. This involves evaluating the quality of the data and addressing any errors, inconsistencies, or missing values. Consistency and uniformity across different data sources or variables should also be assessed. Inconsistencies in data formatting, units, or naming conventions can lead to biased or erroneous results. As a solution, organisations can establish data standardisation processes to ensure reliable and coherent data. However, understanding the specific preprocessing needs of the data is crucial to ensure data quality and prepare the data for successful machine learning training.

Ronnberg and Areback (2020) identified a few requirements for successful implementation of AI, in their case study on initiating AI transformation in SMEs. They listed automation, data, and internal capabilities as main requirements for successful implementation of AI. By assessing technical feasibility, data availability, and data quality, organisations can make informed decisions in their machine learning journey. They will be able to identify potential challenges in advance, mitigate risks, and allocate resources effectively, and as such, be better prepared to unlock the full potential of machine learning in their respective domains.

7.4 Define a timeline and budget

Setting a specific time frame for machine learning implementation enables the establishment of a well-defined and structured timeline for the process. A defined timeline can provide stakeholders with realistic expectations regarding project duration, reduce uncertainties and help mitigate risks associated with potential delays or disruptions. The survey results on Slovenian SMEs revealed that 30% of the respondents did not have plans to implement ML in the near future. Others were in the planning stage but did not have a specific timeline for implementation yet (28%). Whereas 22% had a plan to implement ML in the next 6-12 months, and 18% had a plan to implement ML within the next two years. McKinsey's (2019) case study on AI in Nordic businesses revealed that nine out of ten executives responded they would like to increase AI implementation over the next three to five years. There are several factors that need to be considered when organisations define timelines for ML implementation. Firstly, project complexity and scope can significantly impact the time required for ML implementation. The accessibility of data, and the ease of integration with existing internal systems or processes can help assess realistic time limits for machine learning implementation. Finally, resource availability and technical skill sets can play a vital role in determining timelines for ML implementation.

The literature case study analysis revealed that financial barriers and lack of sufficient resources can be major barriers to AI adoption in SMEs. Our survey results from ML adoption in Slovenian SMEs revealed that almost half of the respondents (46%) experience budget constraints as the main challenge to ML implementation. Regarding the budget that the SMEs are willing to dedicate to ML adoption and development, 38% of our respondents were not sure. The rest were willing to allocate less than 25,000 euros (24%), between 25,000 and 50,000 euros (18%), between 50,000 and 100,000 euros (10%), and more than 100,000 euros (10%). In our analysis of the results, we observed that the size of the SME has an impact on their budget for machine learning.

Budget can play a paramount role in the planning and execution of machine learning initiatives. It can significantly impact not only the scope of the ML application and use case, but also its implementation, the tools and resources used, the timeline, and ultimately the success of the project. A well-considered and defined budget can provide a solid foundation for an SME's machine learning journey, helping ensure that every step taking is economically viable and sustainable. Furthermore, it can ensure optimal resource allocation and financial planning, preventing cost overruns and facilitating effective project prioritisation. By aligning budget allocation with the ML use case and application, the need for internal skills and resources, and the technical and data requirements, SMEs can set realistic expectation of the ML project. Moreover, SMEs can strategically plan for the ML implementation journey, balancing the financial constraints with the desired outcome, and set the stage for a successful implementation of machine learning capabilities.

7.5 Promote internal communication and foster innovation culture

The Technology-Organisation-Environment Framework emphasises the importance of the organisational factor in technology acceptance. According to UTAUT, external opinions and recommendations can positively impact technology acceptance, whereas according to TAM, lack of awareness, familiarity, or limited exposure to ML technology can make users hesitant to accept it. Moreover, Ronnberg and Areback (2020) found in their case study that lack of internal communication can become a major challenge in AI adoption within SMEs. Internal communication can involve communicating company objectives, establishing cross-communication processes, cooperating between departments, and clearly formulating common goals across different teams when preparing for ML implementation. Their case study also emphasises the importance of involving employees in the technology transformation process, and investing in their knowledge and skills as a way to overcome cultural resistance to change. Our survey results from Slovenian SMEs and machine learning revealed that 50% of the companies had employees with overall positive attitude towards ML implementation. The rest were neutral (34%), not sure (12%), or had negative attitude towards ML implementation (4%). Regular communication, workshops, and training sessions can help in disseminating the necessary knowledge and reducing resistance to the new technology. Furthermore, effective communication can aid in gathering feedback and suggestions from various employees across different departments. The feedback and suggestions can further lead to improvements in the ML journey and increase its chance of successful implementation.

