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CHALLENGES OF ADOPTING AI IN ESTONIAN COMPANIES IN MANUFACTURING AND RETAIL FIELDS

Master's thesis

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TABLE OF CONTENTS

ABSTRACT

This thesis researches the experiences of Estonian companies in the Manufacturing and Retail fields with Artificial Intelligence (AI), aiming to identify the obstacles and challenges they face in implementing AI technologies and proposing solutions based on existing cutting-edge best practices and expert recommendations. To achieve this, a qualitative research method using a hybrid approach was applied. Semi-structured interviews were conducted with 11 C-level leaders or AI initiative leaders from selected companies.

The findings reveal that the primary challenges Estonian companies face during AI adoption include a low level of digitalization, lack of a data-driven mindset, high costs (mainly because of the need for integration with existing systems), and data-related issues, in addition to the challenge of the lack of leadership support, and lack of AI expertise and competencies. These challenges are consistent with existing literature, but the Estonian context highlights the importance of organizational culture and leadership support, and the challenge of integrating AI solutions into an organization's existing ecosystem. To overcome these challenges, Estonian companies can leverage foundation models and employ less data-intensive methods like few-shot learning, off-the-shelf AI solutions, and by hiring in-house high-level AI expert who can lead the AI initiative.

The research contributes to the understanding of AI implementation in the Estonian context, providing valuable insights for Estonian companies to adopt AI and remain competitive and innovative. To validate the proposed solutions and demonstrate AI capabilities, an interactive AI solution was developed, utilizing the knowledge derived from this research, to assist leaders in implementing AI and overcoming challenges. Future research directions include exploring the pitfalls of foundational models in terms of causality and explainability and examining the ethical implications of AI adoption and the role of regulatory frameworks in ensuring responsible and fair AI use.

Keywords: Artificial Intelligence, AI adoption, Challenges of AI adoption, Estonian companies, AI in Estonian Companies, AI in Manufacturing, AI in Retail, AI Strategy

Glossary

AI	Artificial Intelligence
ML	Machine Learning
MLOps	Machine Learning Operations
CRISP-DM	Cross-Industry Standard Process for Data Mining
ROI	Return On Investment
GPT	Generative Pre-trained Transformer
NLP	Natural Language Processing
R&D	Research & Development

INTRODUCTION

The pandemic has rapidly accelerated tech adoption in businesses, and almost every business is basically a technology business now: every corner resto provides a possibility to order food using local food delivery apps such as Bolt Food or Wolt; every small shop has its own webpage with a possibility to shop online, and even entertainment businesses have understood how crucial to have a presence online (e.g. land base casinos created their own online casinos; digital music festivals have been introduced during the pandemic).

All this creates enormous new possibilities where businesses could apply Artificial Intelligence. According to recent IBM research (May 2022), the global AI adoption rate recently grew rapidly and now is 35%, and an additional 42% have reported that they are already exploring AI. We see, that application of AI and Machine Learning "provides new benefits and efficiencies to organizations through new automation capabilities, greater ease of use and accessibility, and a wider variety of well-established use cases" (IBM in partnership with Morning Consult, 2022). According to (Europe’s Digital Decade: digital targets for 2030, 2022) Europe’s Digital target for 2030 is to have 75% of EU companies using Cloud Computing services, Big data and Artificial Intelligence.

Estonia is a very innovative country with its digital society, e-residency, etc., but, for some reason, Estonian companies (except for Unicorns, such as Bolt, Wise, Veriff, etc.) use AI/ML in a very limited way or do not use it at all. "The startup sector has been quick to adopt AI, but more traditional sectors have limited use about how to use it, or to employ it in their operations." (e-Estonia, 2022). According to Chief Data Officer of Estonian Government, usage of Artificial Intelligence across Estonian companies is very low, especially in Manufacturing, it is about 4%.

The problem of the thesis is the limited usage of AI/ML in Estonian companies in the Manufacturing and Retail fields, which negatively affects competitiveness and hinders innovation. The goal is to identify which obstacles and challenges they have with implementing AI in their businesses, and propose solutions to these challenges based on previous experiences of other companies, existing cutting-edge best practices and expert recommendations.

The research questions of this thesis are:

1) What kind of experiences do Estonian companies have with AI/ML?
2) What are the main challenges in implementing AI/ML?
3) How can Estonian companies overcome barriers to adopt AI?

To get an overview of what situation in Estonian companies with AI, the author has done research by conducting semi-structured interviews with C-level and AI initiative leaders of Estonian companies in the Manufacturing and Retail fields about what experiences and challenges they have had with AI, which provided rich insights into the participants' perspectives and experiences regarding the challenges of AI adoption in their companies.

To provide guidelines for successful AI adoption, this master's thesis theoretical framework is combined from state-of-the-art research papers, the latest best practices from books by AI experts, articles, and documents from AI domain practitioners, like Accenture, Deloitte, IBM, and others. Theoretical framework reviews implementing AI solutions, and researches what challenges companies usually have during implementing AI in their businesses, and what are possible solutions to these challenges.

The first chapter of the thesis provides a theoretical framework for the following research. The second chapter focuses on the methodology of the study and the third chapter provides the results and analysis of the qualitative research: it focuses on identifying the main challenges and obstacles of Estonian companies with implementing AI and suggests guidelines for successful AI adoption for Estonian companies.

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1. THEORETICAL FRAMEWORK

This master's thesis' theoretical part reviews the main challenges and difficulties companies face when attempting to implement and adopt Artificial Intelligence. It also reviews cutting-edge solutions to these challenges provided by researchers, AI field experts, and companies that successfully use AI in their businesses. The theoretical part also gives a very brief overview (since it is not the focus of this thesis) of what benefits companies could have by start using AI in their business processes.

1.1. Business needs of using AI/ML

As the manufacturing landscape continues to evolve, Artificial Intelligence is a crucial enabler of industry transformation, which drives business innovation, operational excellence, and workforce enhancement (World Economic Forum, 2022). By harnessing the potential of AI and machine learning (ML) technologies, manufacturers can unlock invaluable insights from vast amounts of data, and give the possibility for the development of smart and sustainable production ecosystems that redefine industry standards (Simone *et al.*, 2023). Moreover, AI could not only enable manufacturers to optimize material and energy usage, but also can significantly increase operational performance, sustainability, and workforce augmentation across various aspects of the industry, including demand-side management, predictive maintenance, and supply chain management (World Economic Forum, 2022).

Furthermore, AI and ML technologies transcend the boundaries of manufacturing, offering valuable applications in such fields as marketing, logistics, material handling, and even business assistance and decision-making (Simone *et al.*, 2023).

To illustrate the potential and practicability of AI in manufacturing, let's review a few real-life applications in an example of Manufacturing companies from Turkey and Canada:

Table 1 A collection of AI in manufacturing use cases, composed by the author

Use Case	Company	AI application	Impact
Predictive maintenance	Sensemore, Türkiye	detecting the machinery failure mode by collecting the continuous vibration data through fault estimation, early warning and maintenance planning with AI on fans and electric motors	– downtime reduced by 90% – maintenance cost reduced by 25% – machine life increased by 20% – operation productivity improved by 25%
Future demand and price forecasting	SmartOpt, Türkiye	forecasting future demand for products, services and raw material prices by automatically training AI model and tuning the model parameters automatically without user input	– forecasting accuracies for the next 6 months reached 85-99%
Warranty and service management	Tofaş, Türkiye	component-based prediction granularity as the components of the vehicles affected by different factors to dwetermine warranty expenditure of the coming years for the sold vehicles	– prediction accuracy increased from 70% (manual prediction) to 95%, which resulted in reduction of reserve fund by 10% per year
Energy optimization	Canvass AI, Canada	analysing thermal efficiencies, ambient conditions to control real-time natural gas optimization and consumption targets across turbines; electricity production targets and steam demand from downstream boilers	– 5.09% gain in thermal efficiency, which translates to 9M lbs/yr and energy cost savings achieved – CO2 emissions reduced – overall equipment effectiveness improved
Line balancing	Khenda, Türkiye	AI-based video analytics to label the actions of manual tasks to eliminate operator-related errors and improve manual manufacturing processes and optimize line balancing	– productivity increased by 25% – by increasing quality and efficiency, error costs eliminated and waste and defective products avoided

Source: World Economic Forum, 2022

1.2. Challenges of applying AI/ML

The adoption of artificial intelligence (AI) has become an essential strategic direction for companies seeking to thrive in the rapidly evolving digital landscape. However, organizations have numerous challenges that must be overcomed in order to take full advantage of AI, making its integration into business processes not an easy task.

