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The Personalization Puzzle

A case-study of employees' perceptions of the factors influencing the adoption of AI for personalization in the Swedish banking industry

Gustav Romert 42547 and Elin Skarin 42562

Abstract

Recent technological advancements have significantly propelled banks into a digital era, intensifying the pressure to discover alternative solutions for maintaining customer relationships in an increasingly digital landscape. Artificial Intelligence (AI) has emerged as a critical tool for achieving this, enabling banks to deliver personalized products and services on an unprecedented scale. While prior research emphasizes the role of AI for personalization in banking and the advantages it can bring in terms of enhanced customer experiences, research on how banks can effectively adopt AI for personalization remains limited. Therefore, this study aims to address this gap by exploring what factors bank employees perceive to influence the adoption of AI for personalization, as well as how and why these factors are perceived to impact this adoption. Utilizing a qualitative, single-case study approach, the research draws on semi-structured interviews with 16 employees from the case bank and four AI experts. The findings of this study reveals that various factors are perceived to influence two different phases of the adoption process, exerting their influence through technological-, organizational-, and environmental context factors. The findings further suggest that the environmental context factors can be understood through the influence of institutional forces present in the environment, driven by the bank's pursuit to maintain legitimacy. The study contributes theoretically by identifying and developing an understanding for the unique factors influencing the adoption of AI for the specific purpose of personalization in the banking industry. Further, the study extends the theoretical understanding by providing a nuanced understanding of the factors influencing AI adoption, by integrating the TOE framework with Institutional Theory. Practically, the study offers guidance for bank managers attempting to adopt AI for personalization into their organizations.

Keywords: Personalization, Artificial Intelligence, Technology Adoption, TOE, Institutional Theory

Supervisor: Patrik Stoopendahl
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Discussants: Vasileios Dimopoulos & Luca Murineddu
Examiners: Emma Bell & Roberto Verganti

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Gustav Romert & Elin Skarin

Table of Content

Definitions

Term	*Definition*
Personalization	A strategy undertaken by organizations with the aim of "delivering the right content to the right customer at the right time". It involves tailoring products, services, or communications, with customers remaining passive in these efforts.
Artificial Intelligence	Commonly described as a systems ability to correctly interpret external data, learn from it and apply those insights to achieve specific goals or tasks through flexible adaptation.
AI for Personalization	The use of Artificial Intelligence to learn about customer's preferences which then are used to generate personalized recommendations for customers, enabling organizations to match their offerings with unique customer needs.
Technology Adoption	Referred to as a process of selecting and implementing a technology for use by an organization.
Institutional Isomorphism	The way in which the external environment influences organizational actions by exerting pressures that encourage conformity to gain legitimacy.
Retail Bank	Banking focused on offering financial services, such as money management, credit offerings, and deposit handling, to individual customers rather than corporate clients. Throughout the study, "the bank" will refer specifically to the retail bank constituting the case company of this study.
Traditional Bank	Historically characterized by physical branches where customers can access financial services and engage with staff face-to-face.

1. Introduction

1.1 Background

Technology adoption and use in organizations has for long been a central concern in research and practice (Venkatesh & Davis, 2000). Over the past few decades, technological advancements have significantly transformed nearly every industry and altered the way business is conducted (Ahi et al., 2022). As a result, organizations face pressure to continually adopt new technologies in order to remain relevant and competitive. The rapid pace of technological advancements today further amplifies this pressure, compelling companies to swiftly adopt innovative solutions (Omol, 2023). Consequently, the importance of understanding and creating conditions under which technology can be adopted by organizations remains, and is increasingly becoming a crucial focus for research and practitioners striving to compete in the fast-paced digital business landscape.

The transformative impact of technology is particularly evident within the banking industry. Developments in this industry have significantly changed how banks interact with their customers (Yalamati, 2023). Today, telephone, internet, and mobile banking have become the primary channels for delivering banking services, consequently leading to a reduction in the number and importance of traditional branch networks (Torres et al., 2019). This shift is for instance evident in Sweden, where digitalization has resulted in the closure of more than 50% of bank branches over the past 15 years (Finansinspektionen, 2023). Consequently, banks face the significant challenge of maintaining customer relationships in an increasingly digital environment where physical proximity is reduced (Torres et al., 2019; Indriasari et al., 2019). With the digital trend expected to accelerate (Euart et al., 2020), traditional banks face pressure to adapt to this new reality and discover alternative solutions for maintaining customer relationships in an increasingly digital landscape (Torres et al., 2019).

The need to maintain customer relationships in this digital banking landscape has recently become attainable due to advancements in artificial intelligence (AI) and machine learning (ML) (Kumar et al., 2019). These technologies enable the delivery of personalized experiences, referring to products and services that are tailored to customers' unique needs and preferences. The analytical capabilities of AI, coupled with the vast amount of customer data available to banks, allow for the extraction of actionable insights and the development of personalized products and services for thousands of unique customers (Agarwal, 2019).

Existing literature on AI for personalization in the banking industry has investigated various application areas for the technology, ranging from investment advice to lending (Mai, 2024; Gigante & Zago, 2023). Further, research has highlighted several advantages of adopting AI for personalization in banks, such as enhanced customer experience and the creation of switching costs (Sheth et al., 2022; Li et al., 2023), while also identifying challenges in terms of privacy concerns (Abdulquadri et al., 2021). The research on AI adoption in banks has been investigated from the perspective of consumers (Belanche et al., 2019; Atwal & Bryson, 2021; Lee & Chen, 2022), and the perspective of the employees (Jang et al., 2021; Mogaji & Nguyen, 2021; Rahman et al., 2021). Regarding the latter, much of the research has concentrated on the adoption of robo-advisors (Jang et al., 2021) or AI in general (Mogaji & Nguyen, 2021; Rahman et al., 2021), exploring various factors, referring to challenges and drivers, influencing the adoption of AI in banks.

1.2 Problematization

The existing research on AI adoption and personalization within the banking industry reveals several limitations warrant further study. Although there is a growing recognition of the role of AI for personalization in banking, (Mai, 2024; Gigante & Zago, 2023) and the advantages it can bring to banks in terms of enhanced customer experiences (Sheth et al., 2022; Li et al., 2023), the literature on how banks can effectively adopt AI for personalization remains limited. Particularly, most research on AI adoption in the banking industry has to a large extent focused on AI adoption from a consumer perspective, exploring what motivates or hinders consumer adoption of the technology (Belanche et al., 2019; Atwal & Bryson, 2021; Lee & Chen, 2022). Conversely, there has been insufficient research aimed at understanding the factors influencing AI adoption from the employees perspective. While some studies have addressed this topic, they have primarily focused on other applications such as robo advisors (Jang et al., 2021) or AI in general (Mogaji & Nguyen, 2021; Rahman et al., 2021). This creates a significant gap at the intersection of AI adoption, from employee's perspective, and its application to personalization. Addressing this gap is essential, given that the context, specifically, the industry environment and the particular application of AI, substantially influences how adoption unfolds (Jöhnk et al., 2021). Hence, while some of the findings from studies on banks' adoption of AI for other applications can be transferred to the application of AI for personalization, this use case is likely to display additional explanations due to its unique characteristics. Therefore, to enhance our understanding of how AI for personalization can be successfully deployed within the banking industry, and to contribute to the broader field of technology adoption in society, it is essential to explore what factors bank employees perceive as influencing the adoption of AI for personalization and to understand how and why these factors impact this adoption.

1.3 Purpose and Expected Contributions

The purpose of this thesis is to explore the factors influencing the adoption of AI for personalization in a bank context. Specifically, the thesis aims to delve into what factors employees perceive to influence the adoption of AI for personalization, as well as how and why these factors are perceived to influence the adoption of AI for personalizing products and services. The expected contribution of this study is twofold. First, by investigating AI adoption in the unique context of the banking industry and for personalization, this study will contribute theoretically by identifying and developing an understanding for the unique factors influencing the adoption of AI for personalization. Second, the study seeks to provide a deeper and more nuanced understanding of the factors employees perceive to influence AI adoption by utilizing an integrated theoretical lens that combines the Technology Organization Environment (TOE) framework with Institutional Theory. Practically, this study will offer valuable insights for decision-makers in the banking industry aiming to adopt AI for personalization within their organizations. To achieve the aim of this study, the following research question will be addressed:

Research Question: What factors do employees perceive to influence the adoption of AI for personalization, and how and why are these factors perceived to impact this adoption?

1.4 Disposition

The aim of this study will be explored using a qualitative approach to understand what factors employees perceive to influence the adoption of AI for personalization as well as how and why these are perceived to impact the adoption. Through semi-structured interviews with bank employees and AI experts, the factors influencing the adoption of AI for personalization will be explored. A theoretical framework will be formed, building on the TOE framework (Tornatzky & Fleischer, 1990), and Institutional Theory (DiMaggio & Powell, 1983). The findings of this study are outlined and analyzed in accordance with the conceptual framework presented in this study. This is followed by a discussion of the findings in relation to previous studies within the field. Lastly, the theoretical- and practical contributions of the study are presented. The study is divided into 6 sections: (*1) Introduction, (2) Literature Review and Research Gap, (3) Theory, (4) Methodology, (5) Empirical Analysis, (6), Discussion.*

2. Literature Review and Research Gap

This chapter aims to define the current state of research relevant to this study. The review is structured into four sections to facilitate the discussion of each area and form the research gap that this study aims to address. The first section, (2.1) technology adoption, provides an overview of how technology adoption, particularly AI, has been studied in various industries, and in banks. The second section, (2.2) personalization, reviews the existing literature on the concept considering its definition and practice in a complex service context. The third section, (2.3) explores the intersection of AI and personalization to explore how the two concepts have been studied together. Last, in the fourth section, (2.4), the research gap that this study aims to address is formed, further justifying the focus of this thesis.

2.1 Technology Adoption

To realize the full potential of technologies, such as AI, widespread adoption is essential (Oliveira & Martins, 2011). Consequently, a thorough review of the theoretical research stream on technology adoption is crucial for understanding the adoption of AI for personalization in a bank context. The concept of technology adoption has been conceptualized in various ways. Carr (1999) describes technology adoption as the stage of selecting a technology for use by an individual or organization. Additionally, a body of research focuses specifically on the organizational technology adoption, referring to the process of selecting and implementing a technology for use by an organization (Hameed et al., 2012; Damanpour & Schneider, 2006). Building upon this foundation, technology adoption has been thoroughly researched providing valuable insights into the adoption of various innovations by individuals and organizations. Models frequently employed within this field include Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation (DOI), and Technological-, Organizational-, and Environmental Context (TOE) framework.

Within the theoretical literature on organizational technology adoption, the adoption of AI has garnered significant attention in recent years. Advances in AI capabilities have expanded its applicability across diverse sectors, prompting a substantial body of research dedicated to understanding the AI adoption across various industries. For instance, Kinkel et al. (2021) explored the prerequisites for AI adoption within the manufacturing industry. The authors found evidence for factors including digital skills, company size, and R&D intensity as a driver for innovation significantly influencing the adoption of AI in a manufacturing context. Similarly, Petersson et al. (2022) examined the challenges associated with implementing AI in healthcare, identifying factors such as the legislative environment, limited engagement from lower level staff, low levels of trust in AI system outputs, and a substantial amount of unstructured data challenging adoption. Moreover, Gupta et al. (2022) examined AI adoption within the insurance industry and found that the insurance industry's workforce lacked the technical knowledge to fully embrace the technology, inhibiting its full adoption. Further, the competition in the industry showed to be a critical driver for accelerating the adoption of AI.