Furthermore, Ronnberg and Areback (2020), and the TOE framework, suggest that clear and good internal communication can foster company culture for innovation and can serve as drivers for technology acceptance. Innovation culture can encourage employees to experiment, take calculated risks, and come up with novel solutions to problems. This is particularly important for machine learning projects, which often require out-of-the-box thinking and creative problem-solving. According to Peter Drucker's book (1985), called *Innovation and Entrepreneurship,* cultivating innovation can lead to new business opportunities, increased competitiveness, and development of unique products and services. Our survey revealed that most of the SME decision makers (46%) feel somewhat confident in starting a ML project for their department or organisation. The rest were very confident (34%), not so confident (14%), extremely confident (4%), and not at all confident (2%). The survey results show that despite the challenges of ML implementation in small and medium-sized enterprises, Slovenian SMEs are demonstrating an openness to ML implementation and strong understanding of its potential benefits. Furthermore, the perception of ML is generally positive among employees, and there is a substantial openness towards third-party collaboration for ML implementation. There are clear barriers to ML adoption, such as budget constraints, lack of internal expertise, and lack of understanding of ML applications and relevant use cases. However, by fostering innovation culture, we trust that the proposed conceptual strategic framework will help guide the SMEs towards successful ML implementation and how to avoid any challenges or risks along their journey. We summarise the five-step guideline from the proposed conceptual strategic framework in Table 4.

Table 4: Guideline summary

Steps	**Conceptual strategic framework for implementing machine learning in SMEs**
1	Define machine learning use case and application, by assessing perceived ML benefits with the organisation's business problems and objectives
2	Evaluate internal technical expertise and get key stakeholders on board
3	Access technical feasibility, data availability, and data quality
4	Define a timeline and budget
5	Promote internal communication and foster innovation culture

Source: Own work.

8 CONCLUSION

The purpose of our thesis was to provide necessary knowledge to SMEs and help them better understand how to successfully implement machine learning in their organisation. Our research aimed to familiarise stakeholders with AI and ML terminology, help them understand the implications of ML adoption, flag potential adoption challenges, and provide a conceptual strategic framework to facilitate a smooth and successful implementation process. Through a systematic literature study, multiple-case analysis, and survey method, our research examined the current stage of machine learning as a form of AI, and focused on how SMEs can effectively integrate ML into their organisation and operations. By integrating the findings from the literature study, multiple-case analysis, and survey, we developed a conceptual strategic framework. The framework provides five-step guideline on how SMEs can define ML use cases, assess technical feasibility and data availability, set timelines and budget, and promote internal communication and innovation culture. It can serve as a practical tool for SMEs to navigate the complexities and challenges of ML implementation, and maximise its potential benefits. We achieved our goal to provide SMEs with a framework that will help executives better understand what is needed for successful machine learning implementation, how to assess the feasibility and risk of their particular use case, and how to scope their project for easy commercialisation.

Although, the field of machine learning implementation for SMEs has gained increased attention in recent years, it can still be considered understudied compared to other areas of research for SMEs. One reason for the relative lack of research in this area could be the complexity and diversity of SMEs themselves. SMEs come in various sizes, sectors, and levels of digital maturity, making it challenging to develop a generalised ML frameworks and recommendations that will cater to their specific needs. While there is a growing body of literature exploring ML in context of large enterprises and different industry sectors, the specific challenges, considerations, and best practises for ML implementation in SMEs have not been excessively covered. Mostly, the focus of ML research has been on technical advancements, cutting-edge algorithms, and large-scale applications in industries such as finance, healthcare, or manufacturing. While these studies provide valuable insights into the capabilities of machine learning, they may not directly address the unique challenges or opportunities that SMEs face. SMEs play a major role in the European economy, creating around 75% of jobs in the European Union (EU), and making up to 99% of all enterprises. The EU understands the importance of SMEs, and as such, initiates networks and focus groups to understand the adoption, use, and impact of AI and ML in SMEs, and put digital SMEs in the center of the EU agenda. As such, we hope that our research contributed in bridging the gap between the theoretical understanding of ML and its practical implementation in SMEs.

