DEMYSTIFYING AI ADOPTION - BEYOND THE HYPE

A qualitative study on why telecom companies decide to adopt AI

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Abstract

Artificial Intelligence (AI) is expected to have a fundamental impact on the way we do business and become a significant source of value to various industries. However, few companies have an AI strategy in place, and telecom companies, which are frontrunners within AI adoption, state that it is the most overhyped emerging technology. On the basis of these contradictions, this qualitative study aims to examine and provide insights on the rationale behind why telecom companies in Sweden decide to adopt AI. Through a multiple case study approach, nine in-depth interviews, with Telia, Telenor and Tele2, were conducted. This was followed by an analysis based on an integrated framework, combining the Technology-Organizational-Environmental (TOE) framework and the Task-Technology-Fit (TTF) framework. The findings revealed three levels of influence for the adoption-decision, including decisive, influential, and uninfluential factors. The decisive factors are: perceived compatibility, perceived relative advantage, customer satisfaction, data utilization, and competitive advantage. The influential factors are: top management support, data availability, task complexity, presence of champions, financial strength, AI hype, and competitive pressure. Finally, the uninfluential factors are: data quality, AI competence, infrastructure, organizational size, and perceived complexity. The thesis explains the influence of factors for the AI adoption-decision, among the studied telecoms, providing both academics and professionals with insights on important aspects to consider when adopting AI. Moreover, it goes beyond the hype and demystifies the phenomenon of AI adoption.

Keywords

Artificial Intelligence, Machine Learning, Adoption, Decision-making, Telecom Industry, TOE-framework, TTF-framework

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Definitions of Recurring Terms

Term	Definition
Artificial Intelligence	“The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.” (Oxford Dictionary, 2020)
Adoption	“A decision to make full use of an innovation as the best course of action available.” (Rogers, 2003, p. 21)
Implementation	“Takes place when an individual puts an innovation into use.” (Rogers, 2003, p. 20)
Innovation	“An idea, practice, or object that is perceived as new by an individual or other unit of adoption.” (Rogers, 2003, p. 12)
Information System (IS)	“The branch of knowledge concerning the purpose, design, uses, and effects of information systems in organizations. IS is an interdisciplinary study, drawing chiefly from computer science on the technical side and from business/management studies on the organizational side; it may also, however, embrace aspects of economics, psychology and sociology, statistics, and operations research.” (Oxford Dictionary, 2020)

1 Introduction

1.1 Background

Artificial intelligence (AI) is one of the most hyped technologies in business today. The development of AI may seem like a relatively new phenomenon, that arose with the internet and big data, but the history of the technology goes back to 1956, when professor John McCarthy coined the phrase "Artificial Intelligence" (Burgess, 2018). However, a widespread practical interest in AI emerged only recently. The current excitement about AI can, to a great extent, be explained by advancements in the field of machine learning (ML), a subfield of AI (Alpaydin, 2011). ML has gained new momentum due to strengthened computational power and increased data availability. Moreover, advancements within this field have enabled, for instance, online recommendation offers and churn prediction (SAS, 2020).

AI is expected to have a fundamental impact on the way we do business (Burgess, 2018) and become a significant source of value to businesses in various industries. In a research report by MIT, 93 percent of over 2500 companies surveyed that they expect value from AI. However, less than 39 percent have an AI strategy in place (Ransbotham et al., 2019), and organizations often fail to incorporate AI into their core business (Fountaine et al., 2019).

The telecom industry, along with high-tech and financial-services companies, are front runners within AI adoption. These industries have an advantage over others, as they have generated and stored large volumes of structured data (Bughin et al., 2017). This access to data was enabled by the ability of digital companies to track user actions and give recommendations, while simultaneously testing and iterating their offerings (Brynjolfsson and McAfee, 2012). However, compared with overall digitalization, even these sectors are far behind in AI adoption (Bughin et al., 2017).

While telecom companies recognize the importance and potential of AI, identifying it as an investment priority, it has been stated as the "most overhyped emerging technology" in a recent survey of leading telecoms. The hype is suggested to originate from a general lack of understanding about AI, unrealistic expectations on its capabilities for businesses, the rate at which it can be deployed and the amount of work needed to manage it (Tilly, 2019). This further implies contradictions to the motivation behind the adoption-decision, bringing the authors to the fundamental question: Why do companies within the telecom industry decide to adopt AI? Indeed, it is widely recognized as an important part of their business development, but is there more to it, or are they just following a hype?

1.2 Purpose and Research Question

The purpose of this thesis is, through a qualitative study, to investigate the rationale behind the AI adoption-decision in the Swedish telecom industry. To gain deeper insights on influential factors, the research question is as follows:

Why do telecom companies in Sweden decide to adopt AI?

1.3 Clarification and Delimitations

In this thesis, the focus will solely be on the decision-making of AI *adoption*, while the preceding process of AI *implementation* will be excluded. It will not be possible to study all factors that could influence the AI adoption-decision. Therefore, potentially influential factors will be selected based on their relevance for studying AI adoption.

The scope will further be limited to the adoption of ML applications and the telecom industry. This narrowing facilitates finding generalizable propositions amongst the studied telecoms, as the adoption-decision may differ depending on different types of AI and across industries. Finally, since telecom companies are in the forefront of AI adoption, this industry was especially interesting for studying the phenomenon of interest.

2 Literature Review

2.1 Artificial Intelligence

AI concerns the theory and practice of developing systems that entail characteristics of human behavior (Tecuci, 2019). It has been adopted since machine automation has the potential to bring relative advantages, such as revenue generation, cost savings, new product development, and efficiency gains (Ransbotham, 2019).

ML, a subdomain within AI, concerns computers learning to perform specific tasks by analyzing big data through algorithms (Alpaydin, 2011). Within the telecom industry, ML applications include customer service chatbots, predictive maintenance, and churn rate reduction (Qi et al., 2007).

As a result of the public interest and technological advancements, AI is perceived to be revolutionary with the potential of transforming humanity. However, the cases for successful AI applications are still relatively few compared to the growing evidence of failed AI initiatives (Brock & von Wangenheim, 2019), indicating a gap between ambition and execution (Ransbotham et al., 2017).

While the AI hype is pervasive, and experts state that we are living through its peak, there is no indication that the buzz, less the potential of AI, will fade away soon (Microsoft, 2018). Analytical forecasts show an expected growth of AI adoptions (Bughin et al., 2017), but underlying factors for *why* organizations decide to adopt AI are not explained. Since telecoms consider AI overhyped, the authors aim to, in-depth, explain the rationale behind their AI adoption-decision.

2.2 Previous Research on AI Adoption

The field of AI is still relatively unexplored within organizational research. Previous research has mainly focused on technical aspects and applications (Qi et al., 2007; Dunis et al. 2016), as well as AI implementation (Sun and Medaglia, 2019), but there is limited existing research on *why* organizations decide to adopt AI. However, AI is arguably similar to other technology adoptions (Brock & von Wangenheim, 2019). Therefore, the applicability of previous theories and models, used to study the adoption-decision of similar technologies within Information Systems (IS) research, are investigated (see 3.1).

2.3 Research Gap

Previous studies on AI have mainly focused on the technicalities of adoption and implementation, while underlying factors, explaining *why* organizations decide to adopt AI, have been overlooked. However, the adoption-decision of similar technologies has been widely studied. On the basis of AI being a highly relevant and modern phenomenon, it should arguably not be an exception within adoption research. To address this research gap, the authors argue that more research is needed on organizational and managerial issues regarding AI adoption. Therefore, underlying motivations for the decision to adopt AI, and whether organizations have a strategic business case for it, will be investigated. Since telecoms perceive AI as both important and overhyped, these contradictions make them interesting cases for studying the rationale behind their AI adoption-decision.

3 Theoretical Framework

The following section presents the theoretical framework, TOE and TTF, and its comprising factors, applied to address the research gap. TOE constitutes the main theory, while TTF is added as a complement to establish a more holistic framework. The analysis builds upon this integrated framework, which aims to give a comprehensive answer to the research question.

3.1 TOE Framework

Several theories have been used within IS-research to study technology adoption, but only the Technology-Organization-Environment (TOE) framework by Tornatzky and Fleischer (1990) and Diffusion of Innovation Theory (DOI) by Rogers (2003) are at an organization-level (Oliveira & Martins, 2011), hence suitable for studying organizational AI adoption.

TOE successfully overcomes limitations of prior innovation theories, that solely focus on technological forces, by identifying three influential contexts - technological, organizational and environmental - for technology adoption (Oliveira & Martins, 2011). It is highly adaptable to a variety of technologies and organizations, while being sufficiently explicit for empirical analysis. On the basis of this and its ability to integrate different contextual factors into a holistic model (Kuan & Chau, 2001), TOE was chosen as the main framework for studying the underlying factors for *why* telecom companies in Sweden decide to adopt AI.

Depending on the studied technology, researchers may investigate different technological, organizational and environmental factors (Baker, 2011). This flexibility allows the authors to derive relevant factors, potentially influential for the AI adoption-decision. Some factors are based on parts of DOI, one of the most widely applied theories when studying technology adoption in organizations. Furthermore, it is consistent with TOE (Oliveira & Martins, 2011), thus suitable for the study. Other factors are derived from previous quantitative IS-research. Numerous scholars have tested factors by applying TOE, often in combination with DOI, to study different technology adoptions, such as e-business systems (Zhu et al., 2006, Zhu et al., 2005; Zhu et al., 2003), e-maintenance (Aboelmaged, 2014), cloud computing (Yang et al., 2015), e-commerce (Oliveira & Martins, 2011), radio-frequency identification (RFID) (Wang et al., 2010), and enterprise systems (ES) (Ramdani et al., 2009).