While the applications of AI in the banking industry share similarities with other industries, the unique characteristics of the banking industry have specific implications for the adoption of technologies like AI (Lazo & Ebardo, 2023). Therefore, understanding the factors that influence AI adoption within the banking industry is of significant importance. Within this field there has been an emphasis on consumer focused adoption, studying the factors motivating and hindering consumer adoption of robo-advisors (Belanche et al., 2019; Atwal & Bryson, 2021), mobile apps (Lee & Chen, 2022).

However, some studies have taken an employee perspective on AI adoption in the banking industry. In this area, Mogaji and Nguyen (2021) specifically focused on investigating bank managers' awareness and challenges in providing AI for marketing financial services. Their study revealed that while bank managers recognize the potential of AI, concerns remain regarding the development of AI algorithms, the role of regulators in keeping stakeholders informed and raising awareness about the implications of AI in financial services, and the adoption of AI systems by consumers. Similarly, Jang et al. (2021) explored managers' perspective of chatbot adoption in the South Korean banking industry. Their findings showed that the main challenge of adopting chatbots was of technological character involving data structure issues. Furthermore, organizational resistance, driven by employees' fears of job displacement, was identified as a significant factor hindering successful implementation of chatbots. Additionally, Rahman et al. (2021) investigated managerial perspectives on the adoption of AI in general within the Malaysian banking sector. Their findings indicated that significant challenges included the lack of robust regulatory frameworks, insufficient employee skills, and inadequate IT infrastructure. Moreover, concerns over customer data privacy and security emerged as additional factors that negatively impacted the adoption of AI in banks.

To summarize, there is a growing body of research investigating AI adoption across a range of industries (Kinkel et al., 2021; Petersson et al., 2022; Gupta et al., 2022). In the banking industry, the theoretical research stream on AI adoption has focused on consumer adoption (Belanche et al., 2019; Atwal & Bryson, 2021; Lee & Chen, 2022), while some studies have explored employee adoption of AI in banks (Mogaji & Nguyen, 2022; Jang et al., 2021; Rahman et al., 2021).

2.2 Personalization

The concept of personalization has gained increased attention over the past 30 years (Ball, 2006). The concept is often described as a differentiation strategy undertaken by companies to achieve a competitive advantage (Shen & Ball, 2009). In marketing, personalization is described as a targeted individual level strategy (Tam & Ho, 2006), where consumers are passive and all personalization initiatives are undertaken by the company (Aguirre et al., 2014). The overall goal of personalization is to deliver “the right content to the right person at the right time” (Tam & Ho, 2006). Despite the enhanced focus on the area of personalization, a universally accepted definition has not been established (Vesanen, 2007).

Literature on personalization emphasizes that personalization can occur both physically and through the use of technology. Traditional personalization has historically been characterized by face-to-face interaction in which frontline customer service employees play a crucial role in tailoring their service offerings to meet the specific preferences of individual customers (Gwinner et al., 2005). However, with advancements in technology, there has been increased attention on how to leverage technology to deliver personalized products and services. In this context, Shen and Ball (2009) introduced the concept of technology-mediated personalization

(TMP) to explore the impact of personalization on customer relationships within complex services. They further distinguish between three TMP strategies: interaction personalization, transaction outcome personalization, and continuity personalization. Interaction personalization refers to individualized treatment during service interaction, such as the use of customer names and mentioning personal hobbies in online channels such as through e-mails and on websites. Transaction outcome personalization is described as the customization of products and services according to customer specifications. Lastly, continuity personalization refers to the ongoing adaptation of products and services, based on unique insights about the customer gained through multiple interactions (Shen & Ball, 2009).

As reviewed, the concept of personalization has gained increased attention (Ball et al., 2006), however, despite the enhanced focus on the area of personalization, a universally accepted definition has not been established (Vesanen, 2007). Research on personalization has emphasized that personalization can occur both physically and through the use of technology (Shen & Ball, 2009). Alongside the advancements in technology, there has been increased attention on how to leverage technology to deliver personalized products and services (Shen & Ball, 2009).

2.3 AI and Personalization

AI is often described as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019). One AI technique that contributes to this capability is ML, described as a tool that empowers the machine to learn without the need for programming (Wang et al., 2019). The primary objective of ML is to train a machine to learn from data, make predictions, and identify relationships that can guide decision-making (Wang et al., 2019). The capabilities of AI and ML are applicable to a wide range of use cases. In recent years its potential for enabling personalization has received significant attention due to its ability to process and analyze vast amounts of data (Kumar et al., 2019). One of the most notable applications is found in recommendation engines, which leverage AI and ML to learn about customer preferences over time (Kumar et al., 2019). These learnings are utilized for generating personalized recommendations for customers, allowing organizations to match their offerings with customers' unique preferences (Kumar et al., 2019). By analyzing past purchases and product usage, these systems can generate tailored recommendations, aligning organizational offerings with customers' unique tastes (Kumar et al., 2019).

The use of AI for personalization has received increasing interest within the banking industry, leading to studies exploring its practical applications (Mai, 2024; Gigante & Zago, 2023). Mai (2024) highlights how banks can leverage AI and ML to analyze real-time data for predicting customer needs and delivering customized, personalized experiences to each customer at an unprecedented scale (Mai, 2024). The study showcases various global examples of practical applications of AI for personalization. For instance, it is highlighted that some banks have developed solutions providing "Netflix-style" product recommendations to give their customers access to personalized banking products and services. Additionally, the study includes a case of a Vietnamese bank that has started to provide personalized loan packages targeted at specific customer groups, including fully digital loan options designed for technology-savvy consumers. The application of AI for personalization in the banking industry is further explored by Gigante and Zago (2023), emphasizing that AI can significantly enhance customer experiences in various areas such as investment advice and lending. Concerning investment advice, it is emphasized that AI enables a more personalized advisory process through its ability to collect and analyze data with greater precision and speed. This contributes to a deeper understanding of clients' investment preferences, including their interest in specific assets and desired level of risk. Regarding lending, it is highlighted that customer experiences in mortgage processes can be enhanced by presenting personalized offers based on individual factors such as their specific location, long-term goals, or financial situation, insights derived from the analysis of AI (Gigante & Zago, 2023).

Furthermore, literature indicates that the application of AI for personalization within the banking industry offers numerous advantages for banks (Sheth et al., 2022; Gigante & Zago, 2023; Li et al., 2023). Sheth et al. (2022) highlights that the use of AI in banking has an immense potential to create personalized experiences, which can lead to several benefits for customer experiences, such as the reduction of service bottlenecks and the enhancement of service quality. Gigante and Zago (2023) further emphasize that utilizing AI for personalization in banking can significantly enhance customer satisfaction and deliver economic benefits to the bank by creating competitive advantages through better tailored advice. Li et al. (2023) provide additional evidence of these advantages by demonstrating that personalization in financial services can effectively enhance customer satisfaction and increase switching costs. These switching costs are described as creating lock-in effects, limiting customers' likelihood of moving to alternative banks.

Besides the advantages of utilizing AI for personalization, research has also emphasized its risks. Abdulquadri et al. (2021) highlights how the use of AI for personalization in banks raises privacy concerns. This creates a balance between achieving the advantages of offering personalized products and services, and the risk of jeopardizing customers' privacy. If not managed carefully, firms risk facing consumer backlash due to perceived violations of privacy expectations. It is essential for managers to navigate this paradox wisely to maintain consumer trust and avoid negative consequences.

In conclusion, AI, especially ML, has transformed personalization by enabling the analysis of vast amounts of data to deliver personalized experiences (Kumar et al., 2019). Its application in banking is increasingly studied (Mai, 2024; Gigante & Zago, 2023), as well as its benefits such as the effect on customer experiences (Sheth et al., 2022; Gigante & Zago, 2023; Li et al., 2023), and risks in terms of privacy concerns (Abdulquadri et al., 2021).

2.4 Synthesis and Research Gap

Based on the literature review of previous studies related to this paper, it is evident that existing literature has thoroughly explored technology adoption, AI, and personalization as distinct topics. The literature on AI for personalization is a growing field, particularly in banking, where research has examined the role of AI for personalizing products and services, and the potential benefits for improving customer experiences (Sheth et al., 2022; Gigante & Zago, 2023; Li et al., 2023). Similarly, literature within the field of AI adoption shows a growing research area where much is known about factors influencing AI adoption in various industries such as manufacturing (Kinkel et al., 2021), healthcare (Petersson et al., 2022), and insurance (Gupta et al., 2022).

However, despite this emerging focus, research on how banks can effectively adopt AI specifically for personalization has been understudied. Research on AI adoption in the banking industry has primarily taken the perspective of consumers, exploring the factors motivating or hindering consumers' adoption of AI (Belanche et al., 2019; Atwal & Bryson, 2021; Lee & Chen, 2022). Consequently, research exploring the factors influencing AI adoption from an employee perspective remains limited. While a few studies have examined AI adoption from the perspective of employees, it has typically been investigated through the lens of other applications such as robo-advisors (Jang et al., 2021) or AI in general (Mogaji & Nguyen, 2021; Rahman et al., 2021), each highlighting different factors influencing its adoption. Since the context, such as the industry environment and the particular application of AI, in which AI is adopted significantly impacts the adoption process (Jöhnk et al., 2021), investigating the factors influencing AI for personalization in banking is crucial. This forms an interesting research gap at the intersection of technology adoption, AI, and personalization in the banking industry. Consequently, this study aims to address this critical gap by specifically exploring the factors influencing the adoption of AI for personalization in a bank context.

3. Theory

Drawing upon the TOE framework (Tornatzky & Fleischer, 1990), and Institutional Theory (DiMaggio & Powell, 1983), this section develops a holistic framework to explore the factors influencing the adoption of AI for personalization within a bank context. The TOE framework offers a broad perspective on technology adoption by integrating the technological-, organizational-, and environmental context, but it tends to overlook the underlying external pressures that influence organizational behavior. Conversely, Institutional Theory delves into these external pressures but does not account for the internal technological- and organizational factors. These frameworks are thus not sufficient for understanding the phenomena of AI adoption on their own. However, combining them provides a nuanced perspective for studying the complex process of AI adoption for personalization in a bank context, thus enabling the phenomena to be studied in-depth. The chapter will be structured as follows. The first section (3.1), introduces the TOE framework, while the second section (3.2) reviews Institutional Theory. The last section (3.3). integrates these perspectives into a unified conceptual framework that serves as the analytical lens for this study.

3.1 TOE

The TOE framework was first introduced by Tornatzky and Flesicher (1990) in their seminal work, “The Process of Technological Innovation”. Due to its proven effectiveness in analyzing organizational technology adoption, the framework has become one of the most prominent and widely used theories for understanding organizational adoption (Baker, 2011). Since its development, the TOE framework has inspired a stream of literature refining and adapting the framework to investigate the adoption of various technological innovations across diverse contexts. The TOE framework concentrates on explaining a key aspect of the process of innovation, focusing on how a firm’s contextual factors influence the adoption of new technologies (Tornatzky & Fleischer, 1990). It emphasizes that three dimensions of a firm’s context shapes the organization’s adoption of new technologies: the technological context, the organizational context, and the environmental context.

The rationale for applying the TOE framework instead of other popular technology adoption theories, such as the technology acceptance model (TAM), theory of planned behavior (TPB), or unified theory of acceptance and use of technology (UTAUT), is as follows. First, in contrast to other theories commonly applied to investigate technology adoption, the TOE framework offers a framework to analyze organizational adoption of innovations, rather than individuals' (Baker, 2011). This aligns well with this study's focus on understanding the bank's adoption of AI for personalization, through the lens of employees' perceptions. Second, the framework offers a holistic perspective to understanding technology adoption, acknowledging that technology adoption is not solely a technological process. Instead, it is also significantly shaped by the social interactions within the organization and the broader environmental context (Tornatzky & Fleischer, 1990). The following sections will explore each of the three contexts within the TOE framework and illustrate how they can be leveraged to better understand the process of AI adoption in this study.