The proposed conceptual strategic framework has the potential to make significant contribution to both theoretical understanding, and practical application of machine learning implementation in small and medium-sized enterprises. By drawing on technology acceptance theories and models, literature case studies, and survey results from SMEs, the proposed framework provides a comprehensive guide for SMEs to navigate the complexities of successful ML implementation. Our research contributes to the ongoing knowledge and understanding of ML implementation in SMEs, and provides practical insights to SMEs and policymakers.

However, our research has some limitations, as the findings and framework may not capture the full range of challenges and opportunities unique to every SME. In addition, the research focuses mostly on the business and strategic side of ML implementation, and does not go in depth to the technical complexities of ML development and implementation. Furthermore, our survey was conducted specifically on Slovenian SMEs, which may limit the generalisability to SMEs from other regions. Lastly, the research focuses primarily on ML implementation in SMEs, and does not extensively cover other forms of AI or emerging technologies.

Future work in this area could include empirical studies to validate and refine the proposed framework, conducting studies on both the short-term and long-term impact of ML in SMEs, and exploring the ethical and legal implications of ML adoption. Additionally, future research could expand beyond ML and explore the implementation of other AI and emerging technologies in SMEs.

In conclusion, this research provides valuable insights on ML adoption in Slovenian SMEs, and offers a conceptual strategic framework aimed to assist SMEs in successful implementation of ML technologies. Our framework can serve SMEs as a guide to successful ML implementation, and therefore contribute to their growth, competitiveness, and innovation. In today's data-driven world, machine learning has the potential to transform and revolutionise whole industries. As SMEs recognise the value of machine learning, its implementation and adoption become a strategic imperative.

REFERENCE LIST

1. Ajibade P. (2018). Technology Acceptance Model Limitations and Criticisms: Exploring the Practical Applications and Use in Technology-related Studies, Mixed-method, and Qualitative Research. *Library Philosophy and Practice (e-journal).* https://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=5294&context=libphilprac
2. Baabdullah, A., Alalwan, A., Slade, E., Raman, R., & Khatatneh, K. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. *Industrial Marketing Management*, *98*, 255–270. https://doi.org/10.1016/j.indmarman.2021.09.003
3. Baker, J. (2011). The Technology-Organization-Environment Framework. In Dwivedi, Y.K., Scott, L.M., Schneberger, L. and Systems, I.S., Eds., *Information System Theory: Explaining and Predicting Our Digital Society*, (pp. 231–245). University of Hamburg. https://doi.org/10.1007/978-1-4419-6108-2_12
4. Barann, B., Hermann, A., Cordes, A. K., Chasin, F., & Becker, J. (2019). Supporting digital transformation in small and medium-sized enterprises: a procedure model involving publicly funded support units. *Proceedings of the 52nd Hawaii International Conference on System Sciences*.
5. Bauer, M., van Dinther, C., & Kiefer, D. (2020). Machine learning in SME: an empirical study on enablers and success factors. *AMCIS 2020 Proceedings 3.*
6. Berghaus, S., & Back, A. (2016, October 26). Stages in Digital Business Transformation: Results of an Empirical Maturity Study. *AIS Electronic Library (AISeL).* https://aisel.aisnet.org/mcis2016/22

7. Bigliardi, B., & Galati, F. (2018). An open innovation model for SMEs. In Vanhaverbeke. *Researching Open Innovation in SMEs* ,(pp. 71–113). World Scientific.

8. Bjerke, M. B., Renger, R. (2017). Being smart about writing SMART objectives. *Evaluation and Program Planning, 61,* 125–127. https://doi.org/10.1016/j.evalprogplan.2016.12.009

9. Burkart, N., & Huber, M. F. (2021). A Survey on the Explainability of Supervised Machine Learning. *Journal of Artificial Intelligence Research , 70,* 245–317. https://doi.org/10.1613/jair.1.12228

10. Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2020). Explainable Machine Learning in Credit Risk Management. *Computational Economics*, *57*, 203–216. https://doi.org/10.1007/s10614-020-10042-0

11. Castagna, F., Centobelli, P., Cerchione, R., Esposito, E., Oropallo, E., & Passaro, R. (2020). Customer knowledge management in SMEs facing digital transformation. *Sustainability*, *12*(9), 3899. https://doi.org/10.3390/su12093899

12. Colli, M., Cavalieri, S., Cimini, C., Madsen, O., & Wæhrens, B. V. (2020). Digital transformation strategies for achieving operational excellence: a cross-country evaluation. *Proceedings of the 53rd Hawaii International Conference on System Sciences*.

