Aligning Ambition and Adoption

Exploring Individual and Organizational Adoption of AI

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Abstract

This thesis examines the organizational dynamics and employee perceptions that influence the adoption of artificial intelligence (AI) tools for internal processes within a large Swedish retail organization. While much prior research has emphasized consumer-facing applications, limited attention has been given to employee-level dynamics and internal adoption processes. Using a qualitative case study design, the study draws on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology-Organization-Environment (TOE) framework to explore both individual and organizational influences on adoption behaviors. As the analysis progressed, it became clear that deeper cultural and structural tensions shaped adoption outcomes in ways these models could not fully explain. Two key organizational paradoxes are identified: the Organizational Limbo paradox, where leadership expects bottom-up experimentation while employees await top-down support, and the Fragmented Engagement paradox, where grassroots initiatives remain isolated without formal mechanisms for scaling. Emotional concerns, workload pressures, and unclear expectations further shape adoption patterns. By introducing organizational paradox theory, the study provides a more nuanced understanding of why AI adoption may stall despite favorable conditions, offering theoretical insight and managerial guidance for aligning strategic ambition with actual adoption.

Keywords: *Artificial intelligence (AI), AI adoption, Technology acceptance models, Organizational dynamics, Employee attitudes, Organizational change, Retail industry*

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1. Introduction

1.1 Background

Artificial intelligence (AI) has emerged as a transformative technology with the potential to reshape business processes across industries. Defined as human-created systems capable of mimicking human intelligence through learning, reasoning, and understanding (Enholm et al., 2021; Lichtenthaler, 2019), AI enables machines to perform complex cognitive tasks. As AI systems advance, they increasingly generate novel outputs, from text and images to strategic insights, offering limitless opportunities for business innovation (Enholm et al., 2021; Mikaelef & Gupta, 2021). However, fully realizing AI's potential requires implementation approaches prioritizing explainability, transparency, ethics, and human needs (Fui-Hoon Nah et al., 2023). Several organizational factors, such as company structure, size, and talent recruitment strategies, have been found to influence how effectively such technologies are integrated (Bruque & Moyano, 2007). For example, recent data indicates a significant rise in AI adoption within the retail sector in Sweden, from 10% of companies in 2023 to 31% in 2024 (Svea Bank AB, 2024), reflecting a broader trend of digital transformation in the industry. However, despite the rising adoption of AI among retailers, limited research has explored how this shift affects internal organizational processes, particularly how employees perceive and respond to the integration of AI tools (Robertson, Botha, Oosthuizen, & Montecchi, 2025).

AI implementation is not just a technical process but also a profoundly human one. Organizations must rethink how decisions are made through technology and human-AI collaboration. Thus, an effective adoption depends on how individuals within organizations perceive, trust, and utilize AI tools. Without employee engagement and confidence in the technology, even the most advanced systems risk underutilizing or resisting (Shrestha, Ben-Menahem & von Krogh, 2019). Since individual behavior directly shapes how technologies are used, organizational adoption is inseparable from individual adoption. How employees engage with AI does not solely influence their work but also impacts how effectively the organization can integrate AI into broader processes and decision-making structures. As AI becomes increasingly embedded into daily operations, implementation strategies must reflect various perspectives, not only those of technical experts. Jordan (2019) emphasizes that "... humans need to understand and shape technology as it becomes ever more present”. These complexities highlight the importance of exploring AI adoption from technical or consumer-centric viewpoints and the employees' perspective within organizations.

1.2 Research Problem

Despite the growing use of AI in retail, successful AI implementation remains challenging, and limited research exists on its impact on organizational structure and internal collaboration processes. Existing studies primarily emphasize technical aspects or consumer-facing applications, leaving a gap in understanding how AI adoption affects internal operations and employee roles (Robertson et al., 2025). As Jordan (2019) highlights, many organizations possess the technological “building blocks” but lack coherent principles for integrating them meaningfully into workflows. As Jordan (2019) highlights, “While the building blocks are in place, the principles for putting these together are not, and so the blocks are currently being put together in ad-hoc ways”. Although research on AI in retailing is expanding, much of it centers on consumer-facing applications, such as chatbots, virtual try-ons, and personalized recommendation systems. These studies often examine personalization, customer trust, and adoption (Frank et al., 2023; Tiutiu & Dabija, 2023). In contrast, considerably fewer studies have explored how employees within retail organizations adopt AI. Some research has addressed general organizational enablers of digital transformation (Bonetti et al., 2018; Enholm et al., 2021), yet limited research exists on the impact of AI integration on organizational structure within retail settings (Robertson et al., 2025).

1.3 Purpose

The purpose of this study is to contribute to this underexplored area by investigating the factors that influence the adoption of AI tools for internal processes within a retail organization. To guide this investigation, the following central research question is asked:

What factors influence the adoption of AI tools for internal processes within a retail organization?

This research question directs attention to the individual and organizational factors that shape adoption behaviors and how they interact. Ultimately, this study enriches theoretical models of technology adoption and provides practical guidance to organizations seeking to support effective, sustainable integration of AI in internal processes. In addition to established adoption models, this study also draws on organizational paradox theory (Smith & Lewis, 2011) to explore tensions between strategic ambition and actual adoption behavior.

1.4 Case Company

The case company in this study is a leading global fashion retailer headquartered in Sweden. It operates in numerous countries and has a broad physical and digital sales channel portfolio. Its cross-functional structure includes design, logistics, IT, and advanced analytics departments. In recent years, the organization has emphasized digital transformation strategically, with AI playing an increasingly central role. These initiatives enhance efficiency, responsiveness, and innovation across departments. The organization's scale, cross-functional structure, and current phase of AI adoption make it a strategically relevant context for studying how individuals and organizations engage with and adapt to AI in their internal processes.

1.5 Scope & Limitations

This study explores internal AI adoption within a single large Swedish fashion retailer, focusing specifically on employee perspectives across departments such as planning, design, and analytics. The scope is limited to one organizational context, which may affect the generalizability of the findings to other industries or cultural settings. A total of nine semi-structured interviews were conducted. While the sample size limits the breadth of perspectives captured, access to participants required internal coordination and approval, underscoring the complexities of conducting qualitative research in organizational settings. In this light, the number of interviews conducted should be viewed as a strength, enabling focused, high-quality insights into individual perceptions and behaviors.

2. Literature Review

The following part will serve as a foundation for the paper's research question. Combining relevant literature will create an understanding of the factors that influence the adoption of AI tools for internal processes within a retail organization. Literature is presented on AI adoption in organizations and individual AI adoption in organizational contexts.