3.1.1 Technological Context

Tornatzky and Fleischer (1990) describe the technological context as the characteristics of the technology that influence the adoption process, both the technologies already in use in the organization and those available in the marketplace (Tornatzky & Fleischer, 1990). It is described that a firm's existing technologies can constrain both the scope and pace of technological adoption. With regards to the technologies available in the marketplace, it is emphasized that these set the boundaries of what is possible, while also illustrating how technology can empower firms to evolve and adapt (Tornatzky & Fleischer, 1990). Therefore, understanding the technological context is crucial for understanding a bank's adoption of AI for personalization, as it influences the bank's ability to leverage AI based on its existing technological infrastructure and the opportunities presented by available innovations.

Within the stream of literature investigating organizational technology adoption, three characteristics of the technological context, compatibility, complexity, and relative advantage, are frequently emphasized as influential in shaping the adoption of new technologies (Horani et al., 2023; Chen et al., 2022). These characteristics were first introduced by Rogers (2003) in his seminal work "Diffusion of Innovation" and has since been frequently utilized to understand the technological context influencing technology adoption in organizations. With regards to compatibility, Rogers (2003) refers to whether the technology is perceived to be compatible with the adopters values and previous experiences. The more compatible a technology is perceived to be, the less organizational change is required, thereby facilitating the adoption of new innovations. However, the concept of compatibility has also been referred to as the compatibility of the technology with the existing IT infrastructure (Wu et al., 2006). When AI technology aligns well with the current IT framework, it can significantly reduce both implementation costs and the time required for integration. Moreover, the concept of complexity, refers to the extent to which an organization finds the technology difficult to understand and use (Rogers, 2003). It is described that technologies that are perceived as more complicated will be adopted more slowly, in contrast to technologies that are easily understood by the organization. As AI is often described as relatively difficult to understand and deploy (Lokuge et al., 2018), understanding the influence of this characteristic is extra crucial in this study. Last, the third characteristic described by Rogers (2003), perceived relative advantage, refers to "the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 2003). Perceived relative advantage is often measured in economic terms such as increased revenue or reduced costs, but more subjective factors such as prestige and satisfaction are also common. The greater the perceived relative advantage, the faster the adoption will be (Rogers, 2003).

Furthermore, in recent years, alongside advancements in AI, the TOE framework has been extended to meet the unique requirements of AI. Specifically, Pumplun et al. (2019) extended the TOE framework to incorporate key aspects crucial for analyzing AI adoption, such as data availability, and data accessibility. In terms of data availability, it was described that availability of data is required for training AI models and enabling them to generate accurate predictions. Hence, data availability serves as a crucial facilitator of successful AI adoption. Further, Pumplun et al. (2019) emphasize the importance of data accessibility for AI adoption. Accessibility refers to the ability of personnel and systems to quickly and easily access all organizational data sources. This requires that data are centralized and democratized, ensuring that everyone in the organization can utilize the data for different purposes effectively. As this thesis investigates the adoption of AI for personalization, understanding the aspects crucial for adopting AI is important.

3.1.2 Organizational Context

Tornatzky and Fleischer (1990) define the organizational context as the set of structures and processes within the firm that facilitates or constrain the adoption of new technologies. These include both formal, such as the organization's division of labor, and informal aspects, referring to naturally occurring behavior patterns. These structures and processes can both support and hinder technology adoption, making it essential to understand the organizational context when investigating the adoption of AI for personalization in this study.

One aspect of the organizational context that is described to influence the adoption of new technologies is the organizational structure (Tornatzky & Fleischer, 1990). Tornatzky and Fleischer (1990) emphasize how various organizational structures could either facilitate or hinder technology adoption. Specifically, structures characterized by high interconnectedness, where different units are linked by interpersonal networks, tend to facilitate the adoption. Building on the importance of organizational structure, Chen et al. (2010) explains that organizations characterized by strong communication and collaboration across different units are in a more favorable position to successfully adopt new technologies.

Furthermore, within the literature on organizational AI adoption, organizational culture is highlighted as an organizational context factor that significantly influences the adoption of new technologies (Pumplun et al., 2019). In this context, organizational culture is described as norms, values, and attitudes that shape the adoption of new technologies in organizations. A particularly well-known dimension of organizational culture is organizational innovativeness (Pumplun et al., 2019). This refers to an organization's willingness and capacity to adopt, imitate, or implement new technologies and ideas in order to develop innovative, unique products and services. Pumplun et al. (2019) argue that organizational innovativeness is particularly crucial for incumbent firms, as they often become overly reliant on the status quo due to a slow and bureaucratically organizational structure. This makes it particularly important to consider this aspect when examining traditional banks. Furthermore, in studies focusing on AI adoption, a culture of data-driven decision-making, where organizations rely on data rather than intuition, is frequently identified as a facilitator of AI adoption (Jarrahi, 2018). In this study, understanding the influence of this cultural element is crucial, as data-driven decision-making constitutes a fundamental practice for adopting and utilizing AI for personalization.

3.1.3 Environmental Context

According to Tornatzky and Fleischer (1990), the environmental context refers to aspects of the environment such as the structure of the industry, the presence or absence of technology service providers, the competitive characteristics of an industry, and the regulatory environment. Tornatzky and Fleischer (1990) emphasize that the environmental context significantly influences an organization's adoption of new technologies. Therefore, understanding how these external aspects influence the adoption of AI for personalization in banks is crucial for gaining a comprehensive insight into this phenomenon. One of the environmental aspects emphasized in the TOE framework (Tornatzky & Fleischer, 1990), is the competitive characteristics of the industry. In line with this, competitive pressure is well-established in literature on technology adoption. On this topic, Wang et al. (2010) explain that high competitive pressure drives companies to adopt technology as they seek to gain a competitive edge. Given the intensifying competitive environment of the Swedish banking industry, particularly with the emergence of fintech disruptors, understanding how the competitive environment influences a bank's adoption of AI for personalization is crucial.

Another aspect of the environmental context highlighted by Tornatzky and Fleischer (1990) is the regulatory environment of an industry. The regulatory environment refers to the laws, regulations, and standards established by the government, which can influence technology adoption. It is emphasized that more stringent government regulations sometimes stimulate the adoption of new technologies and sometimes challenge the adoption of new technologies by posing constraints on industries. Given the highly regulated nature of the banking industry, paired with the AI for personalization purposes which requires the use of sensitive data, it becomes critical to understand how the regulatory environment influences the adoption of AI for personalization within a bank.

3.2 Institutional Theory

Building on the environmental context of the TOE framework, this thesis adds a layer of analysis through Institutional Theory, as introduced by DiMaggio and Powell (1983). The fundamental premise of Institutional theory is that the external environment shapes an organization's actions through external pressures to gain legitimacy. Hence, emphasizing that an organization's decision to adopt an innovation is not purely driven by internal business objectives, but primarily, to gain legitimacy. In the pursuit of achieving legitimacy, organizations within similar fields tend to adopt the same structures, which DiMaggio and Powell (1983) refer to as isomorphism. DiMaggio and Powell (1983) introduces three types of isomorphic pressures through which institutional change happens: mimetic pressure, coercive pressure, and normative pressure. By incorporating an institutional lens, the framework enables a deeper and more nuanced understanding of the environmental context influencing the adoption of AI for personalization.

3.2.1 Mimetic Pressure

Mimetic pressure arises from uncertainties faced by an organization, including ambiguous goals and environmental unpredictability and refers to the tendency to imitate the actions of others to navigate these uncertainties (DiMaggio & Powell, 1983). The benefits of imitating other organizations are substantial. By studying how other organizations handle similar challenges, organizations can find solutions that are both cost-effective and proven. Imitating other organizations is not only a process of finding a solution yielding increased effectiveness, but primarily to enhance the legitimacy (DiMaggio & Powell, 1983). By imitating the actions of others, the organization shows that they are trying to improve their work. Organizations tend to imitate other organizations they perceive as successful.

3.2.2 Coercive Pressure

Coercive pressure arises from both formal- and informal pressures placed on an organization by other organizations or institutions it depends on (DiMaggio & Powell, 1983). These pressures can manifest as a force, persuasion, or an invitation to align with the practices of others. They may originate from various sources such as resource-dominant companies and parent firms. Further, the coercive pressure can be manifested through organizational change as a result of complying with government mandates or regulatory authorities. As organizations and rationalized states grow in influence, organizations tend to become increasingly homogeneous as they conform to institutionalized rules in a pursuit of gaining legitimacy (DiMaggio & Powell, 1983).

3.2.3 Normative Pressures

The third type of isomorphic force is normative pressure, which refers to the influence of norms and professional standards that influence organizations to align their practices with established guidelines within their field (DiMaggio & Powell, 1983). Normative pressure can be manifested in two ways: the first way stems from professional norms in terms of educational background. When individuals share a specific background, it sets expectations within the industry that others should have similar qualifications to be seen as legitimate. The second way normative pressures can be manifested is through professional networks, for instance industry associations, which connects the organizations in the industry. These formal networks form informal rules in the industry, guiding organizations to adapt in order to meet industry standards and establish organizational legitimacy. The social norms and expectations inspire organizations to comply with the standards and best practices within the industry.

3.3 Conceptual Framework

Drawing on the TOE framework and Institutional Theory, this study develops a holistic framework to provide an in-depth understanding of the factors perceived to influence the adoption of AI for personalization within a bank context. The mimetic-, coercive-, and normative pressures outlined by Institutional Theory enhance the environmental context of the TOE framework, enabling a more nuanced understanding of the external factors influencing adoption. This integration responds to calls from prior studies (Sharma et al., 2022; Oliveira & Martins, 2011) to blend traditional technology adoption theories with theories from other management disciplines. Figure 1 illustrates the conceptual framework.

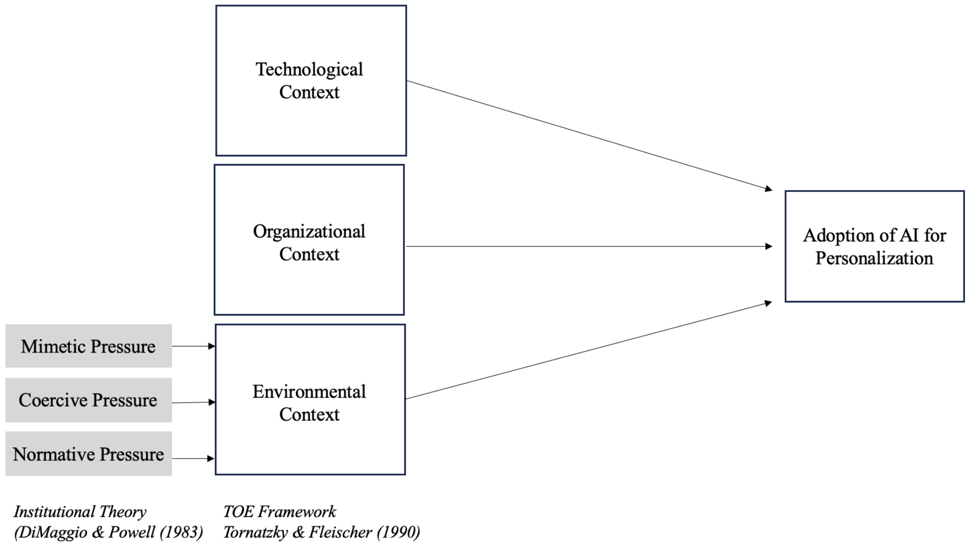

Figure 1. Conceptual Framework

4. Methodology

The aim of this section is to describe how the study has been conducted and justify the choices made. The first part (4.1), introduces the research design and approach of the study. Followed by a detailed description of the data collection (4.2). This is followed by a discussion on the data analysis (4.3), and concludes with an evaluation of the research quality (4.4).