13. Collins, P. D., Hage, J., & Hull, F. M. (1988). Organizational and Technological Predictors of Change in Automaticity. *Academy of Management Journal, 31*(3), *512–542.* https://doi.org/10.2307/256458

14. Davis, F. D. (1985). *A Technology Acceptance Model for Empirically testing new end-User Information Systems*: *Theory and Results* (dissertation). Massachusetts Institute of Technology.

15. Davis, K. (2017). An empirical investigation into different stakeholder groups perception of project success. *International Journal of Project Management*, *35*(4), 604–617. https://doi.org/10.1016/j.ijproman.2017.02.004

16. Deloitte Access Economics (2017). *Business impacts of machine learning Sponsored by Google Cloud.* https://www2.deloitte.com/content/dam/Deloitte/tr/Documents/process-and-operations/TG_Google%20Machine%20Learning%20report_Digital%20Final.pdf

17. Dengler, K., & Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change*, *137*(C), 304–316. https://doi.org/10.1016/j.techfore.2018.09.024

18. Doran, G. (1981). There's a S.M.A.R.T. way to write managements's goals and objectives. *Management Review, 70*(11)*,* 35–36. https://community.mis.temple.edu/mis0855002fall2015/files/2015/10/S.M.A.R.T-Way-Management-Review.pdf

19. Drucker, P. F. (1985). *Innovation and Entrepreneurship practice and principles.* Routledge Classics.

20. European Parliament (2020). *Opportunities of Artificial Intelligence.* https://www.europarl.europa.eu/RegData/etudes/STUD/2020/652713/IPOL_STU(2020)652713_EN.pdf

21. European Commission (2003). Commission recommendation of 6 May, 2003 concerning the definition of micro, small and medium-sized enterprises. *Official Journal of the European Union* (Article 9, Definition of micro, small and medium-sized enterprises adopted by the Commission).

22. European Economic and Social Committee (2021). *Boosting the use of Artificial Intelligence in Europe's micro, small and medium-sized Enterprises*. https://www.eesc.europa.eu/sites/default/files/files/qe-02-21-953-en-n.pdf

23. European Parliament (2021). *Artificial Intelligence Act; Briefing on Initial Appraisal of a European Commission Impact Assessment.* https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/694212/EPRS_BRI(2021)694212_EN.pdf

24. European Parliament (2023). *Small and Medium-sized Enterprises, Fact Sheets on the European Union 2023.* https://www.europarl.europa.eu/erpl-app-public/factsheets/pdf/en/FTU_2.4.2.pdf

25. Feurer, M., Eggensperger, K., Falkner, S., Lindauer, M., & Hutter, F. (2018). Practical Automated Machine Learning for the AutoML Challenge 2018. *International Workshop on Automatic Machine Learning at ICML,* 1189–1232. https://www.tnt.uni-hannover.de/papers/data/1407/18-AUTOML-AutoChallenge.pdf

26. Gherghina, Ștefan C., Botezatu, M. A., Hosszu, A., & Simionescu, L. N. (2020). Small and Medium-Sized Enterprises (SMEs): The Engine of Economic Growth through Investments and Innovation. *Sustainability*, *12*(1), 347. https://doi.org/10.3390/su12010347

27. Gierlich, M., Schüritz, R., Volkwein, M., Hess, T., Xu, D., Jiang, J., & Kim, H. W. (2019). SMEs' Approaches for Digitalization in Platform Ecosystems. *PACIS Proceedings*, 190. https://aisel.aisnet.org/pacis2019/190

28. Haenlein, M. & Kaplan, A., (2019). A Brief History of Artificial Intelligence: On the Past, present, and Future of Artificial Intelligence. *California Management review 61* (4), 5–14. https://doi.org/10.1177/0008125619864925

29. Hamal, S., & Senvar, Ö. (2021). Comparing performances and effectiveness of machine learning classifiers in detecting financial accounting fraud for Turkish SMEs. *International Journal of Computational Intelligence Systems*, *14*(1), 769–782. https://doi.org/10.2991/ijcis.d.210203.007

30. Harvard University (2017). *The History of Artificial Intelligence.* https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/

31. Hussain, J. (2019). *Deep Learning* Black *Box Problem* (independent thesis). Uppsala University*,* Department of Informatics and Media.