This chapter reviews the common challenges identified in the latest research literature exploring the challenges and difficulties companies face when attempting to adopt AI technology. These challenges span four main areas: limited AI skills, expertise, or knowledge; lack of data and applicability of available data; difficulties in integrating AI solutions into an organization's existing ecosystem; and organizational culture, vision, and leadership support.

By understanding these challenges, businesses can better plan and overcome the difficulties and challenges companies may face during the process of AI adoption, and unlock the transformative power of this technology.

1.2.1. Limited AI skills, expertise or knowledge

Several works (Fink *et al.*, 2022; Gavrilova & Gurvits-Suits, 2020; Xu, 2022; Schmitt, 2023; Merhi & Harfouche, 2023) that review challenges regarding implementing Artificial Intelligence mention the issue of lack of needed knowledge and/or expertise in the AI/ML domain.

Let's review how AI expertise influences companies from the top-down leadership perspective.
According to (Mittal & Davenport, 2023), a leader of an AI-driven organization should have at least high-level expertise in AI, which is a huge obstacle for many companies adopting AI. Although there are many different types of AI leadership, still they all share the ability to understand what AI can do in general, how it might help their organizations in particular, and what potential consequences it may have for strategies, business models, processes, and people. They can only plan effective leadership with that understanding (Mittal & Davenport, 2023; Hoffmann *et al.*, 2022).

Even if there is a good understanding of what AI can do on top-level leadership, and support of AI initiatives in the company there still could be a bottleneck due to a lack of knowledge on how to implement needed AI solutions, and how to integrate them into existing products. Instead of concentrating on the maximum influence on business operations, organizations frequently choose AI initiatives based on current technical capabilities. This is the reason why frequently AI solutions do not realize their full potential in businesses not because it is not technically possible to solve some impactful business problem, but because of a lack of technical expertise (Fink *et al.*, 2022).

Another research paper, that was concentrated on Estonian accounting businesses has found that the main problem with using AI in their processes is that employees have a limited understanding of artificial intelligence, knowing its general meaning but knowing little or nothing about its fundamentals or the huge potential of AI applications. Lack of knowledge makes them feel that AI adoption and implementation is complex, time and resource-consuming (Gavrilova & Gurvits-Suits, 2020).

1.2.2. Lack of Data and applicability of available data

Data is the fuel for AI solutions as it provides the foundation for most part of machine learning algorithms, making it crucial in the implementation and adoption of AI. AI solutions use existing data to create new knowledge platforms, create new products, processes, and practices, and also improve existing ML models. And if organizations do not have access to the high-quality datasets necessary for it, they will not be able to take full advantage of the opportunities the AI provides (Moradi & Dass, 2022). Also, the quality of data used for AI is crucial for the adoption of AI and its integration into operational systems (Merhi & Harfouche, 2023).

In most organizations for most use cases, there are no big datasets “cleansed” and ready for use by AI solutions. In contrast, noisy, sparse, or missing data, mostly semi- or unstructured data — remains the biggest obstacle to implementing AI solutions in the majority of organizations. Moreover, often data is locked in legacy systems that are typically isolated, and do not conform to a unified structure, making it challenging, if not impossible, to get multiple types of data to merge together (Daugherty & Wilson, 2022; Silva & Alahakoon, 2022).

There is one more big challenge a lot of organizations are faced with how some specific AI solution deals with situations that happen uncommonly, or what if some rare cases were not represented in used datasets during training and testing AI solutions (Fink *et al.*, 2022; Daugherty & Wilson, 2022; Xu, 2022). The same challenge applies when some specific use case requires ML model with high accuracy (close to 99%) since the better ML model is, the more difficult it is to find reliable datasets of novel edge cases (Daugherty & Wilson, 2022).

In some cases, an absence of enough data leads to inter-organizational data sharing, which in turn introduces new challenges such as data sharing concerns, insufficient data understanding, and incorrect interpretation of data (Neumann *et al*., 2022). These challenges may also be exacerbated by the need to navigate varying data privacy regulations, establish trust among collaborating organizations, and develop standardized data formats and protocols for seamless data exchange.

Some organizations acquire the necessary data for their AI solutions from third-party data providers, such as data markets, to complement their existing datasets or build AI solutions totally relying on acquired data. However, this approach not only poses risks related to data quality but also introduces security challenges, such as poisoning attacks and backdoor attacks, that organizations need to overcome and mitigate to ensure the safety and effectiveness of their AI systems (Silva & Alahakoon, 2022).

Some organizations have also organizational, and regulatory challenges related to data, such as how to ensure that data is stored in a secure place, and protected since data breaches can cause significant financial and reputational damage to organizations. Also, how and what data could be shared across the organization, how to regulate access levels do different data types in the organization, etc. (Neumann *et al.*, 2022; World Economic Forum, 2022).

The latter type of challenges with data brings us to the next section of challenges when adopting AI in organizations: integrating AI solutions into the existing ecosystem of the organization.

1.2.3. Difficult to integrate AI solutions to organization's existing ecosystem

According to (Mittal & Davenport, 2023) one of the top three challenges with AI is integrating AI into the company's existing ecosystem (integrating existing IT platforms, data handling, organization's roles, and business processes). Besides development, the adoption of AI solutions usually involves many other activities, such as changing business processes, personnel training, and integrating with current systems. Also, one of the key challenges of adopting AI is integrating AI solutions with the existing production environment. As a result, "only 31 percent [of companies] said their company had actively deployed AI as part of its business operations." (Mittal & Davenport, 2023).

The need for innovation will increase as AI becomes more essential to businesses of all kinds. But, before start implementing AI solutions, organizations need to implement supporting technologies such as data lakes, data warehouse, and cloud services. And for some organizations, it could mean significant changes not only for IT systems but for daily operations as well.

Also, some organizations need IT infrastructure and legacy systems modernization, since data handling along with other AI technologies is simply too much for outdated IT infrastructure and legacy systems to handle. Yet, the cloud offers access to nearly limitless processing capacity as well as the elasticity that makes AI solutions more affordable and agile from a strategic standpoint (Merhi & Harfouche, 2023; Daugherty & Wilson, 2022).

One more major challenge during AI adoption in many organizations is unclear responsibilities around the productionalization of an AI solution. Although they are often ignored, the responsibilities and expertise needed for AI solution integration into an existing environment, and for ML model deployment are essential for the success of AI initiatives. Deployment is often thought of as being someone else's responsibility, yet it is frequently unclear whose (Mittal & Davenport, 2023; Davenport & Malone, 2021). Frequently organizations find themselves in such a situation when they have put investments into AI solution development, but Return On Investment (ROI) is zero since nobody knows how to use it in a production environment. This creates a negative experience and a wrong impression of AI among the top management of the organization, which brings us to the next types of challenges: organisational culture, vision, and leadership support.

1.2.4. Organisational culture, vision and leadership support

Multiple research papers (Schmitt, 2023; Merhi & Harfouche, 2023; Neumann *et al.*, 2022; Neumann *et al.*, 2022; Mittal & Davenport, 2023; Kreuzberger *et al.*, 2022) have noted, that top management and a supportive climate in an organization are crucial factors for the successful adoption of AI. According to (Merhi & Harfouche, 2023), top management support, organizational culture, and vision & strategy is the second important category of challenges during adopting AI, which makes up 36% of the total weight. A study in (Hradecky *et al.*, 2022) found that an organization without AI solutions blames its CEO's lack of vision and plans for using AI.

Top management is the one who define organizational culture, company vision & strategy. In turn, company vision and strategy show employees the direction to move, the goals, the means, and a mindset. Also, support from top management can affect how much employees believe in AI and lessen their resistance to change (Merhi & Harfouche, 2023).

Moreover, AI adoption often needs significant changes in organizational structure, a cultural shift for employees, and substantial investments to transform an existing organizational ecosystem, as discussed earlier, into one that is compatible with AI-enabled solutions. This comprehensive transformation process may involve upskilling and reskilling the workforce, redefining business processes, fostering a culture of innovation and collaboration, and embracing new technology platforms to fully harness the potential of AI across various aspects of the organization.