4.1 Research Design and Approach

Since this study seeks to explore what factors employees perceive to influence the adoption of AI for personalization, and how and why these factors are perceived to impact this adoption from a subjective standpoint, the authors' adopted an interpretivist perspective. This is particularly apparent in the commitment to giving voice to employees' experiences and perceptions of the factors influencing adoption (Bell et al., 2022). Specifically, the authors' draw on phenomenology to acknowledge the employees' subjective meanings of these factors, intentionally putting aside our own biases (Bell et al., 2022). Accordingly, the authors adopt a constructionist ontological position, viewing the bank and the environment in which it operates as socially constructed by its actors (Bell et al., 2022). As follows from this perspective, a qualitative method has been employed. This method is particularly appropriate as the purpose and research question demand an in-depth understanding of employees' perceptions. The qualitative approach aligns well with this need, allowing for the generation of rich and contextual descriptions of these realities through the participants in these realities (Bell et al., 2022). Hence, allowing the authors to answer the research question of this thesis considering what factors employees perceive to influence the adoption of AI for personalization, and how and why these factors are perceived to impact this adoption. Furthermore, a qualitative research method is suitable for this study because research on the adoption of AI for personalization is still in its early stages, making it an area which is not yet well understood. Therefore, in line with Edmondson and McManus (2007), such contexts require rich, detailed data to build understanding rather than test already existing knowledge.

Furthermore, this study has taken an abductive approach, which is characterized by a dynamic interaction between theory and empirics (Bell et al., 2022). This approach allowed the authors to continuously reflect on the data and iteratively develop and build the conceptual framework in order to understand the empirical data. In line with Dubois and Gadde (2002), this approach is suitable when attempting to understand new phenomena, rather than validating existing theories, making it particularly relevant for this thesis.

4.1.1 Single-Case Study

To explore what factors employees in a traditional Swedish retail bank perceive to influence the adoption of AI for personalization, and how and why these factors are perceived to impact this adoption, a single case study was conducted. According to Flyvbjerg (2006), the case study approach provides an opportunity to thoroughly explore real-life situations and examine perceptions as they relate directly to the chosen phenomenon. Given that this study aims to achieve an in-depth understanding of the phenomenon of AI adoption for personalization, the decision to conduct a single-case study was deemed relevant. The selection of a case study approach was further motivated by the authors' belief that the specific case captured the contextual conditions crucial to understanding the phenomena under investigation. This aligns with Yin (2003), arguing that the case study method is particularly suitable when the contextual environment is relevant to the phenomena being studied. Accordingly, the selected case company, constituting a Swedish retail bank that has recently initiated its journey towards adopting AI for personalization into its operations was chosen as it provides a suitable context for this study. The bank's recently conducted pilot projects and its growing discussions regarding the use of AI for personalization presents an opportunity to investigate employees' perceptions of the factors influencing its adoption.

Furthermore, the case study approach is commonly applied in qualitative research in information system research (Myers, 1997), and has been described as well suited to understanding the interactions between information technology related innovations and organizational contexts (Darke et al., 1998). Therefore, conducting a single-case study approach is appropriate, as it captures the interplay between technology and organizations in the adoption of AI for personalization. While the single case study method has been criticised for its limited capacity to generate generalizable results compared to multiple case studies (Yin, 2003), this is not considered a major concern for this study. The purpose of this study is not to identify generalizable factors influencing the adoption of AI for personalization. Instead this study aims to explore the factors influencing adoption by delving into the perceptions of individual employees.

The selection of case company, in this case a Swedish retail bank, was based on a purposive sampling, deemed useful in situations when the case is especially informative in relation to the research question (Ishak & Abu Bakar, 2014). To ensure that the employees at the bank could offer valuable insights into the research phenomena, several criterias had to be fulfilled. First, in line with the research problem that this study aims to address, it was deemed important to investigate a traditional retail bank. Second, it was of great importance that the selected bank had initiated its journey towards adopting AI for personalization. This included efforts such as launched pilot projects and continuous strategic initiatives, reflecting a growing organizational commitment to AI adoption. This in order to ensure that employees were familiar with the phenomena and had developed perceptions of the factors perceived to influence the adoption of AI in the organization. To safeguard the confidentiality of the sensitive information disclosed during the interviews, the case company will be referred to as "the bank" throughout this research.

4.2 Data Collection

4.2.1 Pilot Interview

To prepare for the data collection, a pilot interview was conducted to ensure that the questions were clearly formulated, minimize the risk of misunderstandings, and increase the interviewers' confidence prior to the main data collection (Bell et al., 2022). Based on the outcome of the pilot interview, identified problem areas were addressed. One significant problem was that some questions were ambiguously phrased, leading to inconsistent responses. As a result, those questions were rephrased to improve clarity and ensure a more reliable data collection. Additionally, the pilot revealed that certain questions yielded similar answers, leading to the decision to remove some questions from the interview guide.

4.2.2 Semi-Structured Interviews

To answer the research question of this study, semi-structured interviews were considered an appropriate approach. This approach was regarded as suitable for its openness and flexibility (Bell et al., 2022). The authors used an interview guide to create a basic structure for the interview, and the semi-structured format allowed the interviewers to introduce questions not explicitly included in the interview guide (Bell et al., 2022). This approach was deemed particularly relevant to this study's purpose of exploring employees' perceptions of these factors. By adding questions in response to the insights gained from interviewees, the authors were able to capture a richer understanding of employees' perceptions. The interview guides are provided in Appendix 1 and 2.

4.2.3 Sampling Strategy

In this study, a total of 20 participants have been interviewed, including 16 employees at the bank and four AI experts. The sampling strategy applied in the study is based on purposive sampling, hence participants have been selected strategically to ensure that they possess relevant knowledge concerning the study's research question (Bell et al., 2022). The criteria for selecting participants within the bank was that they had experience either working with customer-facing inquiries or possessing knowledge of AI and ML. By adhering to these criteria, the study ensured that participants could provide valuable insights regarding the research question. Furthermore, while adhering to the predefined criteria, the authors have aimed to widen the sample diversity by including people from various departments within the bank. This has enabled the authors to capture a broader range of perspectives, thereby reducing the risk of department-specific bias (Andrade, 2020). Additionally, to further widen the perspectives included in the study, the authors aimed at including participants with varying length of experience within the bank. This diversity is important as the characteristics of interviewees can influence their responses (Bell et al., 2022). While the participants from the bank constituted the main part of this study's sample, interviews were also conducted with four AI experts. The inclusion of these AI experts aimed at deepening the understanding of the factors perceived by bank employees to influence the adoption of AI for personalization, and to explore how and why these factors are perceived to impact this adoption. The number of interviewees was not predetermined. Instead, interviews continued until no additional data was found (Glaser & Strauss, 1967). Appendix 3. provides an overview of the interview participants.

4.2.4 Conduction of Interviews

To answer the research question of this study, a deep understanding of the participants' social context was deemed important. Hence, the aim was to conduct most of the interviews in a physical format as this increases the rapport between the researchers and the interviewees (Bell et al., 2022). Despite this ambition, due to limited availability of some participants, some interviews were conducted via Microsoft Teams. While digital interviews can make it harder to build trust and connection compared to face-to-face settings (Bell et al., 2022), this was addressed by starting each interview with a casual conversation, helping to create a more relaxed and comfortable atmosphere. All interviews were conducted in Swedish to support the interviewees' open expressions, and quotes have been carefully translated into English with minor adjustments for clarity while preserving the original meaning.

4.3 Data Analysis

The data in this study was analyzed using thematic analysis, a process of systematically structuring data by identifying patterns and discovering underlying themes in the dataset (Braun & Clarke, 2006). One of the main benefits of using thematic analysis is its flexible nature, presenting the researcher with a variety of options on how to analyze the data, which results in the possibility of generating rich, detailed, and complex insights. This is particularly suitable for this study as we aim to investigate an area that is not yet extensively explored and requires an open and interpretive approach to understand employees' perceptions of AI adoption for personalization in the banking industry.

The data analysis process started with getting familiar with the data (Braun & Clarke, 2006). This involved reading and transcribing the interviews as well as discussing initial thoughts that emerged during the transcription process. The transcripts were then reviewed to identify patterns, recurring concepts, and key insights expressed by the interviewees, in line with what Braun and Clarke (2006) refer to as initial codes. This was performed directly within each interview transcript by adding comments in the transcripts and highlighting frequently observed concepts. These codes were subsequently organized into themes, based on similarities and differences (Ryan & Bernard, 2003), and their relevance to the research question. This process resulted in a thematic map in which each theme covered distinct aspects of the collected data, allowing the researchers to identify the relevance and key insights of each theme. During this process it became evident that the themes could be further organized into two overarching themes, determined by the stage in the adoption process where each theme exerted its influence. The themes, derived directly from the data, were further refined through an iterative process that incorporated relevant theoretical perspectives to deepen the analysis. This iterative process exemplifies the abductive approach of this study, where insights from the data and existing theory influenced each other to develop a nuanced understanding (Bell et al., 2022). Last, the themes were reviewed, which resulted in some themes being divided into separate themes to better capture the data's complexity. For instance, the theme "data" was split into two distinct themes: "data structure" and "data availability". An example of the thematic analysis, including data extracts, initial codes, themes, and overarching themes, is illustrated in figure 2.

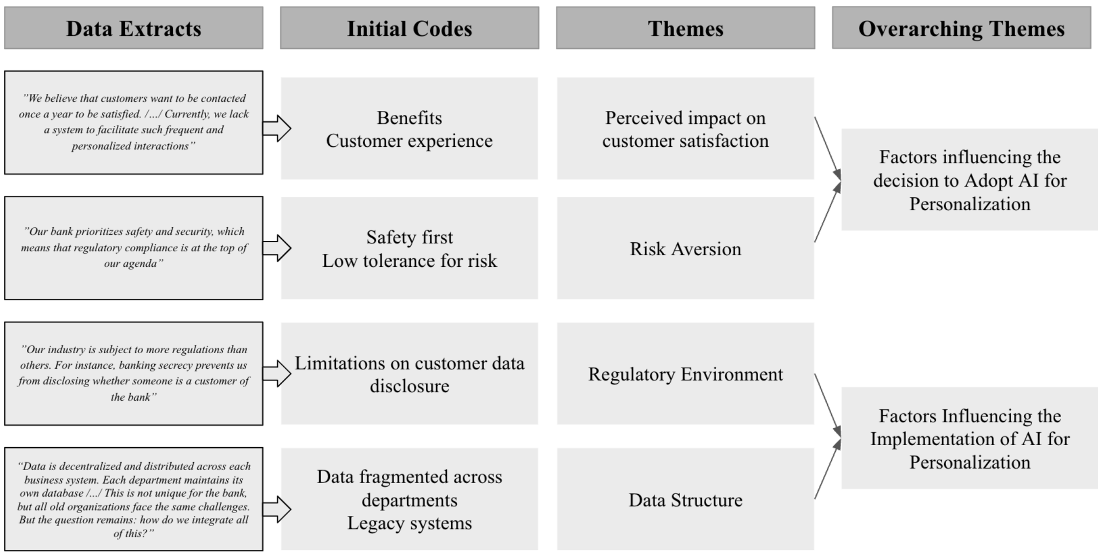

Figure 2. Data Analysis

4.4 Research Quality

To ensure the quality of this study, the criteria for qualitative research presented by Lincoln and Guba's (1985), referring to credibility, transferability, dependability, and confirmability, have been considered. This section presents a discussion on each of these criteria followed by a discussion on research ethics.