3.1.1 Technological context

In the DOI theory, often applied in the technological context, Rogers (2003) identifies five influential attributes for an innovation adoption-decision: complexity, compatibility, relative advantage, trialability and observability. Aligned with Tornatzky and Klein (1983), this study only includes the first three, which are found consistently related to innovation adoption, while excluding the latter two, which are found to be uninfluential (Yang et al., 2015; Wang et al., 2010; Grover, 1993).

Perceived Complexity

Complexity is "the degree to which an innovation is perceived as relatively difficult to understand and use" (Rogers, 2003, s. 257). Several scholars agree that it is an influential factor for innovation adoption (Cooper and Zmud, 1990; Lin and Chen, 2012). Furthermore, Rogers (2003) states that the rate of adoption is negatively related to the perceived complexity of an innovation.

Perceived Compatibility

Compatibility refers to the extent to which an innovation is perceived as consistent with the needs of potential adopters. Scholars find it to be an influential factor, impacting innovation adoption-decisions (Yang, 2015; Lin and Chen, 2012; Wang et al., 2010; Cooper and Zmud, 1990), however uninfluential within SMEs (Ramdani et al., 2009; Kendall et al., 2001). A more compatible technology is perceived to be less uncertain and more suitable for an organization. For successful AI adoption, Bughin et al. (2017) emphasize the necessity of articulating business needs, establishing a solid business case, and aligning it with the organization's strategy. Moreover, when these needs are met, this leads to a faster adoption rate (Rogers, 2003).

Perceived Relative Advantage

Relative advantage is "the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 2003, p. 229). Rogers (2003) claims that when the expected benefits outweigh the costs of adopting an innovation, it is more likely to be adopted. Furthermore, scholars find relative advantage to be an influential factor (Ramdani et al., 2009). Important benefits, incentivizing organizations to adopt a new technology, include economic profitability, cost reduction, a saving of time and effort, and improved status (Rogers, 2003). Moreover, barriers of an innovation needs to be understood since the adoption process may be complicated and costly (Oliveira and Martins, 2010). Within AI adoption, the uncertainty of return on investment (ROI) is one of the biggest barriers (Bughin et al., 2017).

Technology Resources

Technology resources refers to data availability and data quality. Access to data is essential when adopting a new innovation (Aboelmaged, 2014). Since telecom companies have large amounts of data (Bughin et al., 2017), its influence on the AI adoption-decision is considered suitable to study. Moreover, Dishaw and Strong (1999) emphasize the importance of data quality, that is, having structured data (Bughin et al., 2017) that fit the needs of user tasks, thereby making it a useful resource.

Technology Readiness

Technology readiness comprise technology professionals and technology infrastructure, which are complementary to each other. Technology infrastructure is the established platform on which innovation applications, such as AI, can be built. Technology professionals are employees possessing knowledge and skills to develop and implement the technology (Zhu et al., 2006). Scholars find technology readiness an influential factors when adopting e-business (Zhu et al., 2003; Zhu et al., 2005; Zhu et al., 2006).

3.1.2 Organizational context

Presence of champions

A champion is an individual that strongly advocates an innovation, thereby overcoming organizational resistance for adopting a new idea (Rogers, 2003). They have the ability to introduce technology innovations successfully and to communicate a compelling vision of its potential within the organization. Through their enthusiasm to the new idea, they also induce the commitment of others to it (Howell and Higgins, 1990). Thus, champions are essential for promoting joint efforts. Moreover, by taking risks and getting necessary resources, they realize these ideas. Schön (1963, p. 84) states: “The new idea either finds a champion or dies” (Tushman and Nadler, 1988), emphasizing their importance for innovation adoption.

Top management support

Top management support (TMS) is essential for shaping innovation-related strategies and decisions (Hsu et al., 2019), articulating a vision, allocating resources (Yang et al., 2015), providing necessary funds, and fostering cross-functional cooperation and communication (Rodríguez et al., 2008). Several scholars find it influential for technology adoption (Yang, 2015; Wang et al., 2010; Ramdani et al., 2009). Sabherwal et al. (2006) argue that when top management is highly supportive of a technology, more resources are likely to be allocated. Managers can also promote innovation adoption by developing and rewarding individuals embodying innovative work, such as champions. TMS is essential for them to perceive the personal and organizational value of their informal role (Tushman and Nadler, 1988).

Organizational size

Organizational size is a recurring factor in TOE applications, and is found influential for innovation adoption (Aboelmaged, 2014; Zhu et al., 2003; Zhu et al., 2006). Aboelmaged (2014) attributes this to larger organizations having stronger financial and technical resources. Larger firms usually have greater abilities to absorb costs and risks of implementation (Thong, 1999), but they may suffer from structural inertia. Smaller firms, however, are more flexible, facilitating their innovativeness (Zhu et al., 2006). Therefore, a conclusive link between organizational size and innovation does not exist (Baker, 2011).

3.1.3 Environmental context

Competitive Pressure

Competitive pressure refers to peer pressure, inducing organizations to seek competitive advantages through new technology adoptions (Zhu et al., 2006), such as AI. Several scholars identify it as an influential factor, stimulating the decision to adopt an innovation (Zhu et al., 2006; Sabherwal et al., 2006; Wang et al., 2010; Zhu et al., 2003). Zhu et al. (2003) argue that, organizations may leverage new means to outperform rivals by adopting IS, ultimately giving them an advantage over competitors.

3.2 TTF Framework

The task-technology fit (TTF) model by Goodhue and Thompson (1995) is added as a complement since TOE essentially neglects the fit between technology functionality and task characteristics (Awa et al., 2017).

3.2.1 Task context

Task complexity

Task complexity refers to the degree of task analyzability (Goodhue and Thompson, 1995). Dishaw and Strong (1999) find that technology adoption is positively affected when technology functionality support, or fit, the task characteristics. When faced with complex tasks, this forces employees to use technology to manage new problems, such as finding new data and combining it in new ways (Goodhue and Thompson, 1995). Moreover, Awa et al. (2017) claim that organizations adopt technologies to make them less complex.

3.3 Integrated Theoretical Framework

The adaptation of TOE and TTF, and the selected factors to study the AI adoption-decision, is presented in the integrated theoretical framework, summarized in figure 1.

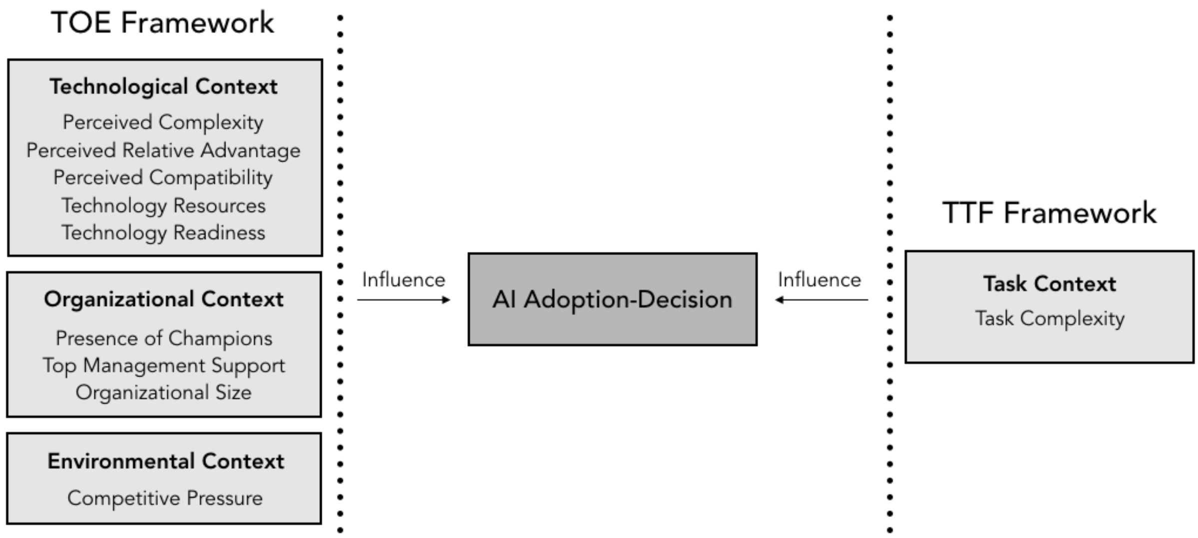

Figure 1 Integrated Theoretical Framework *Johnsen & Lindblom (2020)*

3.4 Theoretical Discussion

The authors recognize that the theoretical frameworks, TOE and TTF, have limitations. However, these were combined into the integrated framework to ensure a comprehensive study. On the basis of the frameworks being flexible, this advantously allowed the authors to adapt them and select potentially influential factors for the AI adoption-decision.

Despite its mentioned benefits, TOE has been criticized for solely being a taxonomy for categorizing factors, not representing an integrated framework (Dedrick and West, 2003). Wang et al. (2010) further claim that it is ambiguous since the identified factors, within each context, may vary across different studies. Therefore, it is perceived to have limited ability to generalize factors for explaining technology adoption across technologies and organizations (Gangwar and Raoot, 2013).

However, TOE is preferred since it is useful framework for distinguishing between different contexts - technological, organizational and environmental - influencing an organization's decision to adopt an innovation (Dedrick and West, 2003). While recognizing its limitations, TOE still enables the authors to closely analyze *why* telecoms decide to adopt AI, and has the ability to provide explanatory power for empirical analysis (Kuan & Chau, 2001).

To make TOE more robust and limit its weaknesses, of not being an integrated framework, TTF is added as a complement in this study. However, Goodhue and Thompson (1995) argue that TTF is limited by solely focusing on fit, providing insufficient notice to that a technology must be utilized to deliver performance impacts. Nevertheless, studying utilization is complex, and depends on various situational factors, such as habits and social norms (Goodhue and Thompson, 1995). Since this requires an individual-level unit of analysis, investigating utilization is beyond the scope of this study.

4 Method

4.1 Choice of Method

4.1.1 A Qualitative Study based on Positivism and Objectivism

Since this study aims to identify generalizable factors influencing the decision to adopt AI, a qualitative inquiry, within positivism, was chosen. A positivist epistemological stance enabled the authors to find consistencies between different factors of reality, whereby identified patterns could be summarized into generalized findings (Cassell et al., 2018).