Organizational culture also plays a fundamental role in AI implementation, since the culture is the one that enables innovations in an organization: it empowers employees to question existing solutions, think differently, and bring new technologies, such as AI. Companies with cultures that are open to adopting new technologies and procedures will probably use them in production systems and be successful with AI (Neumann *et al.*, 2022). Organizational culture also defines mindset, and attitude when designing and developing products. Many organizations struggle to implement AI solutions because they have a more model-driven approach when the main focus is on developing high-accurate ML models when developing AI solution. To effectively develop and operate AI/ML products, a shift in culture is required, moving from a model-driven approach to a product-focused perspective (Kreuzberger *et al.*, 2022).

To sum up all challenges in this category, the success of the adoption of AI depends on multiple parties and requires coordinated and persistent efforts across various organizational units, stakeholders, and probably external parties as well. Therefore in order to succeed in AI adoption, there is a need for strong support of AI initiatives by the company vision, values, and top leaders of the organization.

1.3. Possible solutions for described challenges

The author has found, that there are only a few research studies, that are concentrated not on challenges, but on practical solutions how to overcome these challenges. Nevertheless, to gain more knowledge in this area, the search included non-peer-reviewed literature as well: books (Daugherty & Wilson, 2022; Davenport & Mittal, 2023), articles, and documents from domain experts, like Accenture, Deloitte, IBM, Huggingface, TMForum, etc.

1.3.1. AI Expertise and competences

The works (Daugherty & Wilson, 2022; Davenport & Mittal, 2023; Perry, 2019) suggest that companies can solve the lack of AI expertise in different ways. One approach is to reskill and upskill employees to help develop, interpret, and improve AI systems, as identified by (Davenport & Mittal, 2023). However, (Perry, 2019) highlights that there are quite a lot of challenges in hiring and retaining data scientists, analysts, and engineers due to competition and confusion about job roles.

(Daugherty & Wilson, 2022) suggest to solve the lack of AI expertise by empowering non-data scientists, such as medical coders, to become AI instructors, organizations can scale the vast reserves of untapped expertise present at every level within their company. Rather than being merely passive consumers of AI outputs, these individuals become AI creators. This approach goes beyond deriving knowledge solely from data, as it fully utilizes their specialized expertise.

Overall, the papers suggest that companies can address the lack of AI expertise through a combination of tools, reskilling/upskilling, and involving non-AI experts in the Machine Learning Lifecycle loop to participate in training, AI solution fine-tuning, and testing. Additionally, this approach can help to bridge the gap between technical and non-technical teams, ensuring that the AI initiatives align with the organization's overall goals and objectives, and contribute to creating a more AI-aware and data-driven culture within the company.

1.3.2. Organisational Culture and AI Strategy

Every organization is looking for a common approach, that specifies how to implement AI and guarantee some return on investment. The adoption of AI requires coordinated and lasting efforts across multiple organizational units or with 3rd parties, it may also need significant changes in organizational structure, strategic direction, culture, knowledge, and others, emphasizing the need for a theoretical framework that takes organizational and environmental factors into account in addition to technological ones (Neumann *et al*., 2022; World Economic Forum, 2022).

As was already discussed earlier, organizational vision and strategy must support and encourage bringing new technologies, such as AI. An organization's AI strategy can help with that. AI strategy provides a compelling story that communicates the benefits of AI for the whole organization. Leaders of the company must provide a vision that rallies everyone around a common goal and reassures employees that AI will enhance their roles rather than diminish or eliminate them. Moreover, developing a comprehensive Data and AI strategy helps organizations make important choices like where to invest: for example, whether to develop in-house or acquire externally, which platform and tools to use and where to find AI talents and skills: outsource or develop in-house expertise. Also, AI strategy connects ML models and data science to the objectives of the business (Canals & Heukamp, 2020; Fountaine *et al.*, 2019).

For mature organizations, it is unavoidable to have an outdated IT infrastructure and legacy systems that are unable to handle AI solutions. Consider using cloud services instead of on-premise servers, since the cloud offers access to nearly limitless processing capacity as well as the elasticity that makes AI solutions more affordable and agile from a strategic standpoint. In order to succeed in AI adoption, leaders have to ramp up and cloud-enable the boundarylessness, and adaptability by scaling down and digitally decoupling legacy systems (Merhi & Harfouche, 2023; Daugherty & Wilson, 2022).

Organizations adopt AI solutions through either a top-down approach, which involves the initiatives from top leadership, or a bottom-up approach, which is more common and driven by technological needs. In cases where top-level management lacks AI expertise, a bottom-up approach may be the more suitable solution for implementing AI (Neumann *et al.*, 2022). Organizational culture could be one of the enablers for that: there could be systematic hackathons and similar events, that enable its employees to think out-of-the-box and encourage them to try new approaches without being afraid to fail.

One solution for more successful and faster AI adoption could be to create alliances of different organizations to cooperate, in order to share data and create AI solutions together.
Implementing cross-company AI in a decentralized manner could provide significant benefits for industrial ecosystems. This could create new business models, such as AI-as-a-service offered by

third-party companies. One approach is to implement cross-company AI technologies that can access data from a large sample of companies. This would allow for robust inference and the creation of large-scale representative datasets. While data sharing is a potential solution, many companies are reluctant to share data directly due to confidentiality and risk concerns (Fink *et al.*, 2022).

1.3.3. Solving Data Availability and Quality

As was already mentioned earlier, data is one of the key components for AI solutions, making it crucial in the implementation and adoption of AI. AI solutions use existing data to create new knowledge platforms, create new products, processes, and practices, and also improve existing ML models. And if organizations do not have access to the high-quality datasets necessary for it, they will not be able to take full advantage of the opportunities the AI provides (Moradi & Dass, 2022).

As the solution to one of the main challenges when data is isolated and locked in legacy systems where each component has its own data structure which, in turn, adds additional complexity of mapping data from different sources, and is not ready to be used by AI, is to design and create a centralized data repository across the whole organization, such as a data warehouse, data lake, or data lakehouse, that focuses on centralizing data access, ownership, stewardship, metadata, data ethics, governance, and rules. By establishing a single source of information, companies can operate based on standardized, relevant data across the organization (Silva & Alahakoon, 2022; World Economic Forum, 2022).

A more recent solution to the challenges posed by isolated and differently structured data is to employ AI techniques for creating a meta-layer or unified representation of all the data sources. This can be achieved through advanced methods such as federated learning, representation learning, and latent learning (Silva & Alahakoon, 2022).

As an alternative approach, instead of establishing its own source of data (e.g. data warehouse) and using its own data, there is a widely adopted strategy in, when organization acquires all required data for their AI solutions from data vendors and brokers in aggregated or detailed format. In some cases companies make a one-time purchase for initial training of their Machine Learning model, while others create integrations with such 3rd party data vendors, and constantly improve their AI solutions with the new data (Silva & Alahakoon, 2022).

There is also no need to always use big data to achieve good results with AI. Researchers have made significant progress recently on methods that enable training for new tasks with only a small number of examples (few-shot learning), one example (one-shot learning), or no examples at all (zero-shot learning). These less data-intensive methods could help ensure that AI innovation isn't limited to large technology companies (Daugherty & Wilson, 2022).

Also, one more significant achievement that gives non-large technological organizations great possibilities to catch up in the race of AI adoption is foundation models. According to IBM foundation models will dramatically accelerate AI adoption in organizations (Murphy, 2022).
"Foundation models are large pre-trained language models that have been trained on massive amounts of text data, such as books, articles, and web pages. These models can then be fine-tuned on specific tasks, such as natural language processing (NLP), machine translation, and question-answering, to improve their performance on these tasks. One of the most successful examples of a foundation model is GPT (Generative Pre-trained Transformer), developed by OpenAI. ChatGPT is a specific variant of GPT that has been fine-tuned on conversational tasks, such as chatbot and dialogue generation" - ChatGPT statement about what foundation models are, and how ChatGPT itself is related to it.

Foundation models can be used to build AI solutions without requiring any particular data from the organization, or big data. This makes them very easy to adopt without making large investments to solve data challenges in the organization. Using pre-trained models organizations can use cutting-edge models without having to spend time and money training them from scratch, which significantly reduces computing costs and the organization's carbon footprint (Hugging Face, n.d.).

There is one more alternative approach that could solve the problem many organizations deal with, which is when AI has to deal with situations that happen uncommonly, or when some rare cases are not represented in the organization's datasets (Daugherty & Wilson, 2022; Fink *et al.*, 2022; Xu, 2022). As one of the solutions for this could be inter-organizational data sharing, but it leads to new challenges such as data sharing concerns, insufficient data understanding, and wrong interpretation of data (Neumann *et al.*, 2022). That is the reason why this approach is not very popular.