4.4.1 Credibility

Credibility refers to how the researchers' interpretations of reality coincides with the reality perceived by the interviewees (Lincoln & Guba, 1985). To strengthen credibility, the researcher's interpretations were validated through what Lincoln and Guba (1985) refer to as member-checking. This entailed a process where the transcribed material and the researcher's interpretations were sent back to the interviewees for review which ensured that the participant's perspectives were accurately captured. Additionally, a dual analysis, where both researchers independently analyzed the material, was conducted after each interview to avoid potential misinterpretations.

4.4.2 Transferability

Transferability refers to the extent to which the results of a study can be applied outside the specific context in which it was originally conducted (Lincoln & Guba, 1985). Single-case studies have been criticized for yielding limited transferability (Yin, 2003). In order to improve transferability of this study a detailed description of the research phenomena, including insights into the case company and its operating context, have been provided. Thus, allowing others to assess the applicability of the findings in other settings (Lincoln & Guba, 1985).

4.4.3 Dependability

Dependability refers to the extent to which the same results could be achieved if the study were repeated under similar conditions (Lincoln & Guba, 1985). To ensure high dependability in this study, the research process has been transparent and systematically documented with a clear explanation of the methodological process (Bell et al., 2022).

Further, the authors have employed external auditing where the process and activities were continuously reviewed by the supervisor.

4.4.4 Confirmability

Confirmability refers to whether the collected data accurately represents the information provided by the participants and the interpretation of this material is not shaped by the researchers' subjective values or biases (Lincoln & Guba, 1985). To uphold the criteria of confirmability, and minimize the risk of researchers’ values and biases shaping the findings, the researchers actively practiced reflexivity, continuously acknowledging and critically reflecting on how their experiences and preconceptions might influence how they interpreted the data (Bell et al., 2022). Specifically, the two authors challenged and questioned each other’s interpretations, actively considering alternative explanations to avoid biases in the analysis.

4.4.5 Ethical Consideration

This study has carefully considered several ethical considerations to mitigate potential ethical risks. One of the main ethical concerns considered in this study was to maintain the confidentiality and anonymity of the case company and the individual interviewees (Bell et al., 2022). This was particularly important since the authors and the contact person at the case company had agreed that the company’s name and any information that could be traced to the company should not be disclosed. Hence, information that could be traced to the company has been excluded, and interviewees are identified only by their respective departments or as AI-experts, in accordance with participants’ agreements. Additionally, several actions were taken by the researchers to ensure that participants could make an informed consent to participate in the study (Bell et al., 2022). Prior to the interviews, interviewees were contacted through email, where they were informed about the study’s topic and the main questions that would be addressed during the interviews. It was communicated that participation was optional. Furthermore, the email included a statement informing participants that the interviews would be recorded only with their consent and that all records would be deleted upon completion of the study. This information was also mentioned at the beginning of each interview as a reminder to ensure informed consent.

5. Empirical Analysis

This chapter outlines and analyzes the empirical results using the conceptual framework presented in chapter 3. The chapter is structured into four main parts. Initially, the case company will be introduced (5.1). The following section (5.2) examines the factors influencing the decision to adopt AI for personalization, followed by a section (5.3) which explores the factors influencing the implementation of AI for personalization. The final section offers a conclusion (5.4). The structure of the results into two phases is relevant as the empirical results revealed that different factors are perceived to influence various stages of the process of adopting AI for personalization in the bank. Each section outlines and analyzes technological-, organizational-, and environmental context factors that shape the adoption process, seeking to explore what factors employees perceive to influence the adoption of AI for personalization, and how and why these factors are perceived to impact this adoption.

5.1 The Case Company: The Bank

The selected case company is a large traditional Swedish retail bank with more than 5,000 employees in Sweden. Its primary operations are based in Sweden, an industry characterized by a long-standing tradition of technological innovation, underpinned by a highly digitized society. Moreover, the Swedish banking industry is governed by a comprehensive regulatory framework that puts strong emphasis on data privacy and consumer protection through strict laws such as GDPR and stringent bank secrecy regulations. The bank has historically been characterized by physical branches where customers can access financial services and engage with staff face-to-face. However, in response to industry developments, the bank has during the past 10 years closed numerous branches, shifting its focus toward enhancing digital customer experiences. This shift has increased the emphasis on utilizing AI for personalization. Within the past year, the bank has initiated its journey towards integrating AI for personalization into its operations. Pilot projects have been launched, including initiatives focused on specific personalization topics such as tailored product recommendations and individualized customer communication strategies, and discussions regarding the use of AI for personalization have gained increased strategic attention, reflecting a growing organizational focus on AI adoption. Due to confidentiality considerations, the bank will hereafter be referred to as “the bank” throughout this thesis.

5.2 Factors Influencing the Decision to Adopt AI for Personalization

The factors influencing the decision to adopt AI for personalization, refers to the initial phase of the adoption process, specifically the considerations involved in deciding whether the organization should adopt AI for personalization or not. The interviews revealed that several factors are perceived to influence the decision to adopt AI for personalization. These will be outlined and analyzed in the following.

5.2.1 Technological Factors

Perceived Impact on Customer Satisfaction

From the interviews it was evident that a key factor perceived to influence the decision to adopt AI for personalization is the tool’s perceived potential to enhance customer satisfaction, compared to the current reliance on manual methods for personalizing products and services. Thus, exerting a positive influence on the decision to adopt the tool. In particular, interviewees highlight the tool's ability to engage with a larger number of customers more often. As interviewee 2 pointed out:

> “*We believe that customers want to be contacted once a year to be satisfied, but the latest external customer survey report showed that customers actually like to be contacted every day by the bank, or at least once a week. Currently, we lack a system to facilitate such frequent and personalized interactions, so utilizing AI for this purpose is not only relevant but truly beneficial.”*

In contrast to this, some interviewees emphasized how utilizing AI for personalization may have a negative impact on customer satisfaction, as it can miss out on crucial human elements of personalization. Interviewee 8 noted:

> “*One thing that can be lacking in a more AI-driven approach is the human element. The data we see in our systems is just numbers, but many customers may seek a deeper relationship to*

feel truly understood. For example, in customer meetings, I never jump straight into the agenda, I always start with small talk to build that important personal connection. If this human element is lost, the relationship may be damaged."

The findings indicate that the perceived impact on customer satisfaction from adopting the tool can influence the decision to adopt AI for personalization in both positive and negative directions. The factor aligns with what Rogers (2003) refers to as perceived relative advantage, that is, the extent to which an innovation is perceived as better than the idea it supersedes. Based on this reasoning, the perceived impact on customer satisfaction of adopting AI for personalization can be explained by its perceived potential, or lack thereof, to generate a perceived relative advantage over the bank's current manual personalization methods.

Interpretability

Another technological factor perceived to influence the decision to adopt AI for personalization was the interpretability of the AI solution. Several interviewees from the bank expressed concern regarding the possibility of understanding the underlying rationale behind the recommendations generated by the AI solutions. It was further emphasized that in the banking industry, where transparency and accountability is vital, being able to understand the underlying rationale behind the AI solutions recommendations is of great importance. Hence, the lack of interpretability was perceived to have a negative influence on the decision to adopt the tool. Interviewee 14 stated:

"Relying too heavily on AI can be risky. It may produce recommendations that we simply can't understand, what's really behind this suggestion to the customer? Especially in our sector we might have to take a step back and admit that it can become too much of a black box, we must be able to take responsibility and accountability for what we push out."

According to Rogers (2003), one of the technological factors influencing adoption is the perceived complexity of a tool. According to this reasoning, the lack of interpretability can be explained as perceived complexity to understand the tool and its outcomes. In line with Rogers (2003), the lack of interpretability can thus be understood to negatively influence the decision to adopt AI for personalization, as it increases perceptions of complexity. Moreover, the empirical findings highlight that interpretability is particularly crucial in the banking industry, given the stringent regulatory environment that demands a high level of transparency and accountability. Thus, providing a deeper understanding for why this factor negatively influences the decision to adopt AI for personalization in the banking industry.

5.2.2 Organizational Factors

Strategic Alignment

The interviews showed that the strategic alignment between the AI tool and the bank's strategy and values may influence the bank's decision to adopt AI for personalization. Some interviewees highlighted that utilizing AI for personalization does not align with the bank's strategy and thus negatively influences the decision to adopt the tool. It was emphasized that since the bank's strategy focuses on building close relationships with its customers, a shift toward digital personalization could be seen as a departure from these core values. In particular, interviewee 6 noted:

"One reason why we haven't implemented this type of technology is that the bank has decided to prioritize the importance of building relationships with customers."

On the other hand, some interviewees perceived that adopting AI for personalization aligns with the bank's strategy and values, positively influencing the decision to adopt the tool. It was highlighted that the tool can be used to amplify relationships with customers, and hence aligns with the bank's strategy and values. Interviewee 1 noted:

"As customers, we want to feel valued. Thus, it's all about building trust and showing that we genuinely care. When we communicate and offer products and services tailored to individual needs, we strengthen that connection. Digital personalization is key for creating emotional bonds and loyalty, helping us deepen our relationships with our customers".

According to Tornatzky and Fleischer (1990) this can be explained as an organizational context factor influencing the decision to adopt AI for personalization. Specifically it can be attributed to what Rogers (2003) describes as organizational culture, referring to norms and values that influence the adoption of technologies. Based on their reasoning, the alignment between the technology and the bank's strategy can be understood as an important part of the bank's norms, values and attitudes. While the interviewees generally shared a common understanding of the bank's core values, particularly the emphasis on building personal relationships, they demonstrated different views on whether an AI tool for personalization is compatible with these values. Therefore, in alignment with Rogers (2003), it can be argued that this strategic alignment is perceived to influence the bank's decision to adopt AI for personalization.

Innovative Culture

The interviews revealed that the lack of innovative culture was perceived to negatively influence the decision to adopt AI for personalization. It was emphasized that traditional banks do not have the same sense of urgency as other industries when it comes to technological innovative solutions. The lack of urgency was attributed to the fact that the bank creates revenue growth regardless of if they adopt new innovative solutions or not. Interviewee 20 noted the following:

"There must also be incentives to invest in this area. In other industries, you may have had to fight hard for every single penny of revenue. In the banking sector, interest rates go up and down a bit and suddenly we earn a hundred million more than we did last year just because the central bank does a few things. There is not the same sense of urgency in the banking sector as there is in other industries."

This factor aligns with Rogers (2003) emphasizing that an organization's culture influences the adoption of technologies. The factor can be further explained by what Pumplun et al. (2019) refers to as organizational innovativeness. However, contrary to Pumplun et al.'s (2019) argument that incumbent firms may become overly reliant on the status quo due to bureaucratic structures, the bank's lack of innovation is primarily attributed to a general absence of urgency in the banking industry.

Risk Aversion

Another organizational factor that was perceived to negatively influence the bank's decision to adopt AI for personalization was its risk averse culture. Interviewees particularly emphasized that being a safe and stable actor is a core aspect of the bank's brand. Furthermore, it was emphasized that this risk averse culture is a reflection of the bank's critical role within society. As a result, the bank tends to adopt a risk averse approach towards initiatives like AI, primarily due to concerns about the potential risks regarding customers' data privacy. In particular, interviewee 3 noted:

> *"Our bank prioritizes safety and security, which means that regulatory compliance is at the top of our agenda. We do not take risks; we aim to operate on the safe side, or we risk losing our license. As an ethical and responsible institution in society, we constantly face the challenge of balancing personalized solutions based on data with the need to protect customer privacy."*

The risk-averse culture evident in the bank closely relates to what Rogers (2003) describes as values, attitudes, and norms that influence an organization's adoption of technology. In this context, the risk-averse culture at the bank can thus be explained as inherent values within the bank that have a negative influence on the decision to adopt AI for personalization. As emphasized in the quote, this risk averse culture can partly be attuned to the bank's important role in society, but also to the fear of losing its operational license due to potential breaches of stringent industry regulations. Consequently, this risk-averse culture, driven by both a commitment to societal roles and a fear of regulatory breaches, negatively influences the bank's decision to adopt AI for personalization.