To objectively, and in-depth, identify generalizable factors, an objectivist ontological position was taken, aligned with the chosen positivist epistemology. Ontologically, positivist qualitative research assumes that an objective and external reality can be summarized, however not readily quantified (Cassell et al., 2018). Since the authors claim that previous quantitative research within technology adoption lack reasoning on the rationale behind the adoption-decision, this method was preferred.

Given that AI, within telecom, is still in its early stages and that limited research on AI adoption is available, a qualitative research was chosen. This is preferable when studying an emerging and insufficiently understood phenomenon, which arguably applies to AI adoption. Moreover, a qualitative inquiry enabled the authors to develop new theory (Cassell et al., 2018), such as influential factors for the AI adoption-decision within the Swedish telecom industry. Since the key factors to investigate were rather ambiguous prior to collecting the empirical material, this method was deemed appropriate (Creswell, 1994).

4.1.2 An Abductive Study

The collection of theory and empirical material followed an abductive approach. This iterative process (Bell et al., 2019) was chosen for its potential to generate an in-depth knowledge of the phenomenon of interest and to decrease biased preconceptions, often associated with a strict deduction (Eisenhardt, 1989). Abductive reasoning allows for both testing existing theories, such as previously studied TOE and TTF factors, and developing new theories based on empirical data, such as new factors influencing the AI adoption-decision. Thereby, criticism of rigor related to strict induction and deduction (Alvesson and Kärreman, 2011), could be overcome. Solely relying on deductive reasoning (Bell et al., 2019), would have been rather difficult, given that AI adoption is still in its early stages within the telecom industry, and that existing research is limited within this field.

4.1.3 A Multiple Case Study

On the basis of the research question, a multiple case study was chosen for finding commonalities across cases (Bell et al., 2019). Since it has the potential to, from a positivist stance, find generalizable propositions (Eisenhardt, 1989; Yin, 2014), it was suitable for investigating the influence of factors for the AI adoption-decision. Furthermore, case studies, in general, attempt to provide insights into a *decision* (Yin, 2014), which resonates with the aim of this study.

Since AI adoption within the telecom industry is arguably a contemporary phenomenon, a case study research was preferred (Benbasat et al., 1987; Yin, 2014). Case studies have been found especially well-suited for IS-research as the focus has shifted from technical matters to managerial and organizational ones, aiming to explain the interaction between the context and innovations (Benbasat et al., 1987). Thus, relevant since this study uses contexts, within TOE and TTF, to investigate managerial decision-making and organizational AI adoption, rather than AI implementation. Primarily, the interviewees had a managerial role, making decisions on behalf of their organization. However, the studied organizations, represented by the interviewees, constitute the unit of analysis.

4.2 Choice of Cases

4.2.1 Telecom Companies

The choice of cases was based upon a purposive sampling, thus having the relevance to the research question and the aim of the study in mind. Specifically, a typical case sampling was chosen to exemplify a dimension of interest (Bell et al., 2019), such as AI adoption.

On the basis of AI being both expensive and resource-intensive, studying financially strong organizations was favored. Therefore, Telenor, Tele2 and Telia, which are leading telecom companies in Sweden, in terms of revenue (see 9.2), were chosen as cases. All have adopted AI, more specifically ML, to support their businesses, but the adoption and implementation is in the early stages and a work in progress. With regard to the research question, the authors considered them typical cases for investigating *why* they decided to adopt AI.

Since Telenor, Tele2 and Telia provide the majority (see 9.3) of the Swedish telecom services, they were seen as a suitable representative sample (Bell et al., 2019) for the Swedish telecom industry. Furthermore, to overcome complications of comparability, choosing companies within the same industry, having similar ML applications, was preferred. The initial contact with the companies was made through the network of the authors. Thereafter, the authors were forwarded within the organizations, making further contacts with interviewees.

4.2.2 Interviewees

Nine employees, within the selected case organizations, were individually interviewed. Each of them, except from one (innovation expert), having a managerial position related to AI. The choice of interviewees was strategically based upon their relevance for the research question (Bell et al., 2019) and their ability to provide a holistic investigation of the influential factors. Primarily, top-level managers, engaged in the strategic decision-making of AI adoption, were interviewed, while a few were middle-managers who provided more insights into the practical implications of these decisions. Since the majority of the interviewees were decision-makers on behalf of their organization, this was considered sufficient for the organization-level analysis of this study. In order to obtain a holistic investigation, both top managers and head of different departments were studied. The respondents are presented further in appendix 7.1.

4.3 Interview Process

4.3.1 Forming of Interview Guide

Before forming an interview guide, four main themes could be identified from the contexts presented in the integrated framework (table 1). Within these main themes, 10 sub-themes, or factors, were distinguished.

Main Themes	Technological	Organizational	Environmental	Task
Sub-themes	Perceived Complexity Perceived Relative Advantage Perceived Compatibility Technology Resources Data Availability Data Quality Technology Readiness Tech. Professionals Tech. Infrastructure	Presence of Champions Top Management Support Organizational Size	Competitive Pressure Government Involvement Supplier Partnerships	Task Complexity Task Interdependence

Table 1 Themes before collecting empirical material

An interview guide was formed to outline the topics needed to be covered in the interviews (Bell et al., 2019), mainly based on the structure of the integrated framework, having the identified themes in mind. The questions were formulated with regard to the research question and the abductive research design. To avoid biases, a broad and open question was asked initially as to *why* AI was adopted. Thereafter, more specific questions were asked based on previous research within technology adoption (see theoretical framework). These were grouped, as suggested by Bell et al. (2019), within each context of TOE and TTF to make the interview guide more comprehensible. Mainly subsequent questions were used, with direct "yes" or "no" questions asked prior to open-ended questions. This method was chosen to first obtain clear answers on the influence of contextual factors, further facilitating the analysis of the more open questions. Then, to avoid biases, broader and open questions were asked to in-depth investigate *why* the AI adoption-decision was taken (see 9.5).

4.3.2 Collection of empirical material

Supported by the interview guide, empirical material was collected through nine semi-structured interviews. Since this study included multiple cases, and two authors conducting the interviews, the semi-structure facilitated cross-case comparability, further aiming to enhance the study's reliability and validity (Bell et al., 2019).

The semi-structured format was chosen for its flexibility, allowing departure from the outline of the proposed guide (Bell et al., 2019). This resulted in the interviews having a more natural flow. Occasionally, follow-up and specifying questions were asked by the authors, aligned with the abductive approach of this study, as proposed by Alvesson and Kärreman (2011).

All of the interviews, except from one, were conducted face-to-face. The physical interviews took place at the headquarters of each company in Stockholm. This was agreed upon in advance via email, at the convenience of the interviewees. To ensure an undisturbed environment, and to get the most out of the interviews, they were conducted within closed conference rooms. Due to geographical distance, one interview was conducted digitally via a Skype video call. Although physical interviews are preferred for their interpersonal communication (Bell et al., 2019), a smooth face-to-face interaction was possible via webcam. Thus, making it close to a physical interview.

To ensure that the interview process had a similar overall structure and content, both authors were present when conducting the interviews. One asked questions, while the other took notes and assured that the topics in the interview guide were covered. Initially, introducing questions were asked regarding the background and role of the respondents, followed by more interview specific ones. Since this study focused on an organization-level analysis, the characteristics of the respondents were not of importance, except from the prerequisite of them having a decision-making or influential role in relation to the adoption-decision of AI. The interviews were recorded to obtain the advantages from transcription (Bell et al., 2019), further facilitating the analysis of the empirical material. The length of the interviews roughly varied between 30 and 60 minutes. This time was considered sufficient to cover all the topics during the interview process, as well as to promote an in-depth explanation of factors for answering the research question.

4.3.3 Analysis of empirical material

The interviews were conducted intensively between the end of February and mid-March 2020 (see 9.1), and transcribed continuously. This allowed an efficient processing of theory, aligned with this study's abductive approach, whereby three factors - government involvement, supplier partnerships, and task interdependence - were excluded from the study after the first three interviews, as they were relatively insignificant to other factors (see table 2; marked in red).

Theoretical saturation, as defined by Bell et al. (2019), was considered reached after nine interviews, when common influential factors were repetitively mentioned and distinguished among the cases. Thereafter, the interviews were analyzed, through a thematic analysis, to obtain generalizable propositions among the cases. Initially, the authors coded the transcribed material and mapped different themes individually before discussing their findings. Thereby, greater insights from the empirical material could be obtained, and a biased and narrow analysis could be avoided. Firstly, categories were based on similar quotes, and secondly, themes were identified based on the patterns found in the data (Bell et al., 2019). The thematic analysis enabled a deep understanding of the empirical data and made it possible to conclude themes along the theoretical framework, as well as new factors (see table 2; marked in blue), not initially part of the study.

Main Themes	Technological	Organizational	Environmental	Task
Sub-themes	Perceived Complexity Perceived Relative Advantage Perceived Compatibility Technology Resources Data Availability Data Quality Data Utilization Technology Readiness Tech. Professionals Tech. Infrastructure	Presence of Champions Top Management Support Organizational Size Financial Strength	Competitive Pressure Government Involvement Supplier Partnerships Competitive Advantage Customer Satisfaction AI Hype	Task Complexity Task Interdependence

Table 2 Themes after collecting empirical material

4.4 Ethical Considerations

All of the interviewees were willing to participate in the study. At the introduction of the interviews, they were informed upon their right to anonymity and to participate. Each respondent agreed upon the interviews being recorded, and to their role and company name being disclosed. To enhance the readability of the study, the nine interviewees are referred to as respondents (R#), with numbers ranging from 1 to 9 (see 9.1). With ethical considerations in mind, the transcribed interviews were sent out after being completed. This intended to give the interviewees a chance to confirm and approve their contribution to the content of the empirical material. Furthermore, to assure that they were comfortable with the use of quotes, those wishing to take part in the finalized study were informed upon these rights.