2.1 AI Adoption in Organizations

2.1.1 AI's Strategic Potential and Business Applications

Artificial intelligence (AI) is widely recognized as one of the most disruptive technological breakthroughs of recent years, fundamentally reshaping industries such as retail (Dwivedi et al., 2021; Fui-Hoon Nah et al., 2023; Shankar, 2018). To capture the potential business value AI offers, organizations must integrate AI not only on the supply side, such as logistics and inventory management, but also on the demand side, including customer service, personalization, and sales management (Shankar, 2018). A consistent theme in literature is that AI's transformative power lies in its ability to process vast amounts of data and support intelligent decision-making, thereby enhancing organizational intelligence through collaboration between human and digital actors (Kolbjørnsrud, 2024).

In retail, AI-driven automation and augmentation are central enablers for advancing decision-making processes. Automation refers to tasks performed independently by digital technologies, while augmentation involves AI supporting and enhancing human capabilities (Kolbjørnsrud, 2024; Raisch & Krakowski, 2021; Viswanathan, 2024). Retailers leverage AI for real-time decision-making, demand forecasting, and personalized customer experiences, thus creating more dynamic, efficient, and customer-centric business environments (Enholm et al., 2021; Shankar, 2018; Viswanathan, 2024). Although the short-term impact of AI is sometimes overestimated, research argues that the medium- and long-term implications will be even greater than currently anticipated. Accordingly, firms that adopt AI are expected to gain competitive advantages through operational efficiencies, enhanced decision-making, and personalized customer engagement (Shankar, 2018).

The term AI adoption is consistently conceptualized as an organizational process involving technical integration and human factors (Robertson et al., 2025). It refers to the evaluation, implementation, and assimilation of AI technologies within a company, aimed at improving operational efficiency, decision-making, and customer experience (Shankar, 2018; Kolbjørnsrud, 2024). Prior studies acknowledge the strategic importance of AI adoption in retail. However, much of the existing research has focused on organizational structures and technological capabilities, while paying less attention to individual-level adoptions within organizations, although these dimensions are highly interrelated. The success of organizational AI implementation is shaped by individuals' willingness and ability to integrate AI into their workflows. To understand these human factors is crucial, as realizing AI's potential requires technical infrastructure and active participation and acceptance from those who use it (Robertson et al., 2025).

2.1.2 Enablers, Barriers, and Organizational Research Gaps

Several studies have sought to identify the enablers and barriers to AI adoption. Enholm et al. (2021) categorized influencing factors into three broad areas: technological, organizational, and environmental. Technological enablers include access to high-performance computing and large, structured datasets. At the same time, barriers involve infrastructure limitations, issues regarding data quality, and the lack of transparency in AI systems, which is the black box problem. Organizational enablers focus on an innovative culture, top management support, and investments in AI-skills development, whereas barriers include employee resistance, mistrust of AI, and misalignment with business strategies. Environmental factors, competitive pressures, and customer demand encourage adoption but are counterbalanced by ethical concerns and regulatory challenges.

Building on these insights, Ångström, Björn, and Wallin (2023) further refined these categories, emphasizing cultural barriers alongside technological and organizational ones. Research points to significant challenges in shifting organizational mindsets and decision-making from intuition-driven to data-driven. Resistance from employees and limited AI understanding among managers are critical barriers. They emphasize that overcoming these barriers requires strategic initiatives to embed AI capabilities across the organization, including AI education programs, improving data management, and building cross-functional teams.

Despite these contributions, there is a notable underexplored area in the literature regarding how individual employees experience and adapt to AI in organizational settings. Existing studies mainly discuss barriers and enablers at an organizational and technological level; however, they provide limited insight into the psychological, social, and practical factors shaping individual AI adoption within organizations, particularly in a retail context (Robertson et al., 2025). Much of the previous research on technology acceptance has been conducted using quantitative approaches, which have limitations in capturing the nuanced, individual-level factors that influence adoption (Vogelsang, Steinhüser, & Hoppe, 2013). This lack of qualitative research at the individual level limits organizations' ability to design effective AI integration strategies that align with employees' perceptions, needs, and concerns.

2.2 Individual AI Adoption in Organizations

2.2.1 Trust, Usefulness, and Psychological Acceptance

While organizational-level factors such as technological infrastructure and strategic alignment are crucial to AI adoption, the role of individual employees is increasingly recognized as a decisive factor in successful implementation. However, individual-level adoption remains underexplored, particularly in retail organizations. As AI tools become more embedded in workplace routines, employees' willingness and ability to engage with these technologies determine how organizations can realize AI's full potential (Dabbous, Barakat, & Merhej Sayegh, 2022). One of the key challenges facing AI implementation is the black-box nature of algorithmic systems. Users often struggle to understand how AI systems generate outputs, undermining trust and acceptance (Shin, 2020). Interpretability and explainability are thus central to promoting user confidence and engagement. Shin (2020, 2021) argues that trust in AI is closely tied to causability, users' ability to understand and justify algorithmic decisions. When explanations are accessible and align with users' prior knowledge and beliefs, trust is fostered, facilitating adoption.

This trust-building is not merely a technical concern, but also a socio-psychological one. AI tools' perceived transparency and usefulness directly influence employees' willingness to incorporate these systems into their daily workflows. As Shin (2021) highlights, traditional technology acceptance models, such as the Technology Acceptance Model (TAM; Davis, 1989), may fall short in fully capturing the complexities of human-AI interaction, specifically in contexts where algorithms are unfamiliar. Research by Dabbous, Barakat, and Merhej Sayegh (2022) expands on this view by exploring how individual, organizational, and social factors shape AI adoption. Their study underscores the role of organizational culture, individual habits, and self-image in influencing perceived usefulness and ease of use, the core constructs of TAM. Further, they advocate for integrating habit as a social psychology dimension into TAM, based on models to better capture real-world dynamics of AI use in the workplace.

2.2.2 AI Use at Work

Despite these insights, studies applying TAM or Unified Theory of Acceptance and Use of Technology (UTAUT) to AI adoption within organizations remain limited, particularly in the retail sector. Existing research has predominantly focused on consumer-facing AI applications such as chatbots and personalized recommendation systems, with less attention paid to how retail employees engage with AI in internal workflows (Heins, 2023). According to Heins (2023), although AI is increasingly used in the retail value chain, scholarly contributions focus primarily on narrow applications to enhance customer experience. Considerably less attention is paid to how employees internally adapt to AI systems.

Harbarth, Gößwein, Bodemer, and Schnaubert (2024) emphasize a growing interest in the human dimensions of human-AI collaborations, rather than solely the technical aspects. However, they note that findings in this area remain mixed and highlight the need for more nuanced research into how technological and human factors shape AI adoption outcomes. This call for greater attention to the human side of AI implementation is echoed by Bankins, Ocampo, Marrone, Restubog, and Woo (2024), who argue that while models such as TAM and the TOE framework offer useful starting points, they often fail to capture the complexity of AI systems and the organizational settings in which they are implemented. Crucially, these models overlook how AI reshapes job roles, work processes, and skill demands, directly influencing employee usage. As highlighted in previous research, the limited attention to internal use of AI in retail presents an opportunity to explore how employees perceive, engage with, and integrate AI tools into daily workflows (Heins, 2023). This study investigates the factors influencing individual and organizational AI adoption within a retail organization.