5.2.3 Environmental Factors

Industry Competition

From the interviews, the heightened competition in the Swedish banking industry was emphasized as a factor perceived to influence the decisions to adopt AI for personalization. Several interviewees emphasized that the emergence of Fintech companies has raised industry standards by offering user-friendly and personalized customer experiences. As a result, these actors have placed considerable pressure on traditional banks to adopt similar strategies to remain relevant in the industry. Thus, positively influencing the decision to adopt. Interviewee 10 captured this by stating:

> "*We don't want to lose customers to fintechs because we don't have the digital and personalized services. Companies like Avanza have significantly driven this change since they directly impact one of our core areas by promoting convenient digital tools for savings. Improving in this area is thus crucial for our competitiveness.*"

This factor can be understood through Tornatzky and Fleischer's (1990) perspective emphasizing that intensified competition can influence the organizational adoption of technologies. Consistent with this view, Wang et al. (2010) explained that companies adopt innovative solutions in their efforts to gain a competitive edge within highly competitive environments. Based on this perspective, the intensified competition in the banking industry can be understood as a motivation for the bank to adopt AI for personalization in an attempt to gain a competitive edge in the market or remain relevant in the industry. Moreover, a further explanation for why this influence occurs is found in institutional theory (DiMaggio & Powell, 1983), particularly through the concept of mimetic pressure, which suggests that organizations tend to imitate successful strategies from its peers when operating in uncertain settings. Given the success of fintech companies in providing convenient and personalized customer experiences, it follows that mimetic pressure would push the bank to adopt similar approaches to maintain legitimacy in the fast-paced and uncertain Swedish banking industry.

In contrast to this, some interviewees argued that the intensified competition from fintechs does not influence the bank's decision to adopt AI for personalization. They emphasized that fintechs should not be seen as direct competitors, but rather as niche players with a unique brand positioning. As such, it is emphasized that the intensified competition from fintechs is not perceived to influence the bank's decision to adopt AI for personalization. Interviewee 1 stated:

"*You can't just refer to Klarna and fintechs when it comes to personalization, because it's a niche player and with a completely different brand profile. So when I talk about investing in a personalization tool, I'd rather show another traditional bank that has it than show that Avanza has it. Because then it becomes more: yes, Avanza may have it. So it's important to compare yourself with the right players.*"

This finding nuances the theoretical perspective provided by Tornatzky and Fleischer (1990), suggesting that the intensified competition does not influence the bank's decision to adopt AI for personalization. This is particularly interesting, as it may explain why the bank is lagging behind fintechs in adopting AI for personalization, despite their proven success in this area. The findings offer an explanation for this by revealing that some interviewees do not perceive these fintech disruptors as direct competitors, due to their distinct brand positioning and different risk profiles from traditional banks. Consequently, the mimetic pressure outlined by DiMaggio and Powell (1983) may not be applicable in this context, as fintech companies are not seen as part of the same competitive landscape as traditional banks. As a result, the bank may not feel compelled to imitate fintech strategies to gain legitimacy. This is particularly surprising given that some fintech disruptors actively challenge the core businesses of the traditional banks. Overall, this finding deepens our understanding of how employees perceive the impact of industry competition on the bank's decision to adopt AI for personalization, indicating that mimetic pressure is dependent on the perception of the competition.

Cross-Industry Competition

Another factor perceived to positively influence the bank's decision to adopt AI for personalization was the increasing competitive pressure from companies in other industries to deliver more personalized experiences. Advances in personalized services across other industries, with which customers interact daily, have established new expectations for customer experience. Consequently, customers now expect the same level of personalization from their banks. This was highlighted by interviewee 3, stating:

"Customers now compare their banking experiences to the personalized services of Spotify and Netflix, leading to heightened expectations for convenience and personalization. If we

fail to meet these expectations, the bank risks becoming a frustrating component in customers' lives."

This factor can be explained as an environmental factor, as described by Tornatzky and Fleischer (1990). However, while Tornatzky and Fleischer (1990) emphasize the competitive characteristics of an industry as important for shaping technology adoption, the findings of this study suggest that competition from other industries also has the potential to influence the adoption of AI for personalization. Further, the factor can be understood by what DiMaggio and Powell (1983) describe as mimetic pressure, emphasizing that the bank's decision to adopt AI is influenced by the perceived success of other organizations. While DiMaggio and Powell (1983) emphasize that such pressures arise from the successful practices of organizations within the same field, insights from the interviewees suggest that these influences also stem from outside the banking industry. A potential explanation to this is that, in today's digital environment, customers interact with actors across industries, which shapes their expectations for all service providers, regardless of industry.

5.3 Factors Influencing the Implementation of AI for Personalization

The factors influencing the implementation of AI for personalization refer to the specific phase of adoption focused on implementing the tool within the organization. The interviews highlighted several factors perceived to influence the implementation of AI for personalization.

5.3.1 Technological Factors

Customer Data Availability

Several interviewees emphasized the bank's availability of customer data as a technological factor perceived to positively influence the implementation of AI for personalization. It is highlighted that, as a bank, the organization possesses an extensive amount of data about its customers. As data serves as an important factor for effectively utilizing AI, particularly in the context of personalization, this was perceived as a great opportunity. As Interviewee 17 describes it:

"We are sitting on a gold mine. If we can harmonize this data and make it accessible in the right way, we have tremendous opportunities to use modern platforms to create relevant and personalized offers."

This can be understood through the reasoning of Pumplun et al. (2019), explaining data availability as a key enabler for effective training and the generation of accurate predictions by the AI solution. Accordingly, the extensive amount of customer data available to the bank can be regarded as a significant factor perceived to positively influence the implementation of AI for personalization within the bank.

Data Structure

The bank's current data structure was highlighted as a technological factor perceived to negatively influence the implementation of AI for personalization. A primary challenge associated with the current data structure is the presence of data silos within the organization, referring to data being scattered across various systems. These silos are perceived to create challenges to utilizing AI for personalization, as the lack of centralized data limits the ability to conduct cross-analysis between different sources, which is crucial for developing tailored products and services. Interviewee 6 particularly stated:

"Data is decentralized and distributed across each business system. Each department maintains its own database, credit management has one system, fund management has another, and securities operate on yet another. This is not unique for the bank, but all old organizations face the same challenges. But the question remains: how do we integrate all of this? We don't have that much magic each on our own."

This finding can be explained by the theoretical perspective provided by Wu et al. (2006), highlighting the critical importance of ensuring compatibility between the AI technology and the existing IT infrastructure. It is emphasized that when such compatibility is lacking, the implementation may become costly, and it would increase the time taken to implement the tool. A potential explanation for this perceived incompatibility and the emergence of data silos highlighted in the bank may lie in the bank's long history. As new systems have been introduced over time, customer data has been retained in legacy systems, leading to fragmentation and the development of silos across the organization.

Data Accessibility

Another factor perceived to negatively influence the potential of implementing AI for personalization concerns the accessibility of data. This factor is described as a potential challenge for implementing AI for personalization and stems from employees not having access to all data sources. Several interviewees at the bank, as well as AI experts, highlight that for data to be accessible it must be democratized. This refers to the act of making the data understandable and actionable for everyone in the organization. Interviewee 6 noted:

> *"The challenge often lies in structuring quality data to be accessible and actionable for all employees, ensuring it fits diverse use cases. If the bank doesn't have the data structured or if we can't make it accessible, it doesn't matter if we have an AI solution for personalization because it won't help us anyway."*

This finding can be understood through the perspective of Pumplun (2019), underscoring the importance of data accessibility, referring to enabling personnel to efficiently access organizational data sources as a prerequisite for successful AI adoption. Pumplun et al. (2019) further explain how lack of accessibility causes problems when attempting to use the data for different purposes. Hence, a potential explanation for the factor influencing the implementation of AI for personalization is the lack of accessibility across the organization, creating challenges for utilizing data from various sources needed for effectively implementing AI for personalization.

5.3.2 Organizational factors

Cross-Functional Collaboration

Cross-functional collaboration emerged from the interviews as a key organizational factor perceived to influence the implementation of AI for personalization. A key aspect highlighted in the interviews was the need to strengthen collaboration between the IT department and operational units, due to past challenges in joint initiatives. Interviewee 15 noted:

“New initiatives must be driven collaboratively by both the IT department and the business. While IT is responsible for developing the technology, it is essential to have someone close to the business who understands the customer's needs. They (the operational units) need to have a lot of influence over how the tool is designed and how it works.”

This finding can be explained by the reasoning of Tornatzky and Fleischer (1990), emphasizing how the organizational structure influences the adoption of technologies. Specifically, it is emphasized that an interconnected organization, where units are linked through strong interpersonal networks, allows organizations to adopt technologies faster and more easily. This is further emphasized by Chen et al. (2010) explaining that collaborations across units puts the organization in a more favorable position to adopt technologies. Following this reasoning, the limited collaboration between the IT department and the operational business units in the bank is perceived as limiting a successful implementation of AI for personalization.

Confidence in Data

Furthermore, the lack of confidence in data was highlighted as an organizational factor perceived to negatively influence the implementation of AI for personalization in the bank. Several interviewees indicated that for the bank to successfully implement AI for personalization, it must encourage the organization to trust and feel confident in using the data. While the bank is moving towards this approach, there remains a reliance on intuition in some areas. This was highlighted by interviewee 1:

“Marketing has traditionally been cozy and fluffy, focusing on the aesthetics. Now, it has shifted to a more analytical and systematic role in many cases. Yet, there are still signs of the old-school left, where the importance of data isn’t fully recognized.”

This factor can be explained by Tornatzky and Fleischer (1990), highlighting how organizational culture, referred to as norms, values, and attitudes, has a significant influence on technology adoption. More specifically, the factor can potentially be explained through what Jarrahi (2018) refers to as a data-driven culture, described as a key enabler for AI implementation. Based on this reasoning, the cultural orientation within the bank that favors experience-based intuition over relying on data may limit the trust in the recommendations provided by the AI solution, and hence perceived to negatively influence its implementation.

5.3.3 Environmental Factors

Regulatory Environment

Several interviewees perceived that the regulatory environment negatively influences the bank's implementation of AI for personalization. In particular, GDPR was identified as a highly influential regulation. While GDPR was not emphasized as hindering the implementation of AI for personalization, it was perceived to pose challenges to the implementation by constraining what the bank is allowed to do in this area. Interviewee 20 described the influence from GDPR in the following way:

> *"It's not that we're unable to act because of GDPR but rather, GDPR can at times act as a barrier that restricts our actions. For example, we need to have consent from customers to do things. But the bank doesn't have a consent solution in place. And now you're discovering that 'Oh, we don't have consent. Oh, now we have to.' Everything can be done but you have to adapt a little and be a little proactive."*

Adding to the complexity of the regulatory landscape in the banking industry, several interviewees perceived the bank secrecy as a factor negatively influencing the implementation of AI for personalization. It was emphasized that, in contrast to other industries, the bank is not allowed to reveal that a person is a customer of the bank. This was highlighted as causing challenges when communicating personalized offerings to customers, underscored by interviewee 3:

> *"Our industry is subject to more regulations than others. For instance, banking secrecy prevents us from disclosing whether someone is a customer of the bank. A leak of that information would breach confidentiality. This adds to the complexity of the banking*

landscape in contrast to other industries. For example, in retail, no one cares if someone is a customer of Adidas or Nike."