4.5 Method Limitations

The authors have strived to achieve a high reliability and validity in the thesis, taking into account Yin's (2009) stance on reliability, construct validity and external validity, to judge the quality of the research design. Since the study does not intend to establish causal relationships, the concept of internal validity was omitted (Yin, 2009).

4.5.1 Reliability

With the ambition to enable replicable findings, the authors collected and stored case study notes, such as recordings, transcribed interview material, and tabular material. These measures aim to heighten the reliability, and reduce errors and biases, aligned with Yin's (2009) research recommendations. To increase the reliability, Yin (2009) further recommends authors to establish a case study protocol and database, but for a bachelor thesis, this was considered too time consuming.

A multiple case study approach was preferred since it is more robust than that of a single case study. Even with two cases, direct replication is possible (Yin, 2009). Thus, three cases was considered sufficient. However, the authors acknowledge that getting access to the same interviewees might limit exact replication of the same case again.

4.5.2 Construct validity

To enhance construct validity of the study, and overcome limitations of biases and subjectivity, (Yin, 2009), a thesis draft was reviewed by peers and respondents. The aim of the latter was to avoid misunderstandings and misrepresentations of the empirical material. Yin (2009) further recommends authors to use multiple sources of evidence and establish a chain of evidence, however this was beyond the scope of this study.

4.5.3 External validity

Case study research has been criticized for its poor basis to generalize findings beyond the case study (Yin, 2009). However, Flyvbjerg (2006) and Yin (2009) disagree, as any case is based on context-dependent knowledge. To ensure external validity, Yin's (2009) recommendation upon a literal replication logic, for multiple case studies, was followed, by choosing similar cases (telecom companies) with the aim to obtain similar results (generalizable propositions). Moreover, since a multiple case study, in contrast to that of a single case study, enables finding commonalities among the studied cases, it was chosen to provide external generalizability to the study.

5 Empirical Material

The AI applications, of Telenor, Tele2 and Telia, will shortly be presented below, followed by an explanation for *why* these companies decided to adopt AI.

5.1 AI Applications

5.1.1 Telenor

Telenor applies AI to personalize products and services for customers. They also use it to increase efficiency in business processes, such as customer call centers, stores, digital media purchases, and in the network. Moreover, they use it for preventative maintenance, predicting and preventing failures before these impact customers.

5.1.2 Tele2

On the commercial side, Tele2 applies AI on customer data to predict churn rate, enabling them to take actions to keep customers. Other use-cases include chatbots and customer service solutions. On the network side, AI is applied to create a normal behavior baseline and to detect anomalies in the network. This enables them to be proactive in the maintenance and operations of the network, increasing internal efficiency.

5.1.3 Telia

Telia clusters AI into three areas. Firstly, internal efficiencies, including optimizing business processes, networks and other systems. AI is used for speech-to-text conversion in customer service, and for predictive maintenance of the network. The second area is customer-facing AI solutions, including customer interactions, sales and products sold to them. Both chatbots and natural language processing are used. Thirdly, experimental AI, where Telia, independent from concrete operations or services, explore future AI use-cases.

5.2 Importance of AI Business Case

A recurring theme in the interviews is the importance of having an AI business case. All respondents claim that AI initiatives should be purpose-driven, emphasizing that the decision to adopt AI should be based on problem-solving and value-creation. R3 describes: “First you need to face a problem [...] this is where companies often go wrong and say: ‘We need to work with AI’. But the question is what and how.”. To highlight that AI-usage should not be exaggerated, R7 states: “AI has never been a goal in itself. The problems have been in focus. AI has been the key in some cases, but not all.”. Rather than being a goal in itself, the respondents describe AI as a tool or an enabler to achieve the higher organizational goals. R9 emphasizes: “ [...] there is a lot of hype and resources being invested in AI just for being AI [...] being very clear on: ‘What are we trying to accomplish?’ is important”.

Most respondents mention the importance, but also the challenge, of integrating AI into the organization’s core business. R1 says: “This (AI) needs to be very close to the business” and “It is very important that you do not set up this function in isolation, or in IT, because that is far from where the business is happening.”. Likewise, R6 describes: “It is problematic that it is a technology-driven push. It should be a business and organizational driven investment.”.

5.3 Motivations for AI Adoption

5.3.1 Increase efficiency

Since machines perform some tasks better than humans, automation increases efficiency in business processes. All respondents refer to this as a motivation for adopting AI. Within Telenors marketing department, R2 explains: “The idea to buy through AI, instead of humans, is based on that a machine, in these types of manual and easy processes, such as trading (digital media), always beats a human”. R3 describes that AI-usage facilitated mail management within the customer service: “Before, this was a big black hole. You can imagine thousands of incoming mails, no human could keep track on all of them the moment they arrived.”. Increased efficiency further promotes increased revenues and reduced costs, which are both described as motivations to adopt AI. In some cases, AI applications intend to increase revenues by attracting new customers, mostly from competitors, and by avoiding existing customers to churn. Alternatively, reduce costs by making the internal processes more efficient.

5.3.2 Increase customer satisfaction

All interviewees describe increased customer satisfaction as a reason to adopt AI. R9 says: “If we can improve customer satisfaction with the help of AI, that is the main driver above all.”.

There are many ways to do this, but several mention using AI to personalize products and services for customers, a matchmaking business. R1 states: “We look at the customer and what products and services that are relevant for that customer. This is only possible when having the right data and analytics capabilities.”.

Increasing customer satisfaction further relates to increasing revenues. R2 explains this: “It (AI) needs to support the larger goals in the company, thereby the financial goals in the end. You create good customer experiences to make the customers buy more, use our service more, like us more, stay longer.”. R4 agrees: “In the end, it is always about a) make the customers more satisfied by being more relevant in our communication with them and in what we offer them, b) make as much money as possible for Tele2 and the stockholders.”.

R8 further describes that satisfied customers may promote the organization’s reputation: “The services that we provide to our customers need to be of a higher quality [...] that will usually lead to a good reputation in the market.”.

5.4 Organizational Prerequisites

5.4.1 Big data within telecom

Big data is apparent within these telecom companies. In their favor, desirable results can be obtained by running a vast amount of data through AI algorithms. Thus, all respondents acknowledge the importance of having access to data. R3 argue: “It is entirely vital. If you do not have the right data, then you cannot train anything in terms of AI, less make the right decisions.”. However, R8 states: “The availability of data is very high, but the capability of actually making it visible, making it trustworthy and basing your decisions on it, that is the tricky part for most of the telcos.”. The respondents describe that data availability gives telecoms prerequisites for adopting and using AI, but the organizations do not make the adoption-decision simply because there is access to data.

Nevertheless, everyone confirms that utilizing data more effectively induced them to adopt AI. R9 explains: “AI allows you to use data in a much better, more efficient and targeted way.”. Some respondents also claim that they were drowning in big data, seeing a lack of value in it, prior to adopting AI. Post adoption, data could be analyzed and correlated more efficiently, further improving the quality of their services. This was seen as essential for the adoption-decision.

5.4.2 Need for task automation

Since big data is hard for humans to process, the need for automation of tasks was a prerequisite for adopting AI. All respondents, except R6, claim that AI was adopted to enhance understanding and processing of information. R7 explains this within data analytics at Tele2: "We pick insights from our network. It is possible to do this manually, but with the help of these algorithms, we reduce the complexity enormously and make it much easier to use it.". However, R6 states that maturity in AI-usage differs across Tele2's departments: "Our tasks (chatbots and customer service solutions) are seldom of the nature that they are very complex so that you need to put an AI algorithm on it. We are not there yet.".

While AI facilitates understanding of information, several respondents argue that the task complexity itself remains. R8 explains it merely being hidden by AI. R1 describes: "You might not be able to reduce the inherent complexity because that is the nature of the business. But your ability to understand what is going on (through AI) improves the decision-making.".

Despite facilitating employees' work, some argue that technical complexity increases with AI while reducing task complexity. R9 argues: "AI as a tool or solution can definitely help reduce the complexity. The question is how you get there. So the solution as such, yes, but there are complexities in actually adopting AI.".

5.4.3 AI investment

Adopting AI may entail a heavy investment, requiring financial strength. All respondents agree that financial strength, often prevalent in bigger companies, influenced the adoption-decision. R5 explains: "Organisational size implies two things - often bigger companies have access to more data and also have abilities to swallow the large costs to have a department working on AI. This kind of competence is not cheap.". However, some argue that AI investments are relatively small to that of other investments within telecom. R4 explains: "Of course you need the necessary financial strength to invest in AI, but in the context of Tele2 the AI investments are not large compared to other investments we make.".

5.5 Telecom Industry in Sweden

5.5.1 Fear of falling behind

There are conflicting opinions amongst the respondents regarding the competitive landscape. R1 admits competitive pressure influenced the AI adoption-decision, induced by that " [...] more and more companies are actually developing their capabilities in this front.". Five respondents deny experiencing pressure from fellow telcos to adopt AI. Some respondents at Tele2 devote this to them being in the forefront, ahead of the competition. It is also devoted to telecoms not being AI providers, but solely AI adopters. R8 continuous: "We are the ones adopting AI to help us become better and more innovative. Therefore, I do not feel a big pressure from peers [...] ". R3 agrees: " [...] we do not sell AI [...] our competition is to have the best customer service which we do with the help of different techniques. One of them is AI.".

However, a majority of the respondents express fears of falling behind, that is, having a competitive disadvantage. R7 explains this: "It is a recurring topic at conferences: 'How far have you come?', 'What are you doing within AI' [...] 'Are we falling behind?' [...] This has driven the development of AI and ML much in the industry. The sense that: 'This is a train that we must jump on'". R9 emphasize: " [...] it is really important to be in the forefront, to start thinking about what we can do within the company and to be one of the first adopters.". Both R9 and R1 claim that AI will become more pervasive and less optional. Thus, companies will need to have a progressive mindset on this, otherwise they will lose in the long run. R6 describes measures taken to avoid falling behind: "We have a strategy department monitoring everything that happens. Someone might make a giant leap, causing us to panic a little.".