3. Theoretical Framework

The selection of the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology-Organization-Environment (TOE) framework as the guiding theoretical lenses in this study is grounded in their extensive prior use, credibility, and continued relevance in contemporary technology adoption research. These frameworks have been widely applied and empirically validated across diverse industries and technologies, providing a robust foundation for analyzing both individual- and organizational-level determinants of adoption (Dube, Van Eck, & Zuva, 2020). Moreover, they serve as reference points in newer research, with many recent studies building upon or extending their core constructs (Gupta, Nair, Mishra, Ibrahim, & Bhardwaj, 2024). By focusing on these well-established models, this study ensures analytical rigor, aligns with established scholarly practice, and enables comparability with prior research in the field.

3.1 Technology Acceptance Model (TAM)

Previous research consistently shows that adopting information technology and system utilization in workplaces remains problematic. As AI adoption accelerates, understanding conditions that impact user adaptability has become a critical concern for researchers and organizations (Robertson, 2025; Khanfar, Kiani Mavi, Iranmanesh, & Gengatharen, 2024). TAM represents progress in explaining, understanding, and predicting user acceptance of technology (see Appendix 1). TAM explains that two key factors determine an individual's behavioral intention to use a technology, Perceived Usefulness (PU), the extent to which an individual believes using a system will enhance job performance and Perceived Ease of Use (PEOU), the extent to which an individual believes using a system will be free of effort (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008).

Research suggests that PU predicts usage intention to a greater extent than perceived ease of use PEOU. Even if a system is challenging to use, users are more likely to adopt it if they believe it improves their job performance. PEOU indirectly influences adoption through PU; when a system is perceived as easier to use, it is also perceived as more useful. Both PU and PEOU affect users' attitudes toward using the technology and their behavioral intention to use it (Davis, 1989).

Further developments have been made to TAM. The second version, TAM 2, developed by Venkatesh and Davis (2000), extends the original TAM by incorporating social influence and cognitive instrumental processes to better explain the determinants of perceived usefulness (PU). Social influence processes include *Subjective norms*, the perception that essential others believe one should use the system. Subjective norms significantly influence usage intention in mandatory contexts, but not in voluntary settings. *Image*, the perception that using a technology enhances one's status within a social group, positively influences PU and *Voluntariness*, a moderator that strengthens the effect of subjective norms in mandatory contexts. Cognitive Instrumental Processes include *Job relevance*, the extent to which the system applies to one's tasks; *output quality,* the degree to which the system delivers quality results; *result demonstrability*, the tangibility of the system's benefits; and *Perceived ease of use*, which continues to influence PU indirectly.

The third version, TAM 3, integrates TAM 2 and extends it further by emphasizing the role of experience as a key moderator. As users gain more experience with a system, PU and PEOU become stronger predictors of usage intention, and computer anxiety diminishes. TAM 3 also introduces new determinants of PEOU, such as perception of external control, computer playfulness, computer anxiety, perceived enjoyment, and objective usability. These predictors influence PEOU and not PU.

In summary, in its three versions, the TAM model provides a robust understanding of individual-level determinants of technology adoption, emphasizing PU and PEOU. A key limitation is its focus on individual behavior, overlooking environmental and organizational influences.

3.2 Unified Theory of Acceptance and Use of Technology Model (UTAUT)

The UTAUT model integrates elements from eight previous models of information and technology systems acceptance and usage (Venkatesh, Morris, Davis, & Davis, 2003; see Appendix 2). UTAUT identifies four core determinants of intention and usage behavior and four moderating factors: gender, age, experience, and voluntariness of use. The four core determinants are *performance expectancy and* the degree to which using the system will help users achieve gains in job performance. It is the strongest predictor of usage intention and integrates concepts such as perceived usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectations. *Effort expectancy*, the degree of ease associated with system use, is particularly influential during the early stages of adoption. It integrates constructs such as perceived ease of use, complexity, and ease of use. *Social influence* is how individuals perceive that essential others believe they should use the system. Social influence plays a stronger role in mandatory contexts and diminishes over time in voluntary settings. *Facilitating conditions* are the belief that technical and organizational infrastructure exists to support system use. Its influence is greater during the initial stages of adoption.

Previous research shows that UTAUT captures key overlapping determinants recognized in earlier literature (Davis et al., 1989; Thompson et al., 1991; Moore & Bensabat, 1991), providing strong empirical support for its conceptual model. UTAUT has been applied to the study of AI adoption, identifying general challenges, such as lack of transparency and algorithmic biases, and employee-specific difficulties, such as cognitive biases, loss of autonomy, and fear of replacement, contributing to resistance to technology adoption. These challenges can be grouped into four areas: individual characteristics, technology characteristics, environmental factors, and interventions, implying training and demonstrations (Venkatesh, 2022).

Although UTAUT introduces moderators that enhance its practical applicability, it shares a key limitation with the TAM model, which primarily emphasizes individual-level determinants while neglecting broader organizational and structural factors that may be critical for understanding technology and system adoption. In response to these limitations, Venkatesh, Thong, and Xu (2019) proposed a revised version of the UTAUT model. This updated model challenges the applicability of the original moderators, identifies the absence of a direct path from facilitating conditions to behavioral intention, and advocates for the inclusion of individual characteristics. A central innovation in the revised model is the emphasis on attitude as a key determinant of technology acceptance and use. Attitude is shaped by facilitating conditions and social influence, directly impacting behavioral intention and usage behaviors. This refinement is significant, as it highlights the necessity of incorporating individual characteristics into theoretical frameworks addressing information technology and systems acceptance (Venkatesh et al., 2019).

3.3 Technology-Organization-Environment Framework (TOE)

The Technology-Organization-Environment (TOE) framework, developed by Tornatzky and Fleischer (1990), explains technology adoption at the organizational level by examining three interrelated contexts. *Technology*, characteristics of existing and emerging technologies, including relative advantage, complexity, and compatibility. *An organization's* internal characteristics include firm size, resource availability, managerial support, and communication processes. *Environment* and external factors include industry characteristics, regulatory policies, competition, and supplier-customer relationships. The TOE framework suggests successful technology adoption requires alignment across these three contexts.

Further research by Awa, Ojiabo, and Orokor (2017) extended the TOE framework by integrating UTAUT (Venkatesh et al., 2003) and Task-Technology Fit (Goodhue & Thompson, 1995) models. This integration introduces two additional drivers, task and individual contexts, leading to a twelve-factor model, encompassing technology, organization, environment, task, and personal dimensions. According to Awa et al. (2017), organizational and task-related factors such as task complexity, interdependence, management support, and firm size are stronger drivers of adoption than technological or environmental factors. This highlights the importance of treating individual and task-related influences separately from the traditional TOE dimensions. Integrating personal and organizational perspectives enables a richer and more holistic understanding of technology adoption processes.