32. Koga, B., Vanderweide, T., Zhao, X., & Zhang, X. (2021). BlinkNet: Software-Defined Deep Learning Analytics with Bounded Resources. *3rd Workshop on Accelerated Machine Learning (AccML) Co-located with the HiPEAC 2021 Conference.* https://par.nsf.gov/biblio/10290174.

33. Kuhl, N., Goutier, M., Hirt, R., & Satzger, G. (2020). Machine Learning in Artificial Intelligence: Towards a Common Understanding. *ArXiv (Cornell University).* https://doi.org/10.48550/arXiv.2004.04686

34. Li, L., Su, F., Zhang, W., & Mao, J. (2017). Digital Transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal, 28*(6), 1129–1157. https://doi.org/10.1111/isj.12153

35. Lieberman, M., & Montgomery, D. (1988). First-mover advantages. *Strategic Management Journal, 19*(12), 1111–1125. http://dx.doi.org/10.1002/smj.4250090706

36. Mahesh, B. (2019). Machine Learning Algorithms-A review. *ResearchGate*, *9*(1). https://www.researchgate.net/publication/344717762_Machine_Learning_Algorithms_-A_Review

37. Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *Journal of Business Research*, *123*(C), 642–656. https://doi.org/10.1016/j.jbusres.2020.10.033

38. Matt, D. T., & Rauch, E. (2020). SME 4.0: The role of small-and medium-sized enterprises in the digital transformation. *Industry 4.0 for SMEs*, 3–36. https://doi.org/10.1007/978-3-030-25425-4_1

39. McGrath, K., & Maiye, A. (2010). The role of institutions in ICT innovation: Learning from interventions in a Nigerian e-government initiative. *Information Technology for Development ,16(4),* 260–278. https://doi.org/10.1080/02681102.2010.498408

40. McKinsey (2018). *AI adoption advances, but foundational barriers remain*. McKinsey. https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain

41. McKinsey (2018). *Notes from the AI frontier: Applications and value of deep learning.* https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-applications-and-value-of-deep-learning

42. McKinsey (2019). *How artificial intelligence will transform Nordic businesses.* https://www.mckinsey.com/featured-insights/artificial-intelligence/how-artificial-intelligence-will-transform-nordic-businesses

43. OECD, (2021). The Digital Transformation of SMEs. In *OECD Studies on SMEs and Entrepreneurship.* https://www.oecd.org/industry/smes/PH-SME-Digitalisation-final.pdf

44. Pelletier, C., & Cloutier, L. M. (2019). Challenges of Digital Transformation in SMEs: Exploration of IT-related Perceptions in the Service Ecosystem. *Proceedings of the 52nd Hawaii international conference on system sciences*. http://hdl.handle.net/10125/59934

45. Peppard, J., Ward, J. & Daniel, E. (2007). Managing the realization of business benefits from IT investments. *MIS Quarterly Executive, 6*(1). https://aisel.aisnet.org/misqe/vol6/iss1/3

46. Radziwon, A., & Bogers, M. (2019). Open innovation in SMEs: Exploring inter-organizational relationships in an ecosystem. *Technological Forecasting and Social Change, 146,* 573-587. https://doi.org/10.1016/j.techfore.2018.04.021

47. Rassool, R., & Dissanayake, R. (2019). Digital transformation for small and medium enterprises (SMEs): With special focus on Sri Lankan context as an emerging economy.