5.5.2 Competitive advantages of AI adoption

All respondents agree that AI brings competitive advantages. Moreover, it is essential in a rather saturated telecom industry. R1 states: "How do you grow as a company in a market that is not growing? You need to take customers from your competitors while simultaneously keeping your current customers. This is driven by AI.".

5.6 AI Initiatives

5.6.1 Bottom-up driven initiatives with top management support

Since needs for AI occur at an operational level, all respondents, except for R1 and R6, explain the AI initiative as bottom-up driven. R3 states: “It has never really been a management decision. That has been ‘We need help with the customer service, can the IT department help us with something here?’”. R9 explains: “It was very much bottom-up driven and then we (top management) lifted it to top-down.”.

All respondents mention having people driving and advocating AI initiatives. R8 describes: “It was bottom-up. It basically came from a group of very passionate people in the organization saying: ‘We think we can do something unique here’.”. The majority, apart from R1 and R2, recognize AI champions as important for successful AI adoption. R6 emphasize: “We had one (AI champion), and without this person I do not think that we would have done it (adopt AI) [...] It was absolutely crucial.”. R1 states not having such a champion: “It has been the top management. For example, the CMO has been the biggest sponsor of this.”.

Everyone underlines that to realize AI initiatives, they need support from top management who have the final say in investment decisions. R4 describes: “It is extremely important that you get support from top management. In the end, it is about money and investments [...] If top management does not understand the value of an initiative you will never get it through.”. R9 agrees: “You need to have C-level buy-in and a strategic approach to AI. You cannot drive this on a case by case basis. It is too big and too important to let go.”. R8 further describes their importance for prioritization: “Otherwise you do not get the priority. If you do not prioritize really hard [...] prioritizing the resources [...] then it is hard to see that you can succeed.”.

However, R7 puts less emphasis on top management support for AI, explaining it as a favored tool by them “ [...] as long as it (AI) gives results, works, keeps costs down and so on.”. Thus, relating their support more to higher organizational goals.

5.7 Barriers of Implementation

5.7.1 Perceived ease of use

The adopted AI technologies, specifically ML, are overall perceived as easy to use within the organizations. R9 explains: "It is simply another technology and we are good with technology.". Furthermore, the respondents express enthusiasm. R6 states: "It has been perceived as something fun to work with [...] it has not been very hard to understand it.". R2 says: "I find that this tool has been very easy and intuitive to work with.".

There are, however, differences in perceived complexity between those developing AI tools and those using them. R8 describes: "It is very complex to build it (AI), do not get me wrong, but the usage and the outcome needs to be very simple.". Some respondents also claim difficulties in training AI models and ensuring that these stay up-to-date in a reality where circumstances change continuously.

The respondents describe that AI adoption in itself is challenging, rather than the adoption-decision. R1 explains: " [...] adoption in the company, that is a hurdle, because people still follow gut and the way they were doing things. So, not a barrier for the decision, but a barrier for adoption.". Moreover, the respondents argue that implementing AI into the organization, outside the IT department, is challenging.

5.7.2 Organizational AI readiness

Organizational readiness for AI adoption relates to competence and infrastructure.

The organizations did not have the needed capabilities prior to adopting AI. However, this is not described to have been a barrier for the adoption-decision. Everyone explain AI competence being continuously developed in-house during the implementation. R9 states: "We are building competence, but that does not stop us from taking the decision.". Several respondents claim that there is a very limited amount of people having an AI skill-set, making it difficult to hire them and use third-parties. Nevertheless, R1 reasons: "There is no point in bringing data scientists and highly experienced people in this field, unless you have the right data, infrastructure and capabilities in place.".

Furthermore, the organizations needed to change their platforms to ensure technological support for storing and processing big data. All respondents argue that having the right infrastructure facilitates obtaining structured data, thereby adoption. Thus, infrastructure and data quality go hand-in-hand.

5.7.3 Need for data quality

Having structured data is described as important both for AI adoption and implementation. R8 explains: “The lack of quality limits AI adoption. We want to do more, but the structure of data is becoming more of a hassle.”. All respondents argue the need for data quality, as AI models and algorithms malfunctions using poor data. However, while implementing AI, the organization’s data has needed to be improved and continuously developed. R9 states: “I think it is far from good [...] this is a challenge [...] but we are working on it.”.

Nonetheless, it is not a barrier for the adoption-decision. R8 states: “The decision was very clear. We needed to do this in order to improve the quality of the network. And then, as we went along, we started seeing that there are quality issues in some of the data.”.

5.7.4 Irrelevance of organizational size

The meaning of organizational size varies among the respondents. Some relate it to financial strength, while others relate it to data availability. However, all respondents argue that size in itself does not influence the decision to adopt AI. R1 states: “Size was not necessarily influential [...] irrespective of the size, this (AI adoption) is something that you have to do.” Instead, several argue that data availability is more important, such as R4: “Rather than the size [...] the amount of data we have available is relevant [...] A big company with low amounts of data would of course not invest in AI. A small company with lots of data would be more inclined to do so than a big company with low levels of data.”.

Two respondents, R3 and R9, refer to size as a disadvantage for implementing AI. R9 argue: “I think size is a minus in this case. The bigger the company, the more complex the decision-making, adoption, collaboration and coordination.”. Smaller companies are perceived more flexible and “closer to decisions”, possibly making them more efficient when adopting technologies. But then, financial strength may be lower.

5.8 Driving force of the AI Hype

During the interviews, the topic of the AI hype emerged without being explicitly asked upon. All respondents, except for two, acknowledge AI being a hype and a buzzword. R9 states: " [...] it is highly overhyped [...] many people misuse the word [...] it is the next hot thing [...] over time we will see who are AI pretenders and who are AI adopters.". R7 admits its influence on the adoption-decision: "One of the drivers, that is more irrational, is that it (AI) is a buzz. It is at the top of the hype-curve and therefore you should do it. Many companies jump on the train because: 'Everybody else does it, now we also have to do it' [...] this (AI hype) was an influential factor for us as well.".

6 Analysis

The structure of the analysis is based on the integrated theoretical framework, investigating what factors were influential for the AI adoption-decision among the telecoms.

6.1 Technological Context

Perceived Complexity

AI is described as easy to use and fun to work with, indicating a low perceived complexity, presumably due to telecoms being technological by nature, and implementing new innovations continuously. In a less technology-driven industry, AI would probably be perceived as more complex, possibly affecting the adoption rate negatively as posited by Rogers (2003). Since the studied telecoms are in the early stages of AI adoption, low complexity may further be explained by them not having implemented more complex applications yet. However, difficulties arise when building AI models and aligning them with the organization, thus a barrier for implementation, but not for the adoption-decision. Hence, perceived complexity was uninfluential for the adoption-decision, opposing findings by Cooper and Zmud (1990) and Lin and Chen (2012).

Perceived Compatibility

The interviewees emphasized the importance of having a business case when taking the AI adoption-decision. AI was stressed to not be a goal in itself, but rather an enabler to reach a higher purpose. Since big data is overwhelming, these telecoms established a solid business case and articulated business needs for AI, such as task automation and enhancing understanding of data, aligned with Bughin et al. (2017). AI was described as highly compatible with the needs of the studied telecoms, thereby suitable for their organizations, supporting Rogers (2003), and previous studies (Yang, 2015; Lin and Chen, 2012; Wang et al., 2010; Cooper and Zmud, 1990). Moreover, in line with Bughin et al. (2017), it was stated that AI should not be implemented in isolation, but integrated into the strategy and business of the organization. However, contradictory, AI is still more of a technology-driven, rather than organizational-driven "push". This may once again be due to the early stages of AI adoption, whereby large-scale AI applications have not become an integral part of the business yet, but this was rather a challenge for the implementation.

Perceived Relative Advantage

Relative advantages from AI, including efficiency gains which further leads to revenue generation, cost reduction, and improved status among customers, were consistently stated by interviewees, as main reasons for adopting it. This complies with relative advantages for innovation adoption, stated in DOI by Rogers (2003), and for AI adoption specifically, stated by Ransbotham et al. (2019). Since increased efficiency was promoted by machines superseding humans through task automation, this aligns with Rogers (2003), stating that an innovation is more likely to be adopted if it is better than existing practices it supersedes. Thus, this factor was influential for the AI adoption-decision, supporting Ramdani et al. (2009). However, if technologies with relative advantages over AI enters the market, the authors consider the possibility of these companies abandoning AI. This may be explained by AI only being an enabler, hence the technology in itself does not matter, but rather the things it can achieve.

Barriers regarding uncertainties for ROI, mentioned by Bughin et al. (2017), are opposed. This is attributed to AI investments being relatively small to other investments within these telecoms. However, since these are large organizations and leading telecoms in Sweden, in terms of revenue, their financial strength may be taken for granted, ultimately not impeding their decision to adopt AI.

Technology Resources

The influence of data availability and data quality on the AI adoption-decision differs.

Access to data was perceived a prerequisite for using AI algorithms, aligned with Aboelmaged (2014), but the AI adoption-decision was not taken simply because there is data. Again, since these telecoms naturally possess big data, this may be taken for granted when deciding to adopt it. Hence, data availability is not a decisive factor, although influential.

The data quality was a barrier for these telecoms, further needing improvements during implementation for it to be compatible with AI models and algorithms, thereby fitting the needs of user tasks (Dishaw & Strong, 1999). However, data quality was uninfluential for the AI adoption-decision, perhaps because of relative advantages overshadowing barriers. It may also be a result of these companies being technology-driven, giving them confidence in solving implementational problems.