3.4 Integration of Theoretical Models

Integrating insights from the TAM, UTAUT, and TOE is crucial for a comprehensive understanding of technology adoption. The TAM framework provides a foundation for understanding individual-level factors influencing perceptions and intentions toward technology adoption, particularly focusing on PU and PEOU (Davis, 1989; Venkatesh & Davis, 2000). Importantly, UTAUT explicitly builds on TAM and integrates additional determinants (such as social influence, and facilitating conditions) and moderating factors (such as age, gender, experience, and voluntariness) drawn from multiple earlier models, including TAM, to offer a more comprehensive and unified explanation of individual technology acceptance (Venkatesh et al., 2003).

The TOE framework complements the perspectives from TAM and UTAUT by focusing on organizational resources, internal processes, and environmental pressures that shape technology adoption at the organizational level (Tornatzky & Fleischer, 1990). While UTAUT and TAM address micro-level individual attitudes and behaviors, TOE provides a macro-level view of organizational and environmental conditions. When combined, these frameworks offer a multi-level analytical lens (Awa, Ojiabo, & Orokor, 2017), enabling this study to capture how individual perceptions (from TAM and UTAUT) interact with organizational strategies, cultural dynamics, and external pressures (from TOE), thereby providing a more holistic understanding of the underlying drivers and barriers to AI adoption.

While the combined use provides a robust and multi-level perspective, it is essential to acknowledge the limitations inherent in each framework. Although widely applied, TAM has been criticized for its simplicity and limited attention to social, organizational, and contextual factors beyond the individual user (Benbasat & Barki, 2007). UTAUT, while more comprehensive, has been noted for its complexity, with numerous constructs and moderators that may risk overfitting or reducing practical applicability in some contexts (Bagozzi, 2007). The TOE framework offers strong explanatory power at the organizational level but may lack specificity in addressing individual perceptions, attitudes, and motivations critical in technology adoption processes (Baker, Jones, Cao, & Song, 2011). Recognizing these limitations underscores the value of integrating the three frameworks in this study, allowing for a richer, more nuanced analysis that bridges micro- and macro-level determinants of AI adoption.

Specifically, concerning the study's research question - what factors influence the adoption of AI tools for internal processes within a retail organization - these frameworks offer complementary analytical leverage. TAM and UTAUT illuminate individual-level factors such as perceived usefulness, ease of use, and social influence. TOE captures the organizational structures, leadership dynamics, and cultural conditions shaping the broader adoption environment.

4. Research Methodology

This study employs a qualitative, exploratory case study approach to investigate what factors influence the adoption of AI tools for internal processes within a retail organization.

4.1 Research design

4.1.1 Qualitative Research Approach

A qualitative approach was chosen for its ability to explore in-depth perspectives, which is essential for the study's focus on organizational dynamics. This method captures rich contextual insights into the complex interplay between individual viewpoints and organizational factors (Bell, Bryman, & Harley, 2019, pp. 35, 376). The literature review indicated that past research on technology acceptance has mainly used quantitative methods, which often miss the organizational and relational contexts influencing AI technology adoption. This study, however, seeks to explore the dynamics and socially constructed experiences within an organization that quantitative approaches cannot fully capture. Thus, a qualitative approach was selected to provide depth and generate theoretical insights beyond existing models (Bell, Bryman & Harley 2019, pp. 35, 366-377).

4.1.2 Abductive Logic

This study employs an abductive research approach, facilitating an iterative interaction between theory and empirical data. While frameworks like the TAM (Davis, 1989), extended TAM2 (Venkatesh & Davis, 2000), the UTAUT (Venkatesh et al., 2003), and the TOE (Tornatzky & Fleischer, 1990) informed the interview guide and initial coding, the research process was not limited to these frameworks. Abductive logic enabled openness to new insights from the empirical material. As data collection continued, unexpected patterns emerged that the initial theoretical lens did not foresee. Specifically, while the original focus centered on individual adoption of AI tools, the findings revealed that employees did not strongly resist AI use. This prompted a shift in analytical focus toward organizational-level dynamics, such as leadership communication, middle management support, and cultural tensions, shaping adoption outcomes more profoundly. To better capture these emergent contradictions, organizational paradox theory (Smith & Lewis, 2011) was incorporated into the analysis. This lens enabled the study to conceptualize persistent tensions, such as the gap between top-down ambition and bottom-up behavior, not as failures, but as inherent and manageable organizational paradoxes. These themes challenged existing assumptions and shaped further analysis, illustrating the abductive process of iteratively refining the conceptual framework (Bell, Bryman, & Harley, 2019, pp. 23–24).

4.2 Case Context

This study uses a single-case design to deeply explore AI adoption for internal processes in a real-world organization. Case study research is well-suited for examining complex phenomena in their natural context, enabling a holistic view of organizational processes, behaviors, and interactions. However, it is essential§ to acknowledge that it may affect the generalizability of the findings to other industries or cultural settings (Yin, 2018; Bell, Bryman, & Harley, 2019, pp. 65-67).

The selected organization's size and internal complexity, encompassing a variety of operational domains, provide a valuable setting for generating in-depth insights into the implementation of AI tools. These characteristics align well with the goals of case-based qualitative research, enabling a rich exploration of challenges and practices associated with AI adoption. Throughout this thesis, the company is described in general terms to preserve confidentiality, with all participant names anonymized and no sensitive information disclosed.

4.3 Data Collection

4.3.1 Interview method: Semi-structured interviews

This study utilized semi-structured interviews for data collection, balancing structure and flexibility. This method facilitated exploration of specific themes from the literature while remaining open to unexpected insights (Bell, Bryman & Harley 2019, pp. 435-438).

An interview guide was meticulously developed based on key themes from the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology-Organization-Environment (TOE) framework. The method ensured theoretical alignment between the interview questions and the study's aim of exploring what factors influence the adoption of AI tools for internal processes within a retail organization. The guide included open-ended and exploratory questions for participants to reflect on their experiences, with follow-up questions tailored to their responses (Bell, Bryman, & Harley, 2019, pp. 439-443, 448). It was structured around key themes, with the complete interview guide in Appendix 3.

The interview guide was designed to align with theoretical constructs but used flexibly rather than as a strict script. This semi-structured format enabled interviewers to follow participants' reasoning, explore emerging themes, and adapt questions for deeper insights. This approach maintained theoretical relevance while remaining open to discoveries, supporting the goal of allowing novel insights to inform data collection and analysis.