International Journal of Business and Management Review, 7(4), 59–76. https://www.researchgate.net/publication/335028085
48. Regulation (EU) 2016/679 , General Data Protection Regulation GDPR (Article 1, Directive 95/46/EC).
49. Ronnberg, H., & Areback, J. (2020). *Initiating transformation towards AI in SMEs* (dissertation). Lulea University of Technology.
50. Rowe, F. (2014). What Literature Review is not: Diversity, Boundaries and Recommendations. *European Journal of Information Systems ,21*(3)*,* 241–255. https://doi.org/10.1057/ejis.2014.7
51. Schwertner, K. (2017). Digital transformation of business. *Trakia Journal of Sciences*, *15*(1), 388-393. http://tru.uni-sz.bg/tsj/TJS_Suppl.1_Vol.15_2017/65.pdf
52. Scime, L., & Beuth, J. (2019). Using machine learning to identify in-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process. *Additive Manufacturing*, *25*, 151–165.https://doi.org/10.1016/j.addma.2018.11.010
53. Sessions, V., & Valtorta, M. (2006). The Effects of Data Quality on Machine Learning Algorithms. *Proceedings of the 11th International Conference on Information Quality, MIT, Cambridge, MA, USA, November 10–12.* https://www.researchgate.net/publication/220918649_The_Effects_of_Data_Quality_on_ Machine_Learning_Algorithms
54. Soni, N., Khular Sharma, E., Singb, N. & Kapoor, A. (2020). Artificial Intelligence in Business: From Research and Innovation to Market Deployment. *Procedia Computer Science 167 (*1*),* 2200–2210. https://doi.org/10.1016/j.procs.2020.03.272
55. Stahl, B. (2021). Ethical Issues of AI. In *Artificial Intelligence for a Better Future*, *An Ecosystem Perspective on the Ethics of AI and Emerging Digital Technologies,* (pp. 35–53). Springer, Cham. https://doi.org/10.1007/978-3-030-69978-9_4
56. Szczepanski, M. (2017). Helping European SMEs to grow; Start-up and scale-up initiatives for business ventures in the EU. *European Parliamentary Research Service*. https://euagenda.eu/upload/publications/untitled-108178-ea.pdf
57. Taneja, S., Golden Pryor, M., & Hayek, M. (2016). Leaping innovation barriers to small business longevity. *Journal of Business Strategy 37(3),* 44–51. https://doi.org/10.1108/JBS-12-2014-0145
58. Thiée, L. W. (2021). A systematic literature review of machine learning canvases. *Society for Informatics,* 1221–1235. https://dl.gi.de/items/00eeb297-d331-4d6d-9e06-6cd87d39bd39
59. Tornatzky, L., Fleischer, M., Chakrabarti, A. (1990). *The Process of Technological Innovation*. Lexington Books.
60. Trenkle, J. (2019). Survival in the digital age–A framework for formulating a Digital Transformation Strategy in SME. *Proceedings of The 19th International Conference on Electronic Business,* 428–442. https://iceb.johogo.com/proceedings/2019/ICEB_2019_paper_14_full.pdf
61. Turing, A. M. (1950). Computing Machinery and Intelligence. In *Mind, Vol. 49,* (pp. 433–460). Oxford University Press. http://www.jstor.org/stable/2251299

62. Tushman, M. & Nadler, D. (1986). Organizing for Innovation. *California Management Review, 28,* 74–92. http://dx.doi.org/10.2307/41165203

63. Ulrich, P., Frank, V., & Kratt, M. (2021). Adoption of Artificial Intelligence technologies in German SMEs—Results from an empirical study. In Virtus Interpress. *Corporate governance: A search for emerging trends in the pandemic times* , (pp. 76–84). World Scientific.

64. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

65. Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems, 28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

66. Villani, C., Bonnet, Y., & Rondepierre, B. (2018). *For a meaningful artificial intelligence: Towards a French and European strategy.* Conseil national du numérique.

67. Wamba-Taguimdje, S., Wamba, S., Robert, K., & Tchatchouang, C. (2020). Influence of Artificial Intelligence (AI) on Firm Performance: The Business Value of AI-based Transformation projects. *Business Process Management Journal, 6*(7), *1893-1924.* https://doi.org/10.1108/BPMJ-10-2019-0411

68. Wehle, H. (2017). *Machine Learning, Deep Learning, and AI; What's the Difference?*ResearchGate.
https://www.researchgate.net/publication/318900216_Machine_Learning_Deep_Learning_and_AI_What's_the_Difference

69. Weizenbaum, J. (1983). ELIZA - A Computer Program for the Study of Natural Language Communication between Man and Machine. *Communications of the ACM, 9*(36), 36–45. https://doi.org/10.1145/357980.357991

APPENDIX

Appendix 1: Povzetek (Summary in Slovene language)