Data utilization emerged as a new decisive factor within technology resources. Utilizing data more effectively was emphasized as highly influential for the adoption-decision. Since these telecoms recognized a lack of value in data, this factor was a reason for deciding to adopt AI.

Technology Readiness

Technology readiness (technology professionals and technology infrastructure) was stated inadequate prior to adoption. Nevertheless, these capabilities were continuously developed in-house during the implementation process, likely facilitated by these telecoms being tech-savvy and having necessary organizational prerequisites, such as big data, financial strength, and tasks suitable for automation. Since they had internal capabilities for developing AI competence, they could thereby overcome challenges of AI professionals (developers of AI tools) being a scarce resource in the labor market. Moreover, on the basis of AI arguably not being too different from other technology adoptions, the general technology competence within these telecoms may have facilitated the adoption. Hence, low technology readiness for AI was not a barrier for the decision to adopt AI, contradicting findings by Zhu et al. (2003), Zhu et al. (2005) and Zhu et al. (2006), but for the implementation.

Sub-conclusion (1)

Perceived compatibility, perceived relative advantages and data utilization were concluded decisive factors, while data availability was influential. Finally, data quality, technology professionals and infrastructure, as well as perceived complexity were uninfluential.

6.2 Organizational Context

Presence of Champions

The interviewees stressed that the AI initiatives were mainly driven bottom-up by passionate individuals, or AI champions. Supported by Tushman and Nadler (1998), a majority of the interviewees emphasized that the presence of champions was important for realizing such initiatives. By communicating a compelling vision for AI adoption within these telecoms, as proposed by Howell and Higgins (1990), these champions successfully introduced the idea of

AI and promoted joined efforts. Aligned with Tushman and Nadler (1998), risk-taking champions may promote getting necessary resources, but ultimately, managers made the final decisions and allocated financial resources. Thus, making champions enablers rather than decision-makers. This may explain why some respondents put more emphasis on TMS. Furthemore, the importance of champions can be connected to the compatibility factor, putting emphasis on having a business case. Since the articulated business needs for AI occur at an operational-level, this may explain the essence of AI initiatives being driven bottom-up, rather than top-down.

Top Management Support

Supporting Hsu et al. (2019), top managers ultimately decided on investment-prioritization for AI initiatives. Within these telecoms, TMS for AI was mainly expressed by them allocating resources (Yang et al., 2015) and providing necessary funds (Rodríguez et al., 2008) for adoption. Moreover, top managers were highly supportive of AI, aligned with Sabherwal et al. (2006), and promoted bottom-up initiatives, by bringing these to top-down. However, TMS was less emphasized by one respondent, interestingly a champion, describing that managers only favor AI as tool if it achieves higher organizational goals. Again, this relates to the compatibility factor, where AI was described as an enabler. Perhaps this champion felt a lack of TMS, or recognition, for embodying innovative work. Supported by Tushman and Nadler (1998), this individual may not have perceived the personal and organizational value of his/her informal role. Nevertheless, overall, TMS was influential for the adoption-decision, supporting findings of other scholars (Yang, 2015; Wang et al., 2010; Ramdani et al., 2009). However, the authors argue that TMS is not specific for AI, but of importance for all larger investments.

Organizational Size

Organizational size was an ambiguous factor, supported by Baker (2011), stating an inconclusive link between size and innovations.

These large telecoms were, as stated by Aboelmaged (2014), benefited from having data availability and financial strength. Size, in terms of revenues, enabled these telecoms to absorb costs and risks of AI implementation. However, the interviewees expressed that the AI investments were relatively small, compared to, for instance, their network investments. Financial strength was therefore not considered a decisive factor, although, in agreement with

Thong (1999), it was influential for the adoption-decision. For less financially strong companies, financial strength may be a more decisive factor.

Size in itself was uninfluential for the adoption-decision. However, two respondents claim that decisions to adopt AI were negatively influenced by their large size, due to having more complex decision-making processes, possibly suffering inertia. Thus, contradicting findings of previous scholars (Aboelmaged, 2014; Zhu et al., 2003; Zhu et al., 2006). Smaller companies are stated to be “closer to decisions”, likely giving them greater flexibility and innovativeness, confirming Zhu et al. (2006) findings. But their smaller size may entail less financial strength. Because of the ambiguous nature of organizational size, the authors claim that more specific factors should be investigated.

Sub-conclusion (2)

Presence of champions was concluded influential, critical in some cases. Likewise, TMS was influential. Organizational size in itself was concluded uninfluential, alternatively a negative influence for the AI adoption-decision of these telecoms.

6.3 Environmental Context

Competitive Pressure

Competitive pressure is a conflicted factor. Roughly half of the respondents deny its influence. Tele2 respondents attribute this to them being in the forefront in the Swedish telecom industry, while the respondents in general refer this to telecoms not being AI providers. Still, most of them admit to fears of falling behind. This perhaps simulated the decision to adopt AI, as stated by scholars (Zhu et al., 2006; Sabherwal et al., 2006; Wang et al., 2010; Zhu et al., 2003), more than they would like to admit. Hence, these fears may be explained by an underlying competitive pressure.

These telecoms decided to adopt AI to obtain competitive advantages, which may relate to its relative advantages, including increased efficiency, revenue generation and cost reduction. Aligned with Zhu et al., (2006), the peer pressure may have induced them to seek competitive advantages from AI. Most likely, as suggested by Zhu et al. (2003), to leverage new means, through AI capabilities, for outperforming peers.

AI Hype

The AI hype was a recurring theme when collecting empirical material and emerged as a new factor influencing the adoption-decision. Since most interviewees emphasized the importance of "jumping on the train" to adopt AI because others do so, this suggests an imitative behavior. Moreover, if underlying needs become too defined by imitation, and less by the AI business case, this would contradict the significance of perceived compatibility.

Customer Satisfaction

Customer satisfaction emerged as a new factor in the interviews, not previously studied within TOE. This was stated a main reason for adopting AI, since it may create good customer experiences by enabling personalization of products and services for customers. Improved customer satisfaction, in turn, was described to increase sales, reduce churn and attract new customers through word-of-mouth, thereby increasing revenues. Thus, the authors find this an overarching decisive factor, connected to the factor perceived relative advantage. However, satisfying customers is the ultimate aim of any business having a clientele. Thus, the authors claim its importance is not exclusive for AI adoption.

Sub-conclusion (3)

These telecoms are essentially customer-focused, thus customer satisfaction was concluded a decisive factor. Likewise, competitive advantage was decisive, while the AI hype and competitive pressure was concluded influential for the AI adoption decision.

6.4 Task Context

Task Complexity

Data analyzability may have been difficult due to the vast amount of data and lack of data quality, making tasks complex. Thus, AI was adopted to enhance the understanding and processing of big data. Since these telecoms recognized having a lack of value in data, and since machines are better than humans in performing data analytics, there were strong needs for task automation. This aligns with Goodhue and Thompson (1995), stating that complex tasks forces the use of technology. However, the interviewees state that the inherent task complexity remains. AI only hides it by facilitating understanding of data, thereby contradicting Awa et al. (2017), claiming that organizations adopt technologies to make tasks less complex. Nevertheless, since AI functionalities (data analytics) fit the organizational tasks (analyzing big data), this factor positively influenced the adoption-decision, aligned with Dishaw and Strong (1999).

Sub-conclusion (4)

Task complexity was concluded influential for deciding to adopt AI.

6.5 Influence of Factors for AI Adoption-Decision

Based on the findings, factors have been clustered in table 3 within three levels of influence, being either decisive, influential or uninfluential for the AI adoption-decision. Moreover, each factor has been identified as either influential (+) or uninfluential (-), according to the each respondent, alternatively lack of empirics (Ø). To emphasize the importance of factors, dark blue (highly influential) and dark gray (highly uninfluential) was used.

Level of Influence	Factors	R1	R2	R3	R4	R5	R6	R7	R8	R9
Decisive Factors for AI Adoption	Perceived Compatibility	+	+	+	+	+	+	+	+	+
	Perceived Relative Advantage	+	+	+	+	+	+	+	+	+
	Customer Satisfaction	+	+	+	+	+	+	+	+	+
	Data Utilization	+	+	+	+	+	+	+	+	+
	Competitive Advantage	+	+	+	+	+	+	+	+	+
Influential Factors for AI Adoption	Top Management Support	+	+	+	+	+	+	+	+	+
	Data Availability	+	+	+	+	+	+	+	+	+
	Task Complexity	+	+	+	-	+	-	+	+	+
	Presence of Champions	-	-	+	+	Ø	+	+	+	+
	Financial Strength	+	+	Ø	+	+	+	+	+	+
	AI Hype	Ø	+	+	+	+	Ø	+	+	+
	Competitive Pressure	+	+	-	+	+	-	-	-	-
Uninfluential Factors for AI Adoption	Data Quality *	-	-	-	-	-	-	-	-	-
	AI Competence *	-	-	-	-	-	-	-	-	-
	Infrastructure *	-	-	-	-	-	-	-	-	-
	Organizational Size **	-	-	+	-	-	-	-	-	+
	Perceived Complexity *	-	-	-	-	-	-	-	-	-

Table 3 Level of Influence and Importance of Factors

* Note: Did not influence the adoption-decision, but the implementation.
** Note: Influence marked positive (+) and in red due to large organizational size having a negative impact; inertia.

Supported by the empirical material and analysis, some factors diverged from the initial theory, including Technology Resources (Data Availability; Data Quality), Organizational Size (Size in itself; Financial Strength) and Competitive Landscape (Competitive Pressure; Competitive Advantage). Hence, these have been identified on different levels of influence. Moreover, Technology Resources was separated into AI Competence (technology professionals) and Infrastructure (technology infrastructure) for clarifying reasons. However, these were found similarly uninfluential.

7 Discussion and Conclusion

7.1 Answer to the Research Question

Through a qualitative study, the authors have investigated the rationale behind the AI adoption-decision within the Swedish telecom industry, by answering the research question:

Why do telecom companies in Sweden decide to adopt AI?