4.3.2 Interview Process

All interviews were conducted digitally via Microsoft Teams. Although in-person interviews offer richer interaction and nonverbal observation, remote interviews provide interviewees convenience (Bell, Bryman, & Harley, 2019, pp. 452-453) and help create a relaxed setting to reduce pressure. The interviews were audio-recorded with participants' informed consent and transcribed verbatim for accurate analysis. The Voice Memo app was used for recording, and notes were taken to capture nonverbal cues and identify areas for further exploration (Bell, Bryman, & Harley, 2019, pp. 445-456). All interviews were conducted in Swedish, and quotes in the findings have been translated into English while maintaining meaning and tone (Bell, Bryman, & Harley, 2019, p. 450).

4.3.3 Sampling Selection

This study used purposive sampling to gather diverse perspectives instead of striving for statistical generalizability (Bell, Bryman, & Harley, 2019, p. 391). We initially applied a generic purposive approach, leveraging professional networks and knowledge of the organization's structure to identify departments and roles impacted by the implementation of AI tools (Bell, Bryman, & Harley, 2019, pp. 394-395). This context helped us select initial participants and shape our lines of inquiry.

A snowball sampling technique was used during the study, with participants recommending colleagues across various functions and levels (Bell, Bryman, & Harley, 2019, pp. 395-396). While snowball sampling may have introduced a degree of selection bias, where individuals recommended by peers could share similar attitudes toward AI or organizational culture, potentially skewing the range of perspectives. To mitigate this, the researchers initiated purposive sampling, varied departments and seniority levels, aiming for heterogeneity in background, function, and exposure to AI tools (Bell, Bryman, & Harley, 2019, pp. 394-395).

Nine participants were interviewed to represent diverse functions such as design, planning, analytics, merchandising, and product management. They covered various seniority levels to capture a broad view of AI adoption in the organization (see Appendix 4). Participation was voluntary, with all respondents receiving a study summary and signing informed consent forms. Anonymity was maintained, and no sensitive information was disclosed. The participant count (n = 9) aligns with qualitative research standards, emphasizing depth over breadth. The sample size followed the principle of saturation, with interviews conducted until no new themes emerged. During the data collection, saturation was assessed through iterative coding and memo writing (Bell, Bryman, & Harley, 2019, pp. 397-399).

4.4 Data Analysis

The interview data were analyzed using thematic analysis, a flexible qualitative method for identifying and organizing patterns within complex datasets (Braun & Clarke, 2006; Bell, Bryman & Harley, 2019, pp. 519-520). This approach was ideal for the exploratory nature of the study, allowing both theory-driven and data-driven insights to emerge (Braun & Clarke, 2006).

All interviews were transcribed in Swedish using Klang AI. Each transcript was carefully reviewed and manually corrected for accuracy, preserving participants' original expressions. The cleaned transcripts were imported into NVivo 15 for systematic coding and organization (Bell, Bryman & Harley, 2019, pp. 541-553).

The analysis process utilized both deductive coding, guided by frameworks like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), and inductive coding to reveal unexpected patterns (Braun & Clarke, 2006). This iterative approach reflects the abductive reasoning of the study (Bell, Bryman & Harley, 2019, pp. 518-520). Codes were organized into broader themes, which were then refined to highlight core patterns relevant to the research questions. The final themes were presented coherently, supported by participant quotes to provide contextual depth.

4.5 Ensuring Qualitative Rigor

To ensure the quality and trustworthiness of this qualitative research, the study follows the four evaluative criteria proposed by Lincoln and Guba (1985), as emphasized by Bell, Bryman, and Harley (2019, pp. 48): *credibility, transferability, dependability,* and *confirmability*.

4.5.1 Credibility, Transferability, Dependability, Confirmability

Credibility was achieved through a careful data collection and analysis process. Semi-structured interviews allowed for in-depth exploration of participant perspectives, with the interview guide adjusted based on emerging insights. All interviews were recorded with consent, transcribed verbatim, and analyzed in NVivo 15 using thematic analysis. The coding process considered both theory-driven and inductively emerging themes, with regular reflection ensuring interpretations stayed grounded in participants' experiences. Key quotations were selected to illustrate findings and enhance transparency.

Transferability was supported by contextual descriptions of the organizational setting, participant roles, and AI usage in this case. While findings aren't statistically generalizable, they offer nuanced insights relevant to similar organizations undergoing digital transformation.

Dependability was ensured through a detailed audit trail of the research process, documenting design decisions, coding iterations, and analysis memos for potential replication or reinterpretation.

Confirmability was enhanced by a reflexive approach, with the researcher addressing personal biases and documenting reflections on interpretative choices. The use of NVivo promoted transparency in theme development, ensuring findings were primarily data-driven rather than influenced by preconceived frameworks.

4.5.2 Ethical Consideration

Ethical integrity was upheld throughout the study, following standard qualitative practices. Participants were informed about the study's purpose, procedures, and right to withdraw, and informed consent was obtained before interviews. Names, departments, and roles were anonymized, and the company name was withheld for confidentiality. Audio recordings and transcripts were stored on password-protected devices, and personal data was set to be deleted upon thesis completion. The study complies with GDPR, prioritizing participant privacy and respect.

4.6 Disclosure of Artificial Intelligence

Artificial Intelligence (AI) was used selectively in this thesis to support efficiency and academic clarity. ChatGPT was employed solely to refine the language and enhance the academic tone of the text, without altering the research content, data, or interpretations. No empirical data, including interview materials, were input into ChatGPT at any stage. The author’s original work remains the foundation of the content, structure, analysis, and interpretation.

Klang AI was used to enhance the efficiency of transcribing the recorded interviews. Importantly, all interviews were anonymized before transcription to safeguard participants' privacy and the company's anonymity. The AI transcription produced only an initial draft; all transcripts and audio recordings were subsequently manually reviewed to ensure accuracy and fidelity to the original statements.

Throughout the research process, careful attention has been paid to preserving the anonymity and confidentiality of the participants and the company. For detailed information, see Appendix 5.

5. Empirical Findings

This chapter presents the study's empirical findings, drawing on interviews with employees across diverse functions and departments in a large fashion retail organization. The findings address the research questions by exploring five key areas: (1) how AI tools are currently used across departments, (2) how employees perceive the usefulness, ease of use, and trustworthiness of these tools, (3) how leadership communication and managerial support shape adoption behaviors, (4) how organizational culture influences openness to experimentation, and (5) how grassroots initiatives and local experimentation emerge and either spread or remain fragmented.

5.1 Current Use of AI Tools

This section offers an overview of the company's current AI use cases, providing essential context for understanding its broader relationship with AI. It sets the stage for examining employee perceptions, leadership influence, and organizational dynamics that shape AI adoption.

The findings reveal that AI implementation is cautious across all departments, primarily shaped by cybersecurity priorities. Respondents highlighted that security priorities dictate the available tools and their implementation, as noted by Interviewee 4. "Cybersecurity is a top priority... to prevent hacking attacks or data leaks within the systems."