An alternative approach to this challenge could be Federated learning. Federated learning allows organizations to collaboratively train a shared Machine Learning model without sharing their data, meaning that it eliminates data sharing and security concerns, which appear during inter-organizational data sharing. With federated learning, organizations can leverage the collective power of their data without having to share it (Daugherty & Wilson, 2022; Martineau, 2022).

To sum up, even if an organization has not collected any data from its operations and is not prepared to make significant investments in adopting AI, there are still numerous possibilities for harnessing the power of AI to achieve substantial value for the organization. By leveraging external data sources, utilizing pre-trained models, exploring AI-powered off-the-shelf solutions, or acquiring needed data, organizations still can achieve significant value for the organization by using AI.

1.3.4. Systematic strategic approach to AI adoption: AI project management and ML Operations (MLOps)

As with any other complex project, the implementation and adoption of AI solution needs a systematic approach, a framework, a set of best practices or something similar to help organizations manage the complexity of AI projects, ensure alignment with business objectives, for better risk management, reduce costs, and for increasing the likelihood of delivering a successful AI solution.

Researchers from (Silva & Alahakoon, 2022) have identified that CRISP-DM (Cross-Industry Standard Process for Data Mining), TDSP (Team Data Science Process), and the Microsoft best practices model are the industry and academic standards that could suit contemporary AI projects. While exploring the Case study of one AI Consulting company, researchers from (Vial *et al.*, 2022) have found, that the management of AI projects in the reviewed company is based on components from three methodologies: elements from traditional project management are employed to design and manage the project in broad phases, components from Agile approaches are used to organize the work in iterative, incremental cycles, and elements from AI workflow drive the tasks required for AI model development, training, and fine-tuning.

Another article has confirmed that Organizations need to adopt an agile and experimental mindset toward AI projects, rather than waiting for an idea to be fully developed before deploying it (Fountaine *et al.*, 2019). This approach allows organizations to quickly test and refine their AI initiatives, enabling them to identify potential issues early on, adjust their strategies as needed, and ultimately achieve better outcomes by leveraging the learnings gained from these iterative processes.

In order to cover the AI workflow part mentioned above, and to execute such a customer feedback loop organizations need some tool that would enable them to serve AI solutions to the customers, and would enable them to do it in a systematic and quick way. MLOps addresses the issue of how manual ML processes can be automated and operationalized so that AI solution PoC could be brought into production quickly. "MLOps —precisely addressing the issue of designing and maintaining productive ML. MLOps is aimed at productionizing machine learning systems by bridging the gap between development (Dev) and operations (Ops)" (Kreuzberger *et al.*, 2022).

MLOps practices streamline the process of continuously delivering AI solutions by enhancing them with new data, ultimately generating increased business value. Furthermore, MLOps facilitate the transition from working with isolated ML models to seamless, ongoing delivery of AI capabilities. By adopting an MLOps framework, organizations can more effectively address business challenges using AI solutions and deliver these innovative tools to their customers, while also ensuring easier management and a smoother implementation process (Remes, 2021).

The theoretical framework presented in this study researches several key challenges during AI adoption in organizations: AI expertise and competences, organizational culture and AI strategy, data availability and quality, and a systematic strategic approach to AI adoption. The literature suggests that companies can address the lack of AI expertise through reskilling/upskilling, involving non-AI experts in the Machine Learning Lifecycle loop, and leveraging ready-to-use foundation models. Organizational culture and AI strategy play an essential role in driving AI adoption, with top-down and bottom-up approaches being used depending on the organization's specific situation. Data availability and quality are critical in the implementation of AI solutions, with various strategies such as data warehousing, federated learning, by using foundation models (pre-trained models) as base for company specific AI solutions, and by using less data-intensive methods like few-shot/one-shot learning for fine-tuning ML models, being employed to overcome data challenges.

Despite the insights provided by the existing literature, there remains a research gap in understanding the specific challenges faced by Estonian companies in the manufacturing and retail fields. This study aims to bridge that gap to contribute to the existing body of knowledge on AI implementation and support Estonian companies in adopting AI technology to remain competitive and innovative.

2. RESEARCH DESIGN AND METHODOLOGY

This chapter outlines the methodological approach of this study, including the research design, sampling procedure, data collection, methods of data analysis, and methodological limitations.

2.1. Research method

This study aims to identify which obstacles and challenges do they have with implementing AI to their businesses, and propose solutions to these challenges based on previous experiences of other companies and on state-of-the-art practices. To achieve this, a qualitative research method using a hybrid approach was applied, combining both deductive and inductive coding processes (Grad Coach, 2022). The decision to use a qualitative research method stems from the desire to explore real-life situations and gather a wide spectrum of knowledge and perspectives on the research subject (Õunpuu 2014, 52-53), and since the author also wanted to take into account previous experiences and lessons learned from other companies, and recommendations from the AI field experts, he decided to use a hybrid approach, with a set of a priori codes from the theoretical background (a deductive approach), and then add new findings/codes (an inductive approach) from analyzing gained data from semi-structured interviews (Grad Coach, 2022).

The research design follows the research literature review in order to identify key theories, and challenges related to AI technology adoption, and to find possible solutions to these challenges. Then, analyzing the experiences of 11 C-level leaders or AI initiative leaders of Estonian companies in Manufacturing and Retail fields. To collect data, semi-structured interviews were conducted, which provided rich insights into the participants' perspectives and experiences regarding the challenges of AI adoption in their companies.

2.2. Sampling procedure and sample size

For conducting interviews the author selected the following industries: Manufacturing and Retail. The choice of Manufacturing and Retail fields for this research is based on several factors. Manufacturing was selected due to the significant gap in AI adoption in comparison to other countries, as indicated by Chief Data Officer of Estonian Government, and in comparison to Europe's Digital target for 2030 (~4% vs. 75%). Retail was chosen because of its diverse AI applications, from warehousing to personalized product recommendations in e-commerce. By examining these two industries, the research aims to provide a comprehensive understanding of AI adoption challenges and offer strategies to overcome them across various sectors. Microbusinesses (one- to ten-person companies with small turnover <1 000 000 EUR) were excluded, since in most cases such companies' most of the processes are manual, and they do not have any resources for AI implementation.

The sample has been selected using the following criteria:

1. >10 employees and/or yearly turnover >1 000 000 EUR
2. Head office of the company is based in Estonia;
3. Field of operation: Manufacturing, Retail

The sample consists of 11 C-level or AI initiative leaders of Estonian companies in the manufacturing and retail fields.

The full list of the participating companies and leaders can be found in Appendix 2.

The author has found that manufacturing companies had a lower positive response rate (<50%) to participate in this research compared to retail companies (positive response gave 80% of the potential interviewees). This could suggest that leaders in the manufacturing field may have less lack of awareness or understanding of AI applications and enthusiasm about AI than their retail counterparts. The author recognizes a potential data bias due to this difference in response rates, as the sample may primarily include participants who are positive about AI, with few or no skeptics represented.

2.3. Method and data analysis

In this research, the author used semi-structured interviews for gathering the necessary data that helps to understand what experiences Estonian companies have with AI, how they feel about it, and what obstacles and challenges they have toward AI adoption in the company. As the answers of the respondents lie within personal experience, the authors found that a semi-structured interview would be the best method for gathering data, since it gives freedom for both the interviewee and the researcher, since it gives the possibility to ask additional questions that have not been planned, and as a result to have a more insightful discussion on selected topic (Bryman, 2011).

The interview was based on the interview guide (Appendix 1) that consisted of 4 categories: the current situation with software and data in the company, previous experiences with AI, the main challenges in implementing and adopting AI, the company future in terms of using AI, possible use cases and benefits for the company with AI. The author did not strictly follow the guide but tried to adapt based on the interviewee, his/her background knowledge about AI, and based on the company itself.