The perceived influence from regulation, exemplified by GDPR and bank secrecy, can be understood through Tornatzky and Fleischer's (1990) perspective, which suggests that the regulatory environment can challenge adoption by posing constraints on industries. The perceived influence of the regulatory environment can further be understood through the lens of coercive pressure (DiMaggio & Powell, 1983). From this perspective, the highly regulated nature of the banking industry leads regulatory bodies to exert significant pressure on organizations to adhere to strict compliance mandates. Consequently, the influence of regulations is driven by the coercive pressure to maintain legitimacy.

In contrast to the above reasoning, highlighting the negative influence of the regulatory environment on adoption, several interviewees at the bank as well as AI-experts highlighted how the regulatory environment can be perceived to positively influence the implementation of AI for personalization. Some interviewees specifically referred to the Payment Solution Directive 2 (PSD2). This regulation requires banks to open their APIs and share customer data with third parties, prompting banks to modernize their IT infrastructure. Since AI for personalization depends on structured and accessible data, these infrastructure improvements can facilitate the adoption. Consequently, this regulation was perceived to facilitate the adoption of AI for personalization, as the use case relies heavily on organized and readily available data. Interviewee 20 emphasized:

"Initiatives like PSD2 and open banking, which emerged about five years ago, require the availability of APIs. The implementation of these initiatives necessitates modernization to expose APIs securely and effectively. As the bank modernizes its data infrastructure to meet these demands, they can also make data accessible for personalization purposes, thus serving as a catalyst for improving their data stack."

In alignment with previous reasoning, this can be understood from the perspective of Institutional Theory (DiMaggio and Powell, 1983). Specifically through the concept of coercive pressure, referring to pressure stemming from an organization or authority to which the organization relies on. From this perspective, the coercive pressure to comply with PSD2 can be seen as having a positive influence on the implementation of AI for personalization, through its influence on the bank's data infrastructure.

Industry Norms

Another environmental factor perceived to negatively influence the implementation of AI for personalization, was the industry norm for the bank to act responsibly. Interviewees recognized that, beyond regulatory compliance, the bank has a duty to act ethically and responsibly, given its significant role and influence in society. It is highlighted that this might challenge the implementation of AI for personalization as it is crucial to ensure that such a solution aligns with the ethical principles of ensuring data privacy established in society. On this topic interviewee 3 noted:

> *"I also think about ethics and morality, not only in terms of what we are permitted to do under existing regulations, but also in terms of what we choose to do. While complying with laws is critical, we carry an additional responsibility as a bank. We must consider what is right and consistent with our core values, especially given the societal impact we have."*

The negative influence from this industry norm on the implementation of AI for personalization can be understood as an environmental factor as it stems from an external expectation (Tornatzky & Fleischer, 1990). Furthermore, the factor can be understood through the lens of institutional theory (DiMaggio & Powell, 1983). As highlighted in the interview, the bank feels an obligation to act responsibly beyond mere legal requirements. From an institutional perspective, this obligation can be explained as what DiMaggio and Powell (1983) describe as normative pressure. This normative pressure influences the bank's behavior because acting responsible is tied to maintaining legitimacy in the industry. Consequently, the industry's expectations on banks to act responsible, is perceived to challenge the implementation of AI for personalization, as the bank prioritizes ethical responsibility in order to maintain its legitimacy.

5.4 Conclusion

The purpose of this study was to explore the factors influencing the adoption of AI for personalization in a bank context. Specifically, the thesis aimed to delve into what factors employees perceive to influence the adoption of AI for personalization, as well as how and why these factors are perceived to impact the adoption of AI for personalizing products and services. This has been investigated by answering the research question: What factors do employees perceive to influence the adoption of AI for personalization, and how and why are these factors perceived to impact this adoption? The findings revealed that multiple factors are perceived to play significant roles throughout the adoption process. From the interviews it was evident that these factors were perceived to influence various stages of the adoption process. Therefore, the factors could be divided into two phases of adoption: factors influencing the decision to adopt AI for personalization and factors influencing the implementation of AI for personalization. This classification provides clarity to how the factors are perceived to influence the adoption of AI for personalization, highlighting when in the adoption process each factor exerts its major impact.

Furthermore, the thesis divides the factors into three key categories: technological-, organizational-, and environmental factors. This categorization clarifies the nature of each factors' influence, providing insights into how and why these factors are perceived to influence the adoption of AI for personalization. Lastly, the environmental factors identified could further be understood through the lens of institutional theory, offering a deeper and more nuanced understanding of the institutional forces that influence adoption, driven by organizations' pursuit of legitimacy.

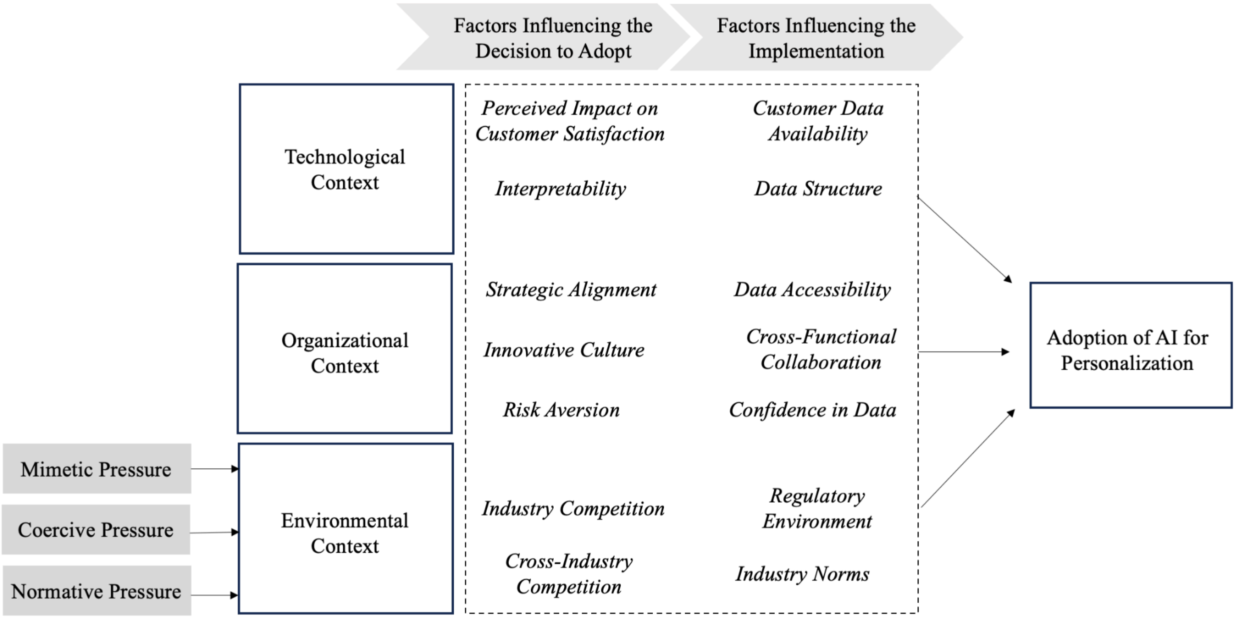

Figure 3. Extended version of conceptual framework

6. Discussion

In this chapter, the study's findings will be discussed in relation to previous research within the area (6.1). Following this, the chapter will present the theoretical contributions (6.2) and practical implications (6.3), before outlining the limitations of the study (6.4) as well as areas for future research (6.5).

6.1 Findings in Relation to Existing Research

The study has concluded that multiple factors are perceived to play a significant role throughout the adoption process. These factors are divided into two different stages of the adoption process, exerting their influence through technological- organizational- and environmental context factors. Thus, providing insights into how and why these factors are perceived to influence the adoption of AI for personalization. Additionally, the influence of environmental factors on the adoption have been further understood through the lens of institutional forces present in the environment, driven by organizations' pursuit of legitimacy.

The categorization of the identified factors into two different phases of the adoption process highlights how various factors are perceived to influence various stages of the adoption process: factors influencing the decision to adopt AI for personalization and factors influencing the implementation of AI for personalization. This explanation of how the factors are perceived to influence the adoption of AI for personalization differs from previous studies on AI adoption in the banking industry, where the adoption process typically viewed as a single stage (Rahman et al., 2021; Jang et al., 2021; Mogaji & Nguyen, 2021). Moreover, while these prior studies have not categorized the influencing factors into technological-, organizational-, and environmental dimensions, they provide consistent support for the identification of factors that exert their influence across all three dimensions (Rahman et al., 2021, Jang et al., 2021, Mogaji & Nguyen, 2021). This highlights the importance for a holistic framework in studying AI adoption in banks.

The technological factors identified in this study provides a deeper understanding to how and why employees perceive various technological factors to influence the adoption of AI for personalization. Some technological factors, such as data structure and data availability, have been identified by previous research on AI adoption in the banking industry (Jang et al., 2021; Mogaji & Nguyen, 2021) as well as in other industries (Petersson et al., 2022). However, this study differs from prior literature by providing a unique perspective on how and why these factors are perceived to influence the adoption in this specific context. Additionally, this study identifies and develops an understanding of some technological factors that can be considered unique for the context of AI adoption for personalization in the banking industry. For instance, to the best of our knowledge, the factor "perceived impact on customer satisfaction" has not been previously explored in research on AI adoption within the banking industry.

Furthermore, concerning the organizational factors identified in this study, both new and previously recognized factors were identified and explored within this specific context. For instance, risk aversion has not been widely recognized as a factor influencing AI adoption. However, this study provides evidence for its influence on the adoption of AI for personalization in a banking context, offering a unique perspective on its significance within this particular context. It was concluded that the combination of the regulatory environment and a sense of responsibility in the banking industry, alongside an inherent risk averse culture in the bank, particularly towards customer-facing solutions, serves to amplify the influence of risk aversion on the adoption of AI for personalization. This insight sheds light on why risk aversion is an influential factor for AI adoption in the banking industry, especially in relation to the adoption of AI for personalization. Furthermore, another interesting finding of this study was the exploration of how and why the lack of an innovative culture influenced the adoption of AI in the bank. While similar factors have been identified in previous studies on AI adoption (Kinkel et al., 2021), this study provides a new perspective to how and why this factor influences the adoption in this context by attributing it to a broader lack of urgency to innovate across the banking industry. These findings not only provide an understanding to how risk aversion and the lack of innovative culture influences AI adoption in this specific context, but also highlights the complex relationship between organizational factors and the external environment in AI adoption.

Regarding the environmental factors, this study, in line with prior research on AI adoption in the banking industry (Mogaji & Nguyen, 2021; Rahman et al., 2021), confirms that the regulatory environment plays a significant role in shaping the adoption of AI technologies. Specifically, this study found that the strict regulations in the Swedish banking industry such as GDPR and bank secrecy are perceived as primary challenges to AI adoption. Interestingly, while Rahman et al. (2021), in their investigation of AI adoption in the Malaysian banking industry, also highlighted the regulatory environment as an influencing factor, they concluded that the absence of appropriate regulatory systems challenged the adoption of AI. The difference between this study and the research conducted by Rahman et al. (2021) are likely attributable to the varying regulatory environments in which the studies were conducted. Given the different regulatory contexts across various banking landscapes, it can be argued that the findings of this study are primarily applicable to the Swedish banking industry. Furthermore, while this study is similar to prior research, emphasizing the influence of competition in AI adoption (Gupta et al., 2022), it challenges traditional views of what constitutes the relevant competitors influencing the adoption process. Specifically, it highlights that the success of fintech companies was not perceived as a significant factor influencing the bank's AI adoption, despite fintechs posing a threat to the bank's core business. Additionally, the study acknowledges that competition from companies in other industries may influence the adoption of AI by raising customer expectations for personalized experiences that span across industries.