To manage these risks, strict internal guidelines were established early in the rollout of AI tools. Interviewee 3 recalled these efforts, noting, "Guidelines were sent out specifying which tools were permitted, and which types of information must not be entered into certain programs."

These insights show that security concerns shape not only the technological landscape but also employees' opportunities for experimentation and adoption.

5.1.1 Data-Driven Operations and Analytics

AI adoption within the organization is most advanced in data-driven functions, such as supply chain operations and analytics. In supply chain management, machine learning (ML) models are well-established and formally embedded in core processes such as demand forecasting and product allocation. As Interviewee 7 described, "The most AI-driven part of our logic lies in the demand forecasts... machine learning models are what we use to generate our forecasts."

These established models enable the organization to make highly granular, data-informed decisions that would be difficult to achieve manually. Interviewee 7 further explained, "The benefit is, of course, that we can get recommendations and decisions on such a granular level that we would not have time to do well manually."

However, human judgment remains critical alongside these automated inputs. As Interviewee 6 emphasized, "Decisions are made by humans but with a suggestion from an ML model."

In contrast, employees reported more recent experimentation with external generative AI tools like ChatGPT Enterprise within the analytics function. Unlike the embedded ML models in supply chain operations, these tools are not fully integrated into formal organizational workflows and often rely on individual initiative. As Interviewee 2 explained, "There were a limited number of licenses, so we rotated them. That’s how it worked. The idea was that everyone who wanted one would eventually get an account."

Despite this openness to experimentation, concerns persisted about aligning such external tools with internal systems. Interviewee 2 noted, "They are still fairly external platforms... and need to be more integrated into our own environment."

Adoption levels depended heavily on personal initiative rather than structured processes. As Interviewee 3 described, "I use it a bit like I do privately. I use it a lot for things like translations or to summarize simpler data," and added, "It’s not like I use it as a formal tool. And many of my closest colleagues don’t use it at all."

These findings highlight a key distinction: while embedded machine learning models support structured operational processes, newer generative AI tools remain experimental, with uneven adoption and limited formal integration into the organization’s systems. Several participants reflected on whether these established machine learning models should even be viewed as “AI tools,” often reserving the term “AI” for more recent, visible technologies like ChatGPT. This distinction shaped their perceptions, framing older ML models as background systems and newer AI tools as novel, experimental innovations.

5.1.2 Design Department

In contrast, the design department shows minimal formal integration of AI tools. Interviewee 8 commented on the current state: "No, it hasn’t gotten that far. It feels like we haven’t really gotten started on the design side."

Some designers reported experimenting independently, outside of official channels. As Interviewee 8 described, "I pay for AI tools myself [...] We don’t have anything like that available to us."

While such isolated experimentation exists, formal integration of AI into creative processes remains limited. The organization uses proof-of-concept projects to assess value and feasibility. Interviewee 1 explained, “It has been quite restrictive to explore different AI tools individually. For our designers, we really need to start opening up and providing some approved tools to begin exploring this more systematically.”

5.2 Employee Perceptions of AI Tools

This section explores employees' perceptions of AI tools, highlighting how their attitudes and emotional responses influence adoption barriers and motivations.

5.2.1 Perceived Usefulness

Many respondents emphasized that demonstrating clear business value is key to sustained AI adoption. Interviewee 1 explained when reflecting on adoption drivers, "To be able to put these tools into people’s hands, you first need to show business value - and to show business value, you need to have put it into people’s hands."

This sentiment was echoed across functions. Interviewee 6 observed, “There needs to be good solutions. That’s often where AI fails,” Interviewee 7 added, “We can’t just say that things go faster, but that our allocation gets worse. That’s not what we’re trying to achieve.”

Similarly, Interviewee 4 emphasized, “Outcome is very important. From the organization's perspective, improving results is the absolutely crucial factor. Of course, for it to deliver good outcomes, it must also be sufficiently user-friendly to make it feasible - but the result comes first.”

Together, these perspectives reveal that employees view AI adoption primarily through the lens of meaningful performance improvements, emphasizing that perceived usefulness is tied to demonstrable business value rather than simply faster processes or technological experimentation.

5.2.2 Ease of Use and Learning Challenges

Ease of use was frequently mentioned as a critical factor for initial adoption. Interviewee 8 highlighted, "I think it's super important that it's pretty easy to use. And then the result needs to follow. Otherwise, it just doesn't work."

However, several respondents emphasized that organizational constraints such as workload and time pressures significantly limit employees' ability to experiment and learn, even when tools are designed intuitively. Interviewee 9 noted, "It's always difficult to learn a new program in the beginning. It takes time, and we work full-time. It's not like you get half the day to test and play around with AI." Faced with heavy workloads and tight deadlines, employees prioritized immediate task completion over learning unfamiliar tools, even when curious.

This sentiment underscores how organizational time pressure can directly reduce perceived ease of use, not because the tools are inherently complex, but because employees feel they lack the bandwidth to explore, test, and integrate them into their workflows.

These perspectives suggest that perceived ease of use (PEOU) is influenced not only by the design of the technology itself but also by organizational factors, where time constraints, workload pressures, and local expectations can significantly limit or hinder how easy a system is perceived to be in practice.

5.2.3 Trust, Understanding, and Transparency Issues

Understanding and trusting AI outputs emerged as essential preconditions for adoption. Interviewee 7 emphasized, "You have to understand what kind of output you are getting and how you can work with it to improve further."

However, several respondents expressed concerns about opaque or overly complex systems. Interviewee 4 described this issue: "The more complicated a solution is, and the more you rely on these advanced systems, the more it becomes what we call a black box."

5.2.4 Emotional Barriers

While many respondents expressed openness toward AI experimentation, emotional concerns also emerged, particularly regarding professional pride and credibility. Interviewee 3 shared these feelings, reflecting, "I think it's more that people don't want to show that they use AI. Or it feels a bit like, since it's still new at the company, people want to do their job themselves. And it's a little like it feels in school sometimes, that it feels like you're cheating."

Some respondents described how the perception that using AI was "cheating" or a shortcut created subtle but meaningful hesitations around openly adopting or displaying these tools.

In addition, Interviewee 8 pointed out anxieties about job security, reflecting, "Everyone is protective of their job. What will happen if AI takes over?… If it becomes like that, we will need far fewer people. That's scary - where will it end?"

These emotional undercurrents illustrate that even when employees are curious or open, fears about the broader consequences of AI can dampen their willingness to embrace new tools fully.

5.3 Leadership Communication and Support for AI Adoption

While individual perceptions and emotional responses shape how employees engage with AI tools, leadership plays a decisive role in creating the conditions for adoption. This section examines how leadership communication at the top-management and middle-management levels influences employees' willingness to experiment with AI.