For the interviews, the author in total has reached 23 intentionally selected leaders from which 15 agreed to have a discussion about AI experiences in their companies, 4 of them did not give their permission to record the interview, and for this reason, these 4 interviews were not taken into account in this research. Interviews have been conducted in the period February 2023 – May 2023 via online conference calls, phone calls, and in face-to-face meetings. Interviewees were explained the goal of the research and asked for permission to record the interviews. The abbreviation INT is used in the analysis part. For transcription, the author used fully automatic speech recognition technology developed by the Laboratory of Phonetics and Speech Technology of the Institute of Cybernetics at TUT (Alumäe *et al.,* 2018). The transcriptions of the interviews were not altered and presented as-is, and due to the presence of inaccuracies that the author noticed, it was necessary to re-listen to each interview recording 3-4 times to extract valuable information. The findings were then documented in the coding frame file. The findings and the direct quotes were organized in Excel table. Audio recordings and transcriptions will be available only during the defense and exclusively only for the defense committee. After the defense, access to the links will be restricted due to confidentiality reasons. Links to the audio recordings, interview transcriptions, and the Excel table can be found in Appendix 4.

The method of data analysis of the thesis is content analysis, which focuses on an in-depth analysis of the research results. Data analysis is conducted using a hybrid approach, which combined deductive and inductive coding methods (Grad Coach, 2022). This approach began with a set of a priori codes derived from a literature review, experiences from companies successfully use AI technology, insights from AI field experts, and followed by the addition of new codes emerging from the data as the analysis progressed. Descriptive coding is used to label and categorize the interview data, while content analysis is employed to identify patterns, relationships, and themes within the data. This combination of deductive and inductive coding techniques enabled the author to explore both established knowledge and new insights in the context of AI adoption challenges.

3. RESEARCH RESULTS AND DATA ANALYSIS

The study results from the author's semi-structured interviews are presented in this chapter of the thesis. 11 C-level leaders and leaders that are related to AI activity in the company, took part in the study through one-on-one interviews: face-to-face meetings, virtual meetings through Teams or Google Meet, and phone calls.

As this thesis is looking for insights into the challenges and obstacles that companies have during trying to adopt AI technology the questions were asked according to the interview guide. The results of the interviews are presented in coded formation: INT1, INT2, INT3, etc.
An analysis is done with the focus on identifying the reasons why companies do not implement AI technology in their processes, on key challenges of AI adoption, and the differences between those companies that use AI technology and those that do not.

The following section is divided into four subchapters: where chapter 3.1 identifies the overall feeling about Artificial Intelligence of Estonian leaders in the Manufacturing and Retail fields and their experiences with AI; 3.2 focuses on identifying the main challenges and obstacles of Estonian companies with implementing AI in their businesses; chapters 3.3 and 3.4 focus on helping Estonian companies with adopting AI: 3.3 covers the needed Company mindset, culture, and adoption approach, and 3.4 proposes solutions to the main challenges based on previous experiences of different companies and on state-of-the-art practices.

3.1. Experiences of Estonian companies with AI

We are currently living in a golden age of technological innovations, where technology enables businesses to create new business models, and some traditional business models are becoming obsolete and being replaced with new ones. This revolution has led to the reinvention of various industries, such as Apple's iPhone redefining communication, Tesla transforming the automotive sector, and Bolt revolutionizing commuting (Denning, 2019).

According to the conducted interviews, the mood of Estonian companies about Artificial Intelligence is very similar: leaders of the companies feel that AI is a huge innovation that is truly changing the world and businesses, and some companies already benefit from AI (INT1, INT4, INT6, INT9, INT10).

In recent months, since the first version of OpenAI's ChatGPT became available, some leaders have had the opportunity to experience AI technology firsthand by applying it to real-life scenarios. ChatGPT has quickly become an essential tool for several companies. For instance, some interviewees (INT7, INT10) mentioned that their company almost no longer uses Google, relying on ChatGPT instead for finding answers. Another leader (INT4) highlighted the use of AI tools like ChatGPT, Midjourney, Elicit, and Dalle for 60-70% of their daily tasks. A third interviewee (INT10) told that they use ChatGPT on a regular basis, even for generating product descriptions, although they have not integrated it into their system beyond its SaaS capabilities, which requires additional effort and investments, which supports the challenge of integrating AI into the company's existing ecosystem (see chapter 1.2.3), which is one of the top three challenges according to (Mittal & Davenport, 2023). One company (INT9) used Midjourney for a marketing project, creating visuals for a campaign, billboards, and a magazine, and ChatGPT is systematically used to write articles for their publications.

But still, for some leaders, AI is more like a big opportunity, which they still do not use in their companies. Some of them do not understand how and where it could help them (INT2, INT3), and they would like some example to lead from the competition or help from external AI expertise to find places where AI could be applied (INT4, INT8), others feel that in order to start using AI significant investments should be made to the existing IT ecosystem (INT8, INT11), which supports the findings that one of the obstacles of AI adoption is the challenge of integrating AI into the company's existing ecosystem (see chapter 1.2.3).

INT4 mentioned that their company is rather conservative when it comes to expansion, and they have limited resources, making it difficult to embark on large-scale projects. The main reason here could be insufficient support from the top management, which is the crucial factor for the successful adoption of AI according to multiple research papers (Schmitt, 2023; Merhi & Harfouche, 2023; Neumann *et al.*, 2022; Neumann *et al.*, 2022; Mittal & Davenport, 2023; Kreuzberger *et al.*, 2022). Insufficient support from the top management leads to very limited AI usage across the company: AI is adopted only there, where it does not require significant investments to start using it. Another leader (INT8) feels that the company needs to make massive investments for systemizing the data and digitizing processes for data collection before AI solutions can be effectively deployed in a live environment. The interviewee mentioned that the company currently lacks resources to systematize the data. In another interview (INT11), the company made a pilot project to automate theft detection in their shops using a third-party AI solution. However, they decided against adopting it for ongoing use due to the high costs of the solution.

Only a small number of the companies interviewed (INT1, INT7, INT10) use fully integrated and/or custom-made AI solutions in their daily operations or products. For example, INT7 said that their company has a core process that is automated using AI and ML, using an off-the-shelf AI solution. Another interviewee (INT10) said, that they use a custom made AI solution developed by their partner for one use case. Similarly, INT5 shared that they have an ongoing pilot AI project focused on automating quality control by comparing actual outcomes against project requirements, but it is not in use yet.

Recent experiences that different companies have had with OpenAI's ChatGPT show, that most Estonian leaders are mentally ready to start adopting AI to their businesses, but since there are major obstacles to using AI with their existing data and in an existing environment (the author will review main obstacles in more details in the next section), off-the-shelf AI solutions (AI SaaS) such as ChatGPT, Midjourney, and others, could be a viable starting point for Estonian companies to adopt AI in their businesses.

3.2 The main challenges toward AI adoption across Estonian companies in Manufacturing and Retail fields

According to the theoretical framework, which is based on previous studies, there are four main groups of obstacles and challenges why companies struggle to start using Artificial Intelligence in their businesses and daily operations:

- Limited AI skills, expertise, or knowledge;
- Lack of Data and applicability of available data;
- Difficult to integrate AI solutions into an organization's existing ecosystem;
- Organizational culture, vision, and leadership support.

The results of the conducted research (interviews with leaders of Estonian companies) made by the author, confirm previous findings, but the Estonian scene has a little bit different situation around AI adoption. There is a difference between the situation around Estonian companies, compared with previous findings based on other countries. Namely: Prerequisites for AI adoption are not done: The level of digitalization is low in many companies, and in many companies, there is no data-driven mindset (mostly across Manufacturing companies). The author has decided to create a separate challenge group called Level of Digitalization in the company because this challenge does not fully suit any of the existing groups (read more in the 3.2.2 subchapter).

Both retail and manufacturing companies share common obstacles to AI adoption, such as high costs, lack of resources, and the need for integration with existing systems. However, the author observed that manufacturing companies had a lower positive response rate (<50%) to participate in this research compared to retail companies (positive response gave 80% of the potential interviewees). This could suggest that leaders in the manufacturing field may have less lack of awareness or understanding about AI applications (same as INT3, INT2) and enthusiasm about AI than their retail counterparts.

Next, the author will review each challenge from the theoretical framework, and additional findings in more detail.

3.2.1 Data availability and readiness

According to conducted interviews, the collected data amount, level of data quality and availability to be used by AI solutions, is very different across Estonian companies in the Manufacturing and Retail fields. The author has found, that this factor correlates with whether the company is using AI technology in the existing processes, or not.

Companies with a higher level of data collection, and further aggregation (storing all data from different systems/platforms in one place such as a Data Warehouse) are more likely to adopt AI technology (INT1, INT5). For instance, INT1 said that in their company there are digitalized and automated applicable processes and they have a data warehouse for collect and aggregating data from different sources. INT5 said that they have their own data warehouse.