Mikro, mala in srednje velika podjetja predstavljajo 99 % vseh podjetij v Evropski Uniji (EU), zagotavljajo dve tretjini delovnih mest v zasebnem sektorju in ustvarijo več kot polovico skupne dodane vrednosti podjetij v EU (Evropska parlament, 2003). S pojavom novih tehnologij lahko napredek na področju umetne inteligence in strojnega učenja bistveno izboljša uspešnost malih in srednje velikih podjetij ter jim ponudi nove poslovne priložnosti (Wamba-Taguimdje, et al., 2020). Poleg tega, Evropski parlament predvideva da bo uvedba umetne inteligence prinesla številne pozitivne učinke za posamezna podjetja ter na družbeni in makroekonomski ravni (Evropski parlament, 2021). Vendar kljub potencialnim koristim umetne inteligence in strojnega učenja njuno sprejemanje in uporaba ostajata izziv. Glede na študijo Evropskega ekonomsko-socialnega odbora (2021) mala in srednje velika podjetja težje izkoristijo to tehnologijo. Številna mala in srednje velika podjetja težko opredelijo primere uporabe, le deloma razumejo vplive tehnologije strojnega učenje in terminologijo, ne razumejo podatkovnih zahtev, potrebnih za učenje algoritma, in nimajo znanja za izdelavo strategije in načrta za uporabo strojnega učenja (Bauer, van Dinther, & Kiefer, 2020). Zato je eden od ciljev tega magistrskega dela seznaniti zainteresirane strani s terminologijo umetne inteligence in strojnega učenja, njunimi vplivi in opozoriti na morebitne izzive pri sprejemanju. Namen tega magistrskega dela je malim in srednje velikim podjetjem zagotoviti potrebno znanje, ki jim bo pomagalo bolje razumeti, kako uspešno uvesti strojno učenje v svojo organizacijo. Poleg tega navajamo zamisli, koncepte in metode, s katerimi bomo MSP pripravili na lažji začetek njihove poti digitalizacije in uvajanja strojnega učenja. Cilj je MSP zagotoviti okvir, ki bo vodstvenim delavcem pomagal bolje razumeti, kaj je potrebno za uspešno izvajanje strojnega učenja, kako oceniti izvedljivost in tveganje njihovega posebnega primera uporabe ter kako določiti obseg projekta za enostavno komercializacijo. Naša raziskava se osredotoča na trenutno stanje strojnega učenja kot oblike umetne inteligence in je izvedena v obliki pristopa sistematičnega preučevanja literature, analize več primerov in metode anketiranja. Glavne ugotovitve in rezultate naše raziskave smo umestili v konceptualni strateški okvir za izvajanje strojnega učenja v malih in srednje velikih podjetjih. Okvir temelji na teorijah in modelih ovir in gonil za sprejemanje tehnologije, ključnih ugotovitvah iz analize literature z analizo več primerov ter rezultatih ankete med malimi in srednje velikimi podjetji v Sloveniji. Naše ključne ugotovitve so bile, da je za MSP na splošno težko razumeti primere uporabe in aplikacije strojnega učenje za njihovo organizacijo, oceniti notranje strokovno znanje, zagotoviti zavezanost najvišjega vodstva, oceniti združljivost z notranjo informacijsko infrastrukturo in zagotoviti potreben proračun. Poleg tega smo ugotovili, da imajo lahko težave s podatki pomembno vlogo kot ovira pri uvajanju tehnologije. Poleg tega smo ugotovili, da imajo lahko dejavniki, ki jih opredeljujejo modeli TAM, UTAUT in TOE za sprejemanje tehnologije pomembno vlogo pri uspešnem uvajanju tehnologije. Zato naš okvir vključuje zamisli, koncepte in metode, ki MSP pomagajo opredeliti primer uporabe in aplikacijo strojnega učenja, oceniti notranje tehnično strokovno znanje in izkušnje ter zagotoviti podporo deležnikov, dostopati do tehnične izvedljivosti in podatkov, opredeliti časovni razpored in proračun ter spodbujati notranje komuniciranje in inovacije. Naša raziskava prispeva k razmeroma slabo raziskanemu področju uvajanja strojnega učenja v MSP in pomaga premostiti vrzel med teoretičnim razumevanjem strojnega učenja in njegovim praktičnim izvajanjem v MSP. Predlagani okvir je vodilo za MSP pri krmarjenju po zapletenem uvajanju in uporabi strojnega učenja ter zagotavlja praktična spoznanja za MSP in oblikovalce politik. Ena od omejitev naše raziskave je, da se osredotoča predvsem na tehnologijo strojnega učenja. Ne pokrivamo obsežno drugih oblik umetne inteligence ali nastajajočih tehnologij. Poleg tega se raziskava ne poglablja v tehnično zapletenost razvoja in uporabe strojnega učenja. Nazadnje, anketna raziskava je bila izvedena izključno na slovenskih MSP, zaradi česar morda ni mogoče v celoti posplošiti na MSP iz drugih držav in regij.