5.3.1 Signals from Top Management

Several respondents described how top management has signaled broad support for AI experimentation, often through high-level or formal communications. As Interviewee 2 summarized: "AI is indeed coming - we have to use it because otherwise, we won't be competitive going forward."

However, despite these strategic ambitions, many employees perceived a gap between top-level messaging and actionable energy in specific functional areas. Interviewee 8 noted: "If the head designers were more excited about it, then maybe it would get started."

This respondent elaborated on the contingent nature of top management's engagement: "As I understand it, interest has to come from the right direction. If they think this is important, they invest energy; if no one wants it, they don't. Eventually, maybe after a while, it might come from above when they realize, wow, we can't miss this."

These reflections suggest that while management expressed enthusiasm, it did not always translate into localized momentum or functional relevance, and that leadership attention was often dependent on whether bottom-up interest first emerged.

Other respondents described formal signals sent through corporate channels but questioned their reach and impact. As Interviewee 3 described: "Yes, it was sent out when we were allowed to start using AI tools - it was communicated quite clearly … but I don't know if everyone has taken part in this, but I've read through it."

Interviewee 5 reflected: "No, I didn't really hear anyone say anything about it [AI]." This indicates that enthusiasm for AI at the organization's top is not reaching lower-seniority-level employees.

Together, these reflections highlight a disconnect between strategic ambition and localized clarity. While top management has formally signaled AI's importance, the communication pathways appear fragmented, leaving some departments unsure how to act and others feeling the energy has not been adequately championed at the functional level.

5.3.2 Middle Management Role

Middle managers were considered crucial for bridging the gap between high-level vision and local practice. Even though the organization was described as relatively flat and participatory, several employees emphasized that local decisions and resource allocations often depended on explicit middle management support. Interviewee 4 explained: "Even though the organization has a flat hierarchy and there is a high level of participation from all employees, it requires a decision from higher up."

Employees described how departmental managers played gatekeeping roles, determining whether AI initiatives were prioritized or remained sidelined. Interviewee 7 emphasized this need for active local leadership: "It's important that management within each department is willing to do these things, because otherwise it won't happen." These findings highlight that even with organizational ambition at the top, middle management acted as a critical filter, shaping whether or not AI initiatives were supported, resourced, and prioritized at the departmental level.

There is further ambiguity regarding the role of middle managers, as the organizational hierarchy often feels unclear. This contributes to uncertainty about who holds authority and the degree of autonomy employees have. For example, Interviewee 5 described:
"There are so many layers, first one manager, then another type of manager, and then yet another one. You don't really know who's in charge or who you're supposed to turn to."

5.3.3 Role Modeling and Local Norms

Beyond formal leadership roles, employees emphasized the importance of role modeling and the social signals that managers and supervisors provided around AI experimentation. While some formal efforts were made to communicate at the organizational level, as Interviewee 1 noted, "We're going to do some type of information town hall to simply avoid rumors or guesswork around how these tools work.", day-to-day communication and behavioral signals from direct managers were often lacking.

Interviewee 3 reflected: "I wouldn't say that my direct managers have discussed it much. It's been mentioned more when the whole company meets." This absence of local-level engagement limited the development of behavioral norms around AI use. Employees noted that visible role modeling by supervisors could have signaled support for experimentation and reduced hesitation. Interviewee 3 explained: "If my senior planners were to start using it and do it openly, I think it would have affected how the rest of the group follows suit."

At the same time, managers who were interviewed expressed optimism about AI's potential, particularly in helping junior employees develop skills and handle complex data. Interviewee 2 highlighted: "AI can help younger people get up to speed faster. It makes it easier to handle large, unstructured datasets and start analyzing quicker than was possible ten years ago."

However, this optimism was not consistently communicated in ways that created actionable expectations or encouraged employees to experiment in practice. As a result, many employees remained hesitant to invest time and energy into AI use, particularly amid competing operational demands.

5.4 Organizational Culture and Internal Dynamics

This section explores how the organization's cultural traditions, values, and norms shape employees' attitudes and behaviors toward AI experimentation.

5.4.1 Cultural Traditions and Simplicity

A recurring theme in the interviews was the influence of long-established work habits and cultural norms on how employees approached new situations.

This preference for hands-on, intuitive approaches was closely linked to the company's creative heritage. As Interviewee 6 observed: "Most people at the company are not technical; it's a creative company. They don't read about AI in their spare time."

Further, Interviewee 4 echoed that: "Things are done in ways that may not have been questioned - they're just part of the culture."

In addition, the organizational culture was described as valuing speed, autonomy, and simplicity. Employees emphasized the importance of quick, practical solutions over complex, abstract systems. As Interviewee 6 put it: "We've always been a bit 'keep it simple.' Do a quick solution, sketch something on a napkin, and move on to the next decision." Interviewee 5 pointed to the intense operational tempo as a cultural feature in itself: "It's such an extremely fast-paced environment. Such fast-paced work environments reinforce the preference for speed, clarity, and low-effort solutions,

This cultural preference made tools that introduced complexity or disrupted the intuitive workflow more likely to face skepticism or resistance. Autonomy in decision-making was particularly valued, with Interviewee 3 summarizing: "I think people want to do their job themselves," reflecting a desire for personal control rather than reliance on automated systems or algorithmic suggestions.

Together, these insights show that resistance to AI adoption was not rooted in hostility toward technology per se but rather in the cultural alignment (or misalignment) between new digital tools and longstanding values around autonomy and simplicity.

5.4.2 Entrepreneurial Spirit and Curiosity

Despite these cultural barriers, many respondents highlighted an underlying entrepreneurial mindset and openness to trying new things. Interviewee 2 said, "There's a lot of curiosity, a big interest in trying things out." Similarly, Interviewee 9 described, "I think people are generally curious. If they see that something can make their job easier or more interesting, they're open to trying it."

These perspectives suggest that while established routines dominate much of the organization, a cultural foundation of curiosity could support broader AI engagement if properly tapped.

Yet, even within this cultural context, some employees engage in local experimentation and grassroots innovation. The final section turns to these bottom-up efforts and the challenges of scaling them across the organization.

5.5 Grassroots Experimentation and Fragmented Adoption

The final section discusses grassroots experimentation, emphasizing how individual "super users" and local initiatives influence AI use within the organization.

5.5.1 Super Users and Local Initiatives

A few employees have taken the initiative to experiment with AI tools independently, becoming informal "super users" who explore the potential of these technologies without formal support or resources. These individuals are typically motivated by personal interest rather than organizational directives or incentives.

For example, several cases of individual initiative were noted in the design department. Interviewee 8 explained: "I pay for AI tools myself […] We don't have anything like that available to us."

Similarly, Interviewee 9 described how she creatively used AI tools to support a design project: "I recently made a nice jacket. I built up the shoulders using AI. And it turned out great."