Conversely, companies with limited data collection or no centralized data storage (INT2, INT3, INT4) face challenges in AI adoption. The reason is that often data is locked in legacy systems that are typically isolated, and do not conform to a unified structure, making it challenging, if not impossible, to get multiple types of data to merge together (Daugherty & Wilson, 2022; Silva & Alahakoon, 2022). INT2 said that their production machines are connected to the internet and specific software for data collection and fine-tuning production parameters, but there is no common place for aggregated data like a data warehouse. Similarly, INT4 acknowledged the benefits of having a common platform with integrations for all systems, such as CRM, marketing, and SAP, to have all data in one place.

Some company leaders (INT3, INT6) mentioned that there is an issue with the amount of data available. INT6 mentioned facing challenges while building an AI solution due to insufficient initial data for training the AI effectively, as there were too few samples. Similarly, INT3 said that although they have data on raw materials used for production, the amount of data is too small to start using AI. Furthermore, they do not possess a unified database that could serve as a foundation for AI solutions.

Other interviewees (INT5, INT8) highlighted that their customized production processes might not see significant benefits from data collection or AI. INT5 said that, although some data is likely collected, using it may not yield substantial advantages due to the their customized production process (every product is unique). Similarly, INT8 told that in their company there is small-scale production of only some parts of their products, and their production machines are not connected to the internet for data collection, as they believe it would not provide any meaningful benefits.

As was already stated before, the author sees the link between the level of data collection and further aggregation with the level of AI adoption. Nevertheless, data availability is not a blocker towards using AI in the company, since some companies have solved data availability problems by using off-the-shelf AI solutions (AI SaaS), which do not require integration with the company's data. But sometimes, the real problem is not only about the lack of applicable data but more about the level of digitalization and data-driven thinking in the company, which brings us to the next challenges.

3.2.2 Level of digitalization in the company

Digitalization refers to the use of digital technology in various aspects of business operations, such as marketing, accounting, or customer experience. Digitalization is seen as a key factor in the transformation of the business environment, with modern technologies changing the way businesses are managed and contributing to the development of new business models (Gartner; Alina, 2018). Digitalization is not only collecting data in digital format but also benefiting from this data. One of the examples could be a data-driven approach of the company in decision-making using analytics (facts), but not relying on gut feeling.

From an AI perspective, a low level of digitalization in a company could not only mean a lack of data and its readiness to be used by AI but also an inability to apply technology to address specific problems that the company faces. This situation may also hinder the integration of AI solutions into existing systems, necessitating substantial investments in IT infrastructure modernization, and create challenges in fostering a culture of innovation and data-driven decision-making among employees.

According to conducted interviews, some Estonian companies in the Manufacturing field have a low level of digitalization, which is one of the main obstacles why they do not use AI technology. INT6 points out that discussing AI implementation is too early, since digitalization level for somecompanies is currently low. INT7 suggests that the varying levels of digitalization and lack of awareness about it among different companies are barriers to AI adoption, as AI is considered the next level of digitalization that requires commitment and belief in its success. INT2 said that they haven't identified any applicable problems where AI could be implemented, and they have limited in-house knowledge about AI. They would consider trying AI if a similar company adopted it or created a ready-to-use solution, but for now, AI programming competence is necessary to start using AI.

A low level of digitalization can hinder a company's ability to adopt AI due to a lack of data and technological awareness. These companies need to raise awareness of why it is better to use data for decision-making, rather than to rely on gut feeling, and then what is AI and how AI can be beneficial for the company.

This challenge is highly related to the next challenge (Organisational culture, vision, and leadership support), but there is a significant difference between them: a case of the first leaders do not see the possibilities and benefits of using AI, but lack leadership support and/or unsupportive culture means that companies are not ready to make investments to adopt AI, even if they are aware of the potential benefits. Let's review this challenge in more details.

3.2.3 Organisational culture, vision and leadership support

The level of AI adoption highly correlates with the top management support factor, data-driven thinking in the company, and ability to apply technology to solve business needs; and it is the most critical obstacle towards successful AI adoption in the company.

Companies with a top management focus on AI, dedicated budgets, and resources, including in-house training, show a high level of AI adoption (there is at least one AI solution in the company). INT1 highlighted that their company's top management is focused on AI, with a specific budget allocated for R&D and AI. They also provide in-house AI training for employees and stakeholders. INT5 also said that their top management fully supports AI initiatives, with a company strategy focused on digitalization. They are willing to try out new AI solutions if they see potential benefits and even participated in an AI bootcamp recently. The fact that they have digitalization/innovation department also demonstrates their commitment to trying out innovations such as AI. INT7 emphasizes that applying AI to their processes is driven by business needs and they believe that AI is the right direction and will be used more in the future, as it can helps to improve efficiency. INT9 stated, that supportive environment encourages innovation and the exploration of AI technologies. The author sees strong correlation AI adoption with organizational culture, that supports innovation: companies that actively experiment with AI (INT1, INT5, INT7, INT9) and have a culture that encourages innovation and risk-taking are more likely to adopt AI and benefit from its potential. Interviewee (INT10) from the company, that also successfully use AI for their business, highlighted that the initiative for AI adoption came from one of the top leadership committee.

Other leaders do not see applicable AI use cases in their business, resulting in no AI adoption in the company. For instance, INT3 mentioned that they had not even considered applying AI, as some situations are impossible to predict, such as the impact of unforeseen events like COVID-19 or clients' decisions. Similarly, INT2 highlights the absence of applicable problems where AI could be applied and the limited in-house knowledge about AI, both of which contribute to the company's lack of AI implementation. As a result, non of these companies use AI.

In some cases, individual leaders who are enthusiastic about AI and see its benefits in simplifying tasks can drive AI adoption within their companies, despite limited resources. INT4, as a quite big AI fan, actively uses AI for daily responsibilities and was the initiator of AI adoption in their company. He also mentioned that there is no need for dedicated in-house AI experts, since they do not feel the need for that.

AI adoption should be motivated by business requirements rather than just the appeal of the technology itself. As INT6 points out, the AI adoption usually needs support from top leadership, and readiness to do investments towards that. But, the need for AI itself should be initiated by the business needs. Similarly, INT7 emphasizes that their company's adoption of AI was driven by the desire to simplify the use of their product in response to business needs.

3.2.4 AI Expertise and competences

According to conducted interviews, the majority of the interviewed companies already relying on external partners (or are ready to use external partners) for AI-related tasks, and do not have plans to hire an in-house AI team: they do not see the need to hire dedicated AI experts like data scientists or machine learning engineers. Also, these companies prefer using off-the-shelf AI solutions that do not require in-depth AI expertise.

For instance, INT5 said their company has a strong IT team but no in-house data scientists or AI experts, and all AI-related competencies handled by an external partner focusing on AI solutions. Similarly, other interviewee (INT7) told that they did not need a data scientist or machine learning engineer because they used ready solution. Instead, they needed someone to pick the right software for their problem. INT3 acknowledges the possibility of piloting AI initiatives but raises concerns about the resources required, suggesting that external assistance would be needed for such initiatives.

In contrast, there are some companies that have recognized the value of AI and have built in-house AI teams with experts, such as data scientists and AI strategists, to define their AI strategy, projects, and budgets. Interviewee (INT1) from the company that successfully uses AI for their business, said that their company hired an in-house AI expert two years ago to define their AI strategy, AI projects, and budgets for R&D and AI. The company also has other AI experts, such as data scientists. Currently, they have 3 full-time in-house employees dedicated to exploring business processes that can be automated with AI.

To conclude, the author did not find any major challenges Estonian companies face in finding AI expertise. Bigger companies who are ready to invest more, have full-stack in-house AI expertise, while others prefer to have only 1-2 high-level AI experts in-house who partner with external AI-focused companies that develop AI solutions.

3.2.5 Integration of AI solutions to existing ecosystem

Despite the fact that in the theoretical framework, the author has found that this challenge is one of the most important during AI adoption, he did not find much resonance across Estonian leaders. Probably, for most companies, the reason is that they are not there yet.
But, let's review this challenge based on those companies, that already have some experience with AI solutions, or were thinking about how potential AI solutions could be integrated into their existing IT ecosystem.