An integrated framework, combining TOE and TTF, was applied to guide the collection and analysis of empirical material, which revealed three levels of influence - decisive, influential or uninfluential - for the decision of these telecoms to adopt AI.

Decisive factors for AI adoption

The decisive factors were crucial for the AI adoption-decision, with Perceived Compatibility and Perceived Relative Advantage being the most influential. Customer Satisfaction was a new factor, not previously studied in TOE, but identified as influential in this study. However, satisfying customers is inherent in all businesses, hence not exclusive for AI adoption. Another new factor was Data Utilization, expressed as highly influential since these telecoms suffered a lack of value in their vast amount of data. Lastly, Competitive Advantage was as an important factor, pervading all interviews.

Influential factors for AI adoption

The influential factors positively supported the decision to adopt AI, but were not main reasons for taking it. Top Management Support, Data Availability, Task Complexity, Presence of Champions and Financial Strength were perceived as important prerequisites, facilitating AI adoption. Competitive Pressure was an influential, but conflicted, factor. AI Hype was identified as a new factor, not initially included in TOE, but emerged as influential for the adoption-decision, both explicitly and implicitly, in the empirical material.

Uninfluential factors for AI adoption

The uninfluential factors were not critical for the decision to adopt AI, but important during the implementation. These include Data Quality, AI Competence, Infrastructure, and Perceived

Complexity. Since their importance appear after taking the adoption-decision, they go beyond the scope of this study. Moreover, Organizational Size was uninfluential, alternatively having a negative influence since these large telecoms have more complex decision-making and business processes, than that of smaller companies.

7.1.1 Conclusion

The studied telecoms were driven by practical needs, whereby the business case was an ultimate motive for AI adoption. AI has mainly been an enabler, helping them to solve problems, facilitate business processes and utilize data more efficiently. Based on these perceived benefits, AI was adopted with the purpose to satisfy customers and obtain competitive advantages. In conclusion, these motivations can be summarized into decisive factors for *why* the AI adoption-decision was taken by these telecoms. While not being decisive, influential factors were important for realizing the AI initiatives. Finally, the uninfluential factors were only of importance for the implementation of AI.

7.1.2 Model of Levels of Influence for AI Adoption-Decision

The findings in this study can be summarized in a model including three levels of influence - decisive, influential or uninfluential - for the AI adoption-decision.

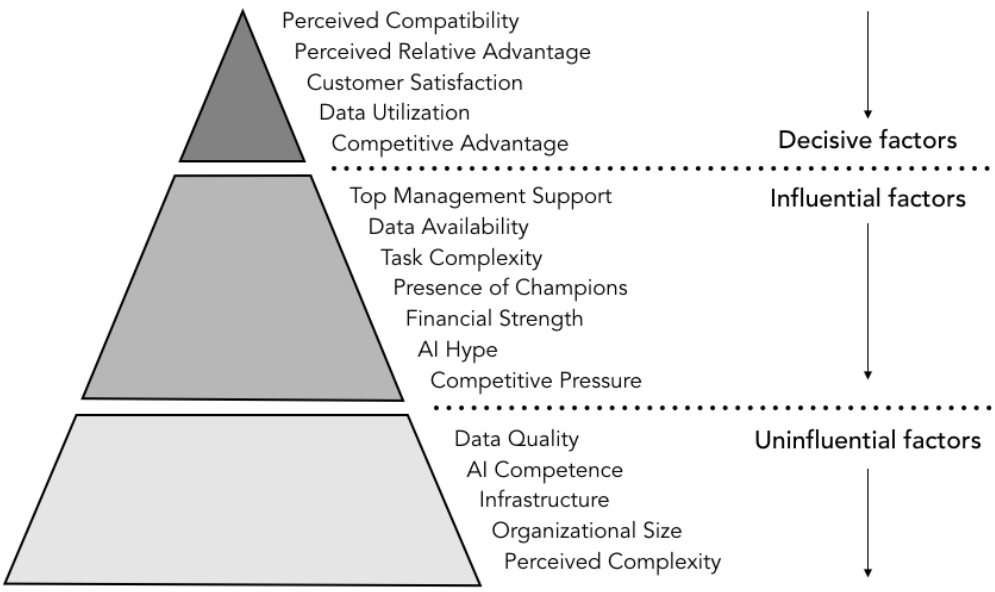

Figure 2 Model of Levels of Influence for AI Adoption-Decision *Johnsen & Lindblom (2020)*

The authors underline that the model does not intend to generalize findings beyond the studied case organizations. It is constructed to holistically visualize the influential factors for the AI adoption-decision within these telecom companies in Sweden. The hierarchical order of factors refers to table 3, indicating their importance for the decision to adopt AI.

7.3 More than an AI Hype?

After concluding upon the influence of factors on the AI adoption-decision, this brings the authors to one remaining fundamental question: Is there more to the AI adoption of these telecoms, or are they just following a hype? Since the AI hype was repetitively mentioned by a majority of the respondents, it is hard to deny its influence. Perhaps it was more of an underlying factor than they would like to admit.

The phenomenon of the AI hype can be further analyzed through mimetic pressure, one type of institutional isomorphism. This refers to the imitative behavior of organizations, which in turn is a response to uncertainty (Dimaggio and Powell, 1983). This may be related to the fears of falling behind, expressed by the interviewees, within the Swedish telecom industry. In media and businesses, the advantages of AI are hyped. Moreover, the empirical material reveal that AI is becoming more pervasive and less optional, which may have influenced the the studied companies to adopt it.

To enhance their legitimacy, Dimaggio and Powell (1983) state that organizations tend to imitate similar organizations, perceived as legitimate or successful, by adopting similar innovations. Since AI is one of the latest technologies, these telecoms may have adopted it in an attempt to legitimize their relevance. This is supported by some respondents claiming that companies failing to act upon this will lose in the long run.

One respondent mentioned that AI enabled them to improve the quality of their telecom services, aiming to promote reputational gains through satisfied customers. Rogers (2003) claims that status seeking is a main motive for imitating innovation-behaviors of others. Likewise, these telecoms may have adopted AI to improve their status in the market, whereby the AI hype was possibly an underlying factor.

7.4 Theoretical Contribution

There is a limited amount of studies on the rationale behind the AI adoption-decision. Therefore, the authors argue that it is still an emerging field, requiring further research.

While the TOE and TTF frameworks have been applied to study other technology adoptions, the specific set of factors investigated, in this study, have not previously been studied for AI. Through the integrated framework, the study contributes to a more holistic explanation for *why* these telecom companies decided to adopt AI. Furthermore, the study extends the theoretical framework as three new factors - Customer Satisfaction, Data Utilization and AI Hype - were identified when collecting the empirical material.

Lastly, while the majority of earlier studies have been quantitative, this qualitative study provides deeper and more nuanced insights into *why* the AI adoption-decision was taken. Previous quantitative studies have been limited to only accepting or rejecting the influence of certain factors. With regards to the holistic and qualitative approach, the study contributes to a general model on the AI adoption-decision for the studied telecoms, whereby three levels of influence - decisive, influential and uninfluential - have been identified.

7.5 Practical Implications

Since AI adoption may have practical implications for companies and society at large, this study concludes the importance of studying this to a greater extent. Big data is overwhelming for many companies, but AI has the ability to bring strong relative advantages over traditional technologies. With increased efficiency, profits may be improved, further contributing to societal economic growth. Moreover, by increasing the quality of products and services, customers may be more satisfied with their telecom operators.

AI is highly relevant today and vastly hyped in media. Many consulting reports and articles, as presented in the introduction, discuss the hype and lack of strategies to adopt it within organizations. The authors wanted to bring forward the voices of practitioners, investigating the rationale behind *why* they decided to adopt AI, to demystify the phenomenon. The study concludes that the AI Hype was an underlying factor, reminding the studied organizations to be up-to-date, but it was arguably far from the most important influence.

With this study, the authors wanted to enlighten companies, foremost within telecom, on influential factors that needs to be taken into consideration when deciding to adopt AI. In turn, this is foundational for a successful AI adoption and implementation.

7.6 Transferability

Since the studied companies - Telenor, Telia and Tele2 - provide the majority of telecom services in Sweden, the authors argue that the findings are transferable to the Swedish telecom industry. However, on the basis of most interviews being conducted at Tele2, and of them having a smaller market share than Telenor and Telia (see 9.3), this may have skewed the study and limited transferability. Overall, the authors considered nine interviews sufficient for answering the research question. However, to make the findings more transferable to the telecom industry in Sweden, conducting more interviews, especially at Telenor and Telia, would have been preferable, providing further depth and breadth.

Although Perceived Compatibility was concluded the most influential factor in the analysis, it has been stated uninfluential in previous studies for SMEs. By investigating whether factors differ depending on size, a comparative analysis, including smaller companies, could have made the study more nuanced and transferable, irrespective of size. However, since large companies may have a bigger impact on society, studying these large telecoms was preferred.

7.7 Limitations

Since the study includes a limited number of theoretical factors, while being open to new ones, these may not be exhaustive. The exclusion of three factors (see table 2) may have limited the findings. These could potentially have been important later on in the interview process and contributed to an interesting analysis. Moreover, there are other factors, proposed by TOE and TTF, that were left out in the adaptation of the theoretical frameworks.

Furthermore, since the studied telecoms were represented by the respondents, this may have limited the objective ontological position. Their subjective perception, on *why* the AI adoption-decision was taken, could be a limitation for the authors' ability to present the cases in a generalizable way.

Finally, to make the study more solid, a qualitative and quantitative method could have been combined. However, this was disregarded due to the limited time and scope of a bachelor thesis.