Lastly, unlike previous studies on AI adoption in the banking industry, the environmental factors identified in this study were further understood through the lens of institutional theory, offering a deeper and more nuanced understanding of the underlying institutional forces that influence adoption of AI for personalization. For instance, it was emphasized that the industry norm within the Swedish banking industry creates pressure to act responsibly beyond regulatory compliance to retain legitimacy, consequently challenging the adoption of AI for personalization. Hence, emphasizing how underlying institutional pressures influences AI adoption for personalization in banks, driven by the organization's pursuit of legitimacy.

6.2 Theoretical Contributions

This study has explored the factors influencing the adoption of AI for personalization. Specifically, the study has addressed the research question: What factors do employees perceive to influence the adoption of AI for personalization, and how and why are these factors perceived to impact this adoption? By answering this research question, this study has contributed theoretically in several ways. First, by investigating AI adoption in the unique context of the banking industry and for the purpose of personalization, this study has extended the theoretical understanding by identifying and developing an understanding of the unique factors influencing the adoption of AI in this specific context, contrasting prior research on AI adoption in the banking industry (Jang et al., 2021; Mogaji & Nguyen, 2021; Rahman et al., 2021). While some of the identified factors are not exclusive to this specific context, this study offers a new perspective on how and why these factors are perceived to influence the adoption of AI for personalization in the banking industry. Second, by drawing on TOE in combination with Institutional Theory, the study has contributed with a deeper and more nuanced understanding of employees' perception of AI adoption in a bank context. Third, this study contributes to AI adoption literature in the banking industry by clarifying when different factors are perceived to exert their influence throughout the adoption process, not extensively addressed by prior research on AI adoption in the banking industry (Rahman et al., 2021; Jang et al., 2021; Mogaji & Nguyen, 2021). Dividing the factors into two phases of the adoption process enhances the understanding of how these factors influence the adoption process, by recognizing that different factors exert their influence at various stages of the process.

6.3 Practical Implications

This study provides valuable insights for bank managers seeking to adopt AI for personalization. First, by enhancing the understanding of how and why certain factors influence the adoption of AI for personalization, managers can develop more informed and targeted strategies to effectively navigate these influences. Second, recognizing that AI adoption is driven by technological-, organizational-, and environmental context factors highlights the importance of taking a holistic approach to ensure a successful adoption. Third, by categorizing the influencing factors into two phases, this study clarifies when each factor exerts its influence. This distinction creates better conditions for developing tailored strategies suited to the respective phases and for identifying the appropriate supporting mechanisms at the right time.

Besides the practical implications for managers, this study also provides implications for policymakers. The findings highlight that the regulatory environment was perceived as a factor exerting substantial influence on the adoption of AI for personalization. For policymakers, this underscores the importance of clear and context-specific guidelines regarding AI applications in banking. By reducing the perceived regulatory challenges for AI adoption in banking, regulatory bodies can enhance innovation and ensure that regulations do not discourage technological advancements.

6.4 Limitations

As with all research, this study is subject to certain limitations. First, as the study is a single-case study, the transferability of the findings to other contexts is limited (Yin, 2003). Consequently, the insights generated in this study may not directly apply to other contexts, such as different banks or countries. However, as the main purpose of the study was to provide in-depth insights into how employees perceive the phenomena, rather than identifying general factors influencing the adoption, this limitation may be less critical. Second, since the bank is in an early stage of adopting AI for personalization, with ongoing pilot projects and active strategic discussions, the perceptions of employees are primarily based on initial experiences. As a result, these perceptions may be more limited in scope and reflect preliminary views, which could influence the depth and nuance of the insights. Third, this study used qualitative interviews during a specific point in time which allowed for in-depth insights regarding the perceptions of AI adoption for personalization. Nevertheless, AI adoption is a dynamic process that unfolds over an extended period. Hence, a longitudinal study could have enhanced the findings by capturing how perceptions develop throughout the adoption process, providing a richer understanding of this evolving process (Pettigrew, 1990). Due to limited time constraints, it was not feasible to conduct such a study.

6.5 Future Research

While previous research has investigated consumer adoption of AI in banks (Belanche et al, 2019; Atwal & Bryson, 2021; Lee & Chen, 2022), this study examines the adoption of AI for personalization from bank employees' perspective. An interesting avenue for future research would therefore be to incorporate the perspectives of other stakeholders, such as regulatory bodies or AI service providers. Examining how these actors perceive the factors influencing AI for personalization may reveal additional explanations to the factors influencing AI for personalization, which would provide a more nuanced understanding of why certain factors emerge and how they shape the adoption of AI within the banking industry. Second, the qualitative nature of this study effectively explores the relationships between factors such as data structure, organizational structures, the competitive environment, and regulatory environment with the adoption of AI for personalization. However, future research could use quantitative methods to test the strength of the identified factors to provide statistical support and more robustness, which could either confirm or reject the relationships identified in this study.

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8. Appendices

Appendix 1 - Interview Guide for Bank Employees

Introductory Questions	• Briefly tell us about yourself and your role at the bank. • How long have you worked at the bank? • Briefly tell us about your department and what you do at the bank.
Personalization	• How do you perceive that the bank works to adapt their products and services to the unique needs of the customer? Can you give an example of this? • How do you work to create a better understanding of your customers' needs today? • Are you familiar with the concept of personalization? If yes, how would you describe personalization? • How does the bank work with personalization in your digital channels? Can you give an example of this? • How does the bank work with personalization in your physical channels? Can you give an example of this? • What do you see as advantages and disadvantages of personalization of products and services? • How willing do you think the bank's customers are to give up data to receive more personalized offers? Do you think this differs between customers? Between different types of data?
AI	• Are you working with any AI solutions today? In what way? • What challenges and opportunities do you see in adopting AI for the purpose of personalizing products and services at the bank? For example, product recommendations based on historical data from customers. • What do you see as advantages and disadvantages of using AI for this purpose within the bank?
Data	• How do you work with customer data to tailor offers to customers? • How is customer data structured within the organization? • Do you have access to other departments' data?
Organization	• Do you think that the use of AI could improve the value of the offering to the customer? • What is the collaboration like between departments within the bank? • How would you rate the technical knowledge within the bank? Who works with technical issues at the bank? • How would you say that this type of technology is prioritized within the bank? From management? Is there support from management for this type of solution? • What value do you think the use of AI to personalize customer offerings could have created for the bank? • How have previous technical innovations/implementations been received by employees?
External Environment	• How do regulations affect the possibility of personalization using AI and customer data? • How do you view the balance between privacy and personalization? • How would you say the industry has changed in recent years? • How would you say the competitive landscape is impacting the bank's efforts in AI and personalization?
Closing Questions	• Is there anything else regarding the use of technology/AI and personalization that we haven't asked you about but that you think we should know?

Appendix 2 - Interview Guide for AI - Experts

Introductory Questions	● Tell us briefly about yourself and your work ● How would you define AI used for increased customer customization/personalization? ● What type of AI is used for these purposes?
Personalization	● How can banks use AI to deliver more personalized offers? ● What are the biggest technological challenges for a large company when it comes to using AI in its operations? ● Do you see any specific challenges here when it comes to banks? ● What are the most important technological factors within banks that enable the use of AI to increase customer customization/personalization? ● What are the biggest organizational challenges for companies when it comes to using AI? ● What are the advantages/disadvantages of being a traditional company when it comes to using AI? ● What skills are crucial within the bank to enable the use of AI for increased personalization? Which departments are most important in the implementation? ● How have the opportunities to introduce AI to personalize offerings changed in the wake of GDPR? ● How do you view the issue of the balance between privacy and personalization within banks? ● What role does the competitiveness of an industry play in a company's motivation to adopt an AI-driven approach?
Closing Questions	● How do you view the development of AI for increased personalization within banks? ● What do you see as the main enablers for banks in using AI for increased personalization? ● What do you see as the main challenges for banks in using AI for increased personalization?

Appendix 3 - Interviewee Overview

Participant	Department	Company	Experience	Date	Format	Length
Pilot	Change Management	The Bank	12 years	2025-02-12	Digital	42 min
1	Digital Communication	The Bank	4 years	2025-03-07	Physical	47 min
2	Branch	The Bank	20 years	2025-03-07	Physical	45 min
3	Business Development	The Bank	7 years	2025-03-10	Digital	46 min
4	Researcher	AI Expert	-	2025-03-10	Digital	37 min
5	Change Management	The Bank	18 years	2025-03-11	Physical	47 min
6	Customer Data	The Bank	4 years	2025-03-12	Digital	45 min
7	Branch	The Bank	11 years	2025-03-19	Physical	35 min
8	Branch	The Bank	7 years	2025-03-19	Physical	32 min
9	Loyalty & Conversion	The Bank	4 years	2025-03-19	Digital	40 min
10	Branch	The Bank	4 years	2025-03-21	Digital	36 min
11	Branch	The Bank	6 years	2025-03-21	Digital	38 min
12	AI - Expert	AI-Expert	-	2025-03-24	Physical	33 min
13	Branch	The Bank	22 years	2025-04-01	Physical	37 min
14	Branch	The Bank	18 years	2025-04-01	Physical	39 min
15	Change Management	The Bank	17 years	2025-04-01	Digital	42 min
16	Business Development	The Bank	4 years	2025-04-02	Physical	41 min
17	Business Development	The Bank	4 years	2025-04-03	Digital	37 min
18	AI - Expert	AI-Expert	-	2025-04-03	Physical	42 min
19	AI - Expert	AI-Expert	-	2025-04-07	Digital	41 min
20	AI & Analytics	The Bank	2 years	2025-04-07	Digital	40 min

9. AI Appendix

9.1 Generative AI Usage

In this study, two types of AI tools have been used in the process of writing this thesis: ChatGPT-3.5 and Grammarly. The following section outlines why and how it has been used.

ChatGPT-3.5 has been used in the study primarily to improve grammar, sentence structure, and clarity in written text. The use of the tool served as a complement in the writing process, providing quick answers and suggestions in refining word choice and improving coherence. However, the authors acknowledge that there are certain risks associated with relying too much on an AI-tool, such as the generation of incorrect outputs which guides the authors in the wrong direction. To mitigate this risk, the generated output from the tool was always critically reviewed, rewritten, and controlled by the authors, and no text was copied directly into the thesis without revision or rewriting. The use of ChatGPT3.5 in the thesis provided the authors with valuable insights into the importance of maintaining a critical perspective when utilizing AI tools. This approach ensured that the tool functioned as a complement in the writing process rather than a substitute for academic judgement.

The AI tool Grammarly has been used as an additional complement supporting our writing. It has been used to detect our spelling mistakes and grammatical errors. This was especially helpful when writing a long and complex text like a thesis, when these mistakes might be overlooked. Additionally, it has improved the clarity and readability of the text by suggesting more structured ways to express our ideas. However, certain risks are associated with relying blindly on this type of tool. For instance, this was apparent when Grammarly constantly suggested we write more assertively in instances where we wanted to use a more cautious approach, such as changing "this may suggest…" with "this shows" or changing "the results could indicate…" with "the results indicated". While this active voice may be stronger, it could result in incorrect phrasing and a complete misinterpretation of our results. To mitigate the risks, we used Grammarly critically and reviewed every suggestion before approving it to make sure it suited our academic tone and meaning.

9.2 Generative AI Sources

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