Based on conducted interviews, companies that have separate systems for different processes (INT3, INT4, INT8) face challenges in AI adoption, as they lack integration between these systems to share data between them, and also lack of unified database such as a Data Warehouse, that could be a foundation for potential AI solutions. For instance, INT3 said that their company doesn't have a unified database needed for AI solutions. INT4 told that one of the possible areas where he sees potential benefit to apply AI is marketing, but they face challenges due to their separate CRM, marketing platform, and other non-integrated systems. Similarly, INT8 described how their company uses separated software components for different roles and teams, without an automated production process or a Data Warehouse, resulting in data being stored across various platforms.

There is another challenge that some companies still rely on printed documents or manual processes (INT5, INT8), which could be also a potential obstacle to adopting AI solutions, as there are concerns about data reliability and input consistency. For example, INT5 mentioned their company's extensive use of printed documents in production, raising problem about the actuality of the printed versions and the responsibility for data input into AI systems. Interviewee also expressed concerns about the reliability of the data and about how to ensure that input images for AI models are captured under the same conditions.

Some companies (INT7, INT4) solve this challenge by adopting ready off-the-shelf AI solutions (AI SaaS) for specific tasks, which do not need any integration with the existing ecosystem.
(INT7): "We do not Google anymore, we use ChatGPT to find answers to our questions". Similarly, other interviewee (INT4) told that he actively use AI tools like ChatGPT, Midjourney, Elicit, and Dalle for 60-70% of his daily tasks.

To conclude the following challenge, companies with integrated systems are more likely to adopt AI, than those who have separated/fragmented systems. However, even with separated systems, it is still possible to benefit from AI by adopting off-the-shelf AI solutions (AI SaaS).

3.3 Company needed mindset and approach for successful AI adoption

The aim of this study is not only to find out what obstacles and challenges Estonian companies have with adopting AI to their businesses but also to propose solutions to these challenges based on previous experiences of other companies and on state-of-the-art practices. Conducted by the author research across Estonian companies has shown, that **Organisational culture, vision, and leadership support** are the most critical group of challenges toward successful AI adoption.

The author sees that in almost all cases AI technology adoption starts with the support of the top-level leadership: it can be just overall company culture that strongly supports innovation and thinking out-of-the-box, as well as by having a strategic focus on data-driven thinking and/or on AI, and by having dedicated budget for R&D and/or AI (INT1).

Any innovation adoption (incl. AI) can be initiated by a top-down or bottom-up approach, and by picking either supporting different initiatives by employees in order to enable innovation or to have a strong focus on a data-driven mindset and on AI, top leadership also defines which approach to support more in the company.

In the case of a top-down approach, at least high-level AI expertise on top-level leadership is a must to pick the right problem to be solved with AI, find the right solution, hire the right people, and define the overall AI strategy of the company. Companies solve this either by hiring high-level AI expert in-house who is capable of leading the whole AI initiative or by partnering with some AI-focused consulting/software development company.

To enable a bottom-up approach, companies should promote an organizational culture that values creativity, and a willingness to experiment, and encourage employees to think outside the box by organizing different contests, hackathons, and workshops for its employees, and by giving them the time and resources they need to develop and implement their innovative ideas.

3.4. Solutions and recommendations

Based on the author's research, the primary obstacles Estonian companies have with AI adoption, aside from the lack of leadership support (which was discussed in the 3.3 chapter), are high costs and data-related issues. High costs are mainly because of the need for integration with existing systems and the need to prepare data, while data issues include the absence of centralized data storage such as a data warehouse, or insufficient data collected in order to start using AI. The research problem can be addressed by using foundation models (pre-trained models) together with less data-intensive methods like few-shot/one-shot learning for fine-tuning these models, and/or adopting off-the-shelf AI solutions (see Chapter 1.3.3 for the details).

Also, the author encourages to think through the following questions before start executing AI initiatives: How much are you willing to invest in AI? Do you prefer having a full-stack in-house AI team or partnering with an external AI-focused consulting/software development company? What is your current situation with data (data availability and readiness)? How accurate should be ML model to start creating business value?
From the experiences of Estonian companies that successfully implement AI (INT1, INT5, INT9, INT10), a crucial factor is having someone in-house with high-level AI expertise who can lead the AI initiative, this person should be a business stakeholder who also understands the technical side

and possibilities of AI, and who could think through the whole end-to-end AI solution, but not just focusing on a developing ML model. The author has noticed the common mistake that many companies have made: instead of hiring such high-level AI expert, they hired a Data Scientist, who was fully concentrated on a developing high-accurate ML model, which led to the problem of using this AI solution in the existing ecosystem, and possibly impossibility of use created ML model in a live environment. Provided recommendations could help lower AI adoption barriers and solve the research problem.

To visualise what is described above, the author has created a guide (Figure 1) for solving a cold-start problem (when there is no AI initiative in the company yet) that many leaders of Estonian companies face, which helps leaders to answer the question "Where to start with AI?", and pick the right initial AI strategy (approach) for the company or for the project.

```
1.Assess your willingness to invest in AI
└── Are you ready to invest BIG in AI initiatives?
        ├── Yes: Go to 2
        └── No: Consider smaller-scale AI projects and off-the-shelf solutions (Go to 4)
2.Choose between a full-stack in-house AI team or external AI expertise (a. or b.)
├── a.In-house: Hire AI experts, Develop In-House AI Expertise, organize AI trainings
└── b.External: Partner with an external AI-focused consulting/software development company
3.Hire a high-level AI expert to lead the AI whole initiative
4.Create a One-Page AI Strategy
├── Define initial budget
├── Outline roles and responsibilities
├── Identify use case(s) for AI
└── Determine how the AI solution should be used (integrated or standalone)
5.Consider between Off-the-Shelf AI Solutions or Custom-made AI (a. or b.)
├── a.Off-the-Shelf: Find AI SaaS or fine-tune a Foundation Model with company data
└── b.Custom-made: Develop AI Solutions specifically for the company's data and problem
6.Align Company Strategy with AI Strategy
├── Prioritize IT Modernization (if needed)
├── Migrate to Cloud Services (if needed)
└── Create Data Strategy
7.Assess the current situation with data and address data availability
├── Align current situation with Data Strategy
├── Centralize Data (if needed)
├── Leverage Foundation Models (if needed)
├── Use Less Data-Intensive Methods (if needed)
├── Acquire Data from Vendors (if needed)
└── Share Data Inter-Organizationally (if needed)
8.Plan Integration and Maintenance of AI Solution
├── Evaluate integration with existing ecosystem (if needed)
├── Consider MLOps for maintaining and monitoring ML models, and for continuous delivery
└── Implement continuous learning loop for AI solution
9.Start execution of the AI initiative
```

Figure 1 A guide for solving a cold-start problem ("Where to start with AI?") for Estonian company leaders created by the author, based on the Theoretical Framework and Interviews

Also, to validate the proposed solution, described above, as well as to demonstrate the capabilities of AI, the author has created an interactive AI solution, which is using base knowledge from this research paper (and used materials), to assist company leaders with implementing AI, help to overcome existing AI challenges, and help to better understand the capabilities of AI.

In (Appendix 3) the author summarizes the main challenges during AI adoption, and possible solutions to these challenges based on previous experiences of other companies, state-of-the-art practices, and the recommendations by AI experts.

CONCLUSION

The pandemic has rapidly accelerated tech adoption in businesses, and almost every business is a technology business now. This creates enormous new possibilities where companies could apply Artificial Intelligence. Europe’s Digital target for 2030 is to have 75% of EU companies using AI. According to the Chief Data Officer of the Estonian Government, usage of Artificial Intelligence across Estonian companies is very low, especially in Manufacturing, which is about 4%.

This thesis aimed to identify which obstacles and challenges Estonian companies have with implementing AI in their businesses, and propose solutions based on previous experiences of other companies, existing cutting-edge best practices and expert recommendations. The study focused on the Manufacturing and Retail fields.

The research questions of this thesis were:

1) What kind of experiences do Estonian companies have with AI/ML?

2) What are the main challenges in implementing AI/ML?

3) How can Estonian companies overcome barriers to adopting AI?