7.8 Future Research

The aim of this study has been to obtain generalizable propositions, among the studied telecoms, for *why* they decided to adopt AI, but not for the AI adoption-decision in general. To make the study more robust and generalizable beyond the studied cases, the authors propose future research to include more organizations, interviewees, and factors. Studying the AI phenomenon from a broader and more international perspective may be of interest, giving different insights, especially on country specific factors such as government involvement. Furthermore, this study concludes that some factors were uninfluential for the AI adoption-decision, but important for the implementation. With regards to the apparent challenges, when implementing and aligning AI with the business strategy and overall organization, the authors argue that more research on success factors within AI implementation and preceding maintenance is needed.

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9 Appendix

9.1 Presentation of Respondents

Respondent	Role	Company	Duration	Date	Type
R1	Head of Analytics and AI (AI Leader)	Telenor	28 min	March 6th 2020	Face-to-face
R2	Head of Sales and Marketing	Telenor	39 min	March 10th 2020	Face-to-face
R3	Innovation Expert	Telenor	36 min	March 9th 2020	Video call
R4	Head of Advanced Analytics B2C	Tele2	53 min	February 28th 2020	Face-to-face
R5	Head of Data Products and Advanced Analytics	Tele2	54 min	March 3rd 2020	Face-to-face
R6	Head of IT consumer	Tele2	46 min	March 5th 2020	Face-to-face
R7	Chief Architect and Head of Innovation	Tele2	57 min	March 12th 2020	Face-to-face
R8	CTO (Chief Technology Officer)	Tele2	47 min	March 6th 2020	Face-to-face
R9	Vice President and Head of Legal	Telia	42 min	March 12th 2020	Face-to-face

9.2 Presentation of Telecom Companies in the Study

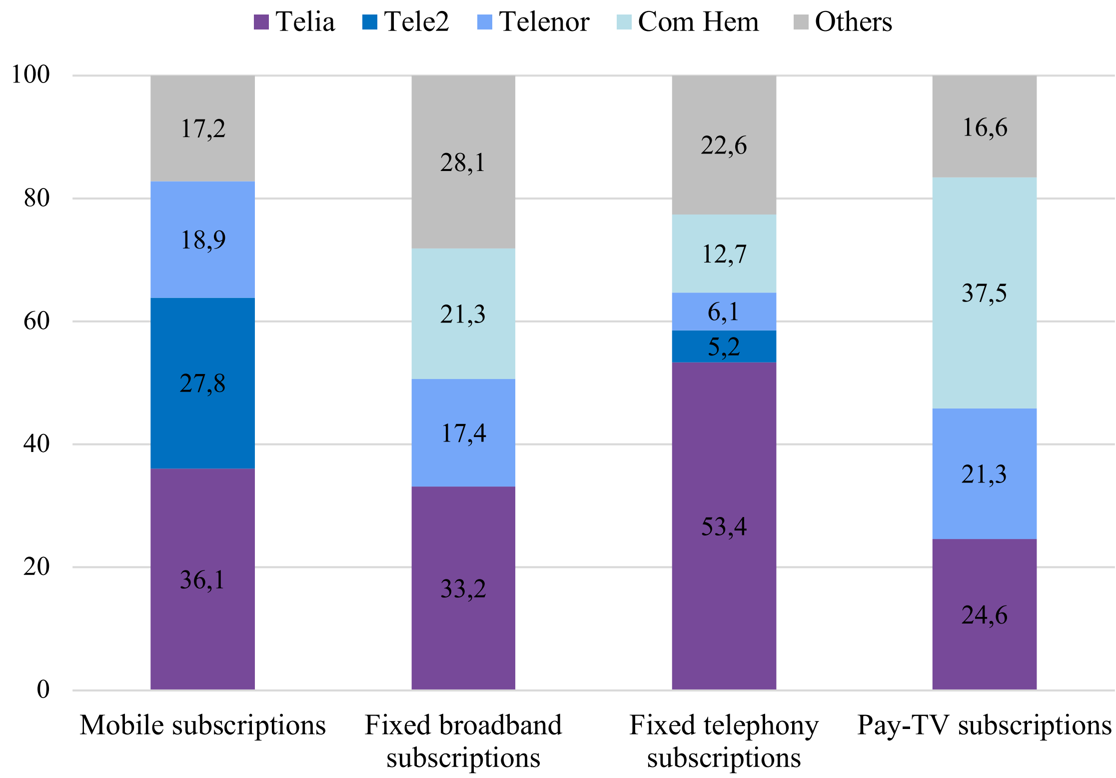
Company	Founded	Origin	Revenue*	Employees*
Telia	1853	Sweden	33.6 bn	7 200
Tele2	1993	Sweden	16.7 bn	2 626
Telenor	1855	Norway	13.4 bn	1 612

Source: Telia, Telenor and Tele2.

* Note: Statistics for the Swedish telecom market in 2018.

9.3 The Swedish Telecom Market

The case organizations - Telenor, Telia and Tele2 - provide the majority of the Swedish telecom services. Below, the market share (%) of each company in 2018 is presented.

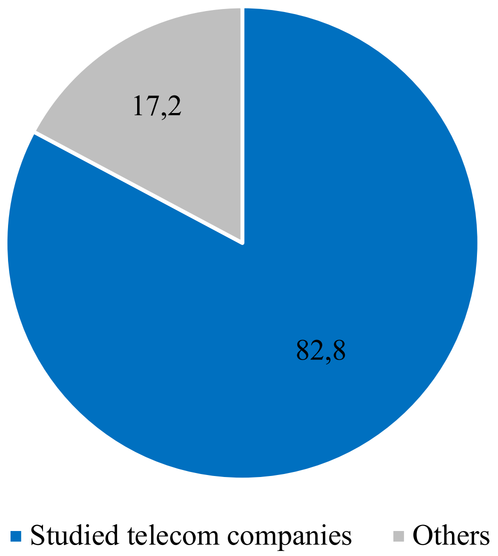


Source: The Swedish Post and Telecom Authority (PST)

Note: Tele2 and Com Hem joined in a merger on November 5 in 2018, thus Com Hem is included in the diagram.

9.4 The Swedish Telecom Market for Mobile Subscriptions

Below, the combined market share (%), of the studied telecom companies, for mobile subscriptions in 2018 is presented.



Source: The Swedish Post and Telecom Authority (PST)

9.5 Interview Guide

Introduction

1. Do you mind if we record the interview?
2. Would you like to be anonymous?
3. What is your background and education?
4. What is your role and responsibility in the organization?

Artificial Intelligence

5. What kind of AI have you adopted in the organization?
6. What tasks or processes are intended to be supported/replaced/enhanced by the adoption of AI?
7. When was the decision to adopt AI taken and how long was the process?
8. How big of an effect will the adoption of AI have or have had on your organization?

Introductory open question

9. Why did you decide to adopt AI? What influenced this decision?

If any of the topics mentioned below were not brought up during the interview, ask the following questions for further insights.

Technological context

10. Did the access to data influence the organization's decision to adopt AI?
11. What kind of data is mainly stored in the organization?
12. What is the level of data quality in the organization?
    a. How did the level of data quality influence the decision to adopt AI?
13. Did the potential to utilize data more effectively influence the decision to adopt AI?
14. How has AI been perceived in the organization in terms of using or working with in terms of complexity or simplicity?
15. Did the organization have the needed infrastructure for AI adoption?
    a. If yes: How did the infrastructure influence the decision to adopt AI?
    b. If no: Why not? How did this influence the decision to adopt AI?
16. Did the organization have the needed capabilities for AI adoption?
    a. What capabilities? What influence did these have on the decision to adopt AI?
    b. If not mentioned, ask about: Built in-house or outsourced to third party vendors? Use of consultants?
17. Did the employees have the needed AI competence before you decided to adopt AI?
    a. If yes: What was the level of competence? How did this influence the decision to adopt AI?
    b. If no: Why not? How did this influence the decision to adopt AI?
18. When making the decision to adopt AI, what were the expected benefits of the AI technology?

    a. How did these benefits influence the decision to adopt AI?
    b. If not mentioned, ask about: Increase revenue? Reduce costs? Facilitation of operations? Efficiency gains?
19. Did the organization experience any challenges when adopting AI?
    a. If yes: What challenges? How did these influence the decision to adopt AI?

Organizational context

20. Did top management of the organization support the decision to adopt AI?
    a. If yes: How was this support expressed?
    b. If no: Why not?
21. Was the support from the top management a necessity for the organization´s adoption of AI?
    a. If yes: How come?
    b. If no: Why not? Who supports the adoption of AI?
22. Was there an individual, an AI champion, that advocated or strongly encouraged the organization to adopt AI?
    a. If yes: How did they influence the decision to adopt AI?
    b. If no: If there would have individual that promoted AI, how could this have affected the decision to adopt AI?
23. Did the size of the organization influence the decision to adopt AI?
    a. If yes: Why did the organizational size influence this decision?
    b. If no: Why not?
24. Did the organization's financial position influence the decision to adopt AI?
    a. If yes: How come?
    b. If no: Why not?

Environmental context

25. Did the organization experience any competitive pressures to adopt AI?
    a. If yes: How did this influence the decision to adopt AI?
    b. If no: If there would have been any competitive pressures, how could this have affected the decision to adopt AI?
26. Did the organization adopt AI as a means to create a competitive advantage?
    a. If yes: How did this influence the decision to adopt AI?
    b. If no: Why not?
27. Did the organization adopt AI as a means to improve the customer satisfaction?
    a. If yes: How did this influence the decision to adopt AI?
    b. If no: Why not?

Task context

28. To what extent are the tasks in your organization complex?
29. Did the organization adopt AI as a means to reduce the complexity of the tasks in the organization?

a. If yes: How did this influence the decision to adopt AI?
b. If no: Why not?

Outcome:

30. Is there something you wish you would have done differently in the decision-making of adopting AI?
31. Are you satisfied with the result of the decision to adopt AI?

Closing questions:

32. Is there anything that you would like to add that you have not had the possibility to express during the interview?
33. Are there any answers you would like to change?

Thank you again for participating in the interview. We will gladly share our thesis with you and let you read it through, if you wish to check it before the final publication.