The theoretical framework highlighted key challenges during AI adoption, such as AI expertise and competencies, organizational culture and lack of the leadership support, data availability and quality, and a systematic strategic approach to AI adoption. The literature suggested several approaches to address these challenges: address the lack of AI expertise through reskilling/upskilling, involving non-AI experts in the Machine Learning Lifecycle loop, and leveraging ready-to-use foundation models. Organizational culture and AI strategy play an essential role in driving AI adoption, with top-down and bottom-up approaches being used depending on the organization's specific situation. Data availability and quality are critical in the implementation of AI solutions, with various strategies such as data warehousing, federated learning, using foundation models (pre-trained models) as a base for company-specific AI solutions, and employing less data-intensive methods like few-shot/one-shot learning for fine-tuning ML models, being employed to overcome data challenges.

The qualitative research conducted through semi-structured interviews with C-level and AI initiative leaders in Estonian companies revealed some unique aspects of AI adoption in the local context. While many findings were consistent with the existing literature, the low level of digitalization and the lack of a data-driven mindset in some Estonian companies emerged as a significant challenge. Also, the research has shown that organizational culture, vision, and leadership support are the most critical group of challenges for successful AI adoption. Furthermore, the research identified high costs (mainly because of the need for integration with existing systems and the need to prepare data) and data-related issues as the primary obstacles to AI adoption in Estonian companies, aside from the lack of leadership support.

To address these challenges, the author proposed Estonian companies to leverage foundation models together with less data-intensive methods like few-shot/one-shot learning for fine-tuning these models and/or adopting off-the-shelf AI solutions. Also, the important factor is having someone in-house with high-level AI expertise who can lead the AI initiative. This person should be a business stakeholder who understands the technical side and possibilities of AI and can think through the entire end-to-end AI solution. Avoiding the common mistake of focusing solely on developing a high-accuracy ML model without considering its integration into the existing ecosystem can significantly improve the success of AI adoption in Estonian companies.
To validate the proposed solutions and demonstrate AI capabilities, an interactive AI solution was developed, utilizing the knowledge derived from this research, to assist leaders in implementing AI and overcoming challenges.

This research contributes to the existing body of knowledge on AI implementation and provides valuable insights to help Estonian companies in the Manufacturing and Retail fields adopt AI technology to remain competitive and innovative. The author considers that the research questions are answered and the aim of the thesis is fulfilled. Based on this work, we now have a deeper understanding of the experiences of Estonian companies with AI, the framework of possible solutions to the challenges they face, and guidance on how to start their AI journey. The author hopes that these insights will encourage companies to explore AI and its potential, ultimately leading to increased competitiveness and the enablement of innovation.

In terms of the future directions of this research, there are several important areas to explore. One significant topic is the potential pitfalls of foundational models, particularly in terms of causality

and explainability. Understanding the trustworthiness of these models and developing methods to ensure their transparency and interpretability will be essential for fostering AI adoption.
Another direction for further research could be AI ethics and regulations. As Estonian companies increasingly adopt AI technologies, it will be crucial to examine the ethical implications of AI.

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APPENDICES

Appendix 1. Interview guide

Introduction
Purpose of the interview and reminder of duration time ~30min Ask for permission to record the interview
I Current situation with software being used and data availability in the company
1. Type of business and development approach (in-house/outsource/SaaS) 2. Availability of the data (data warehouse/datalake/only main db) 3. Storing data (Cloud or on-premise)
II Previous experiences with AI/ML in the company
1. Feeling about using AI/ML overall? *(if negative: no need? too expensive? not sure where to start?)* 2. Any AI/ML solutions that you use in production now? NO: 1. Understanding of possible applications of AI, and benefits? 2. Did try out something or PoC'ing something? 3. Reasons why not tried / not in production? 4. Any challenges of finding AI expertise? YES: 1. What kind of solutions do you have? 2. How do you feel about existing solutions (in terms of ROI)? 3. How Project management / end-to-end development process looks like? 4. Any data scientists, ML engineers, other AI experts in your company? 5. How do you maintain AI solutions? MLOps platform?
III Main challenges in implementing and adopting AI/ML
1. How much time did it take to put 1st AI solution to production?

2. Cost of development? 3. Main challenges during development? 4. Expertise. In-house AI experts who knew how to do it, consulting, or trial-and-error? 5. ML solution: Open-Source, SaaS, or own custom solution?
III AI/ML vs Company future
1. Further interest in using AI solutions in business? 2. What would you do differently if you would have to start from the beginning again? 3. Willingness to pay (R&D projects, when not sure about ROI)? 4. Organizational changes in your company for adopting AI/ML? 5. What is the biggest challenge you have now in your company?
IV Discussion about possible AI applications
1. In the process of production (Predictive maintenance, defects detection, raw materials optimization, etc.) 2. Forecasting (sales, events, etc.) 3. Marketing (personalised experience, loyalty, chatbots, etc.)

Appendix 2. Table of interviews

Code	Company's Field of Activity	Turnover (2021)	Position	Interview Method	Interview Date
INT1	Manufacturing / Electricity production	-	CEO	Video call	17.02.2023
INT2	Manufacturing / Food Products	1 230 954 EUR	CEO	F2F meeting	28.02.2023
INT3	Manufacturing / Beverages	3 669 738 EUR	CEO	F2F meeting	02.03.2023
INT4	Manufacturing / Consumer Electronics	5 752 174 EUR	Founder	Video call	04.04.2023
INT5	Manufacturing / Construction of buildings	137 981 000 EUR	Project Manager of Digital Solutions	F2F meeting	12.04.2023
INT6	Republic of Estonia	-	Government Chief Data Officer	Video call	13.04.2023
INT7	Manufacturing / Electricity production	3 830 764 EUR (2022)	COO	Phone call	14.04.2023
INT8	Wholesale and Retail Sale / Manufacturing	3 666 388 EUR	CEO	Video call	17.04.2023
INT9	Wholesale and Retail Sale	81 765 000 EUR	Marketing Director, Member of the Board	Video call	26.04.2023

INT10	Wholesale and Retail Sale	19 172 367 EUR	Head of Software Development and Ecommerce	Video call	27.04.2023
INT11	Wholesale and Retail Sale	447 654 596 EUR	CIO	Video call	02.05.2023

Appendix 3. Key challenges and guidelines for successful AI adoption

Challenge	Possible Solutions
Organisational culture, vision and leadership support	• Define an AI strategy to guide investments, AI solutions selection, and talent acquisition (top-down approach) • Encourage a bottom-up approach when top-level management lacks AI expertise; Implement an innovative company culture through hackathons and other events (bottom-up approach) • Support of outdated IT systems modernization, and usage of cloud services instead of on-premise servers for scalable and flexible AI implementation • Create alliances between organizations for data sharing and cooperative AI solutions development
Lack of Data and applicability of available data	• Address isolated and differently structured data by creating a centralized data repository (data warehouse, data lake, or data lakehouse) • Use AI for creating a meta-layer or representation of all data sources (by using federated learning, representation learning, and latent learning) • If no data, then acquire required data from data vendors and brokers in aggregated or detailed format • If data is limited, then utilize less data-intensive methods like few-shot learning, one-shot learning, and zero-shot learning • Leverage foundation models, such as pre-trained language models, for AI solutions without requiring organization-specific data • Address rare cases in datasets through inter-organizational data sharing or federated learning, which allows collaborative model training without sharing data • Adopt ready off-the-shelf AI solutions (AI SaaS)
Limited AI skills, expertise or knowledge	• Reskill and upskill employees to develop, interpret, and improve AI systems • Empower non-data scientists (e.g., medical coders) to become AI instructors, scaling untapped expertise at every level within the company

	• Adopt ready off-the-shelf AI solutions (AI SaaS)
Difficult to integrate AI solutions to organization's existing ecosystem	• Combine elements from traditional project management, Agile approaches, and AI workflow for effective AI project management • Use industry and academic standards, such as CRISP-DM, TDSP, and Microsoft best practices model for AI projects management • Implement MLOps to automate and operationalize ML processes, enabling faster transition from PoC to production • Use MLOps practices for continuous delivery of AI solutions, enabling continuous improvement and increased business value • Adopt ready off-the-shelf AI solutions (AI SaaS)

Appendix 4. Coding frame based on semi-structured interviews

Link to the Coding frame file:

https://www.icloud.com/numbers/082RZrcsGu-J8zgpagYxaFkZA#Categories

Link to interview recordings:

https://drive.google.com/drive/folders/1neEpafIIhzQGrRmdHe0LgwiJy42QjxBe?usp=share_link

Link to the transcribed interviews:

https://drive.google.com/drive/folders/1G0u6pv8Y5jbCastoogwQyrNZJW5PNQhL?usp=share_link

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