While these examples highlight the potential for grassroots innovation, such experimentation remained private and fragmented. Interviewee 8 reflected that general interest among design peers was relatively low: “People think: what does it even give me? What can I get out of it?”

These observations suggest that while motivated individuals were eager to explore new tools, they often did so in isolation, without strong peer engagement or systematic efforts to embed these innovations within team or departmental practices.

5.5.2 Informal Knowledge Sharing

Alongside individual experimentation, some grassroots knowledge-sharing efforts have emerged within the organization. Super users occasionally shared their AI-driven work with colleagues, sparking curiosity and admiration. For example, Interviewee 9 described how peers reacted to her AI-generated designs: “‘Wow, did you really make this?’ They think it looks amazing.”

Despite these moments of enthusiasm, employees noted that there were few formal structures to build on local initiatives. Super users often lacked opportunities to present their experiments at higher organizational levels or receive feedback from leadership. As Interviewee 3 observed: “I would say I’ve never received encouragement from my closest division to use it.”

Employees emphasized that the visible actions of respected colleagues, especially senior figures, could significantly shape their willingness to experiment. Interviewee 3 noted: “If my senior planners were to start using it and do it openly, I think it would have affected how the rest of the group follows suit.”

At the same time, cultural hesitations limited the broader influence of these informal efforts. As noted earlier, employees were often reluctant to openly display their use of AI tools, fearing it might be perceived as a shortcut or sign of diminished competence - a perception previously described as feeling “like cheating, like in school.”

Employees described how, despite informal networks and super-user initiatives, these efforts often remained limited in scope, with few formal structures to reinforce or amplify them. Respondents noted that cultural hesitations and the absence of formal support contributed to the continued fragmentation of AI experimentation across departments.

6. Analysis & Discussion

This chapter analyzes the study's findings through the lens of the previously introduced theoretical framework. It starts at the individual level, examining how personal perceptions, emotions, and context shape engagement with AI tools. It then shifts to organizational dynamics, including leadership communication, structural conditions, and cultural norms affecting adoption practices. The discussion connects these findings to existing literature, identifying two organizational paradoxes that can hinder AI adoption despite favorable conditions. The chapter concludes with practical recommendations to enhance AI adoption in retail organizations.

6.1 Individual-Level Factors in AI Adoption

6.1.1 Emotional Factors: Credibility, Pride, and Status Anxiety

While established models like the Technology Acceptance Model 2 (TAM2) and the Unified Theory of Acceptance and Use of Technology (UTAUT) focus on perceived usefulness, perceived ease of use, and social influence, this study uncovers a more complex pattern of resistance rooted in credibility and competence concerns. In TAM2, social influence focuses on the perception that using a system enhances one's status. However, the findings indicate that some employees are more concerned about potential loss than gaining status through AI adoption.

Junior employees expressed concerns that using AI tools could imply incompetence or laziness. One participant described tools like ChatGPT as potentially "cheating," suggesting they might compromise the authenticity of their work. This credibility anxiety challenges TAM2's assumptions about image and UTAUT's social influence dimension, indicating that social influence may deter technology adoption in particular cultural contexts. Instead of enhancing status through AI, employees aim to protect their professional credibility by avoiding it - a behavior reflecting selective non-adoption, where employees actively choose not to engage with AI tools despite general openness or curiosity. While TAM2 and UTAUT conceptualize social influence as a mechanism of aspiration and alignment with valued others, our results suggest it can also be a protective mechanism, guiding individuals away from technology use to avoid negative social judgment. This implies that the social influence construct may require contextual redefinition to account for reputation preservation and fear of deviation, not just image enhancement.

Despite senior leadership's support for AI experimentation, this message did not reach everyday practices. Junior employees felt a lack of encouragement from their managers, leading to caution and ambiguity. Without strong role models, they tended to adopt conservative behaviors to mitigate reputational risk.

These findings reveal that fear of status loss drives technology resistance, challenging traditional views. Adoption decisions are shaped by cultural concerns about identity and belonging, rather than just rational assessments of usefulness. This indicates that models like TAM2 and UTAUT may need to be rethought to include defensive motivations, such as reputation protection. While emotional issues like credibility anxiety are significant, employees also encounter contextual and social barriers to experimentation. This refinement shows that social influence can hinder adoption when reputational risks are at play, potentially suppressing technology use when professional credibility is fragile.

6.1.2 Contextual Factors: Social Signals, Time Pressure, and Uncertainty

Beyond emotional concerns, several contextual challenges shaped employees' willingness to engage with AI tools. Many respondents described how high workload and time pressures made it difficult to prioritize experimentation. In a fast-paced environment, employees focus on completing immediate tasks, viewing time spent learning unfamiliar tools as risky or inefficient. This directly connects to the concept of effort expectancy in the UTAUT model, where the perceived ease of system use is not only shaped by the technology itself, but also by the broader work context in which employees operate.

Unclear expectations and weak social signals from managers further reinforced this hesitation. Several respondents reported that their supervisors rarely discussed AI in routine conversations, which created ambiguity about whether experimentation was encouraged, required, or valued. Without explicit encouragement or visible role modeling, teams defaulted to conservative behaviors - delaying or avoiding AI use despite access to tools. This reflects a form of passive non-adoption shaped by uncertainty. While some managers expressed optimism about AI's potential to support junior employees in tasks such as data analysis or decision-making, this enthusiasm was not consistently reflected in their daily practices or priorities. Consequently, managerial silence was often interpreted as a lack of support, contributing to hesitation around AI experimentation. This lowered adoption and weakened the effect of social influence as conceptualized in UTAUT, where perceived support from important others is expected to shape behavioral intention positively.

The patterns correspond with the organizational dimension of the TOE framework, highlighting the role of internal structures, leadership, and resources in technology adoption. While technical systems were accessible, the organization was unprepared for large-scale adoption due to time constraints, conflicting priorities, and poor communication. This suggests that 'organizational readiness' includes not only structures and resources but also the interpretive climate that influences the legitimacy of experimentation. Thus, TOE should consider that organizational readiness is dynamic, shaped by employee perceptions of managerial priorities, cultural signals, and formal resources.

This underscores the importance of UTAUT and TOE models in AI adoption while highlighting the need for refinement. It suggests that adoption is influenced by perceptions of experimentation as safe and feasible in the local work environment. These findings expand UTAUT's facilitating conditions and TOE's organizational domain, emphasizing that perceived support is structural and interpretive, shaped by informal norms and the emotional climate. Thus, adoption readiness is both logistical and psychological.

6.1.3 Structural Factors: The Isolation of Super Users

Most employees approached AI tools cautiously, but a few superusers actively experimented, especially in departments with low AI maturity, like the design department. Their small-scale, personal efforts to gain inspiration and improve efficiency were largely informal.

Designers often viewed AI tools as unnecessary or poorly aligned with their creative workflows. While some super users engaged in individual experimentation, they rarely shared their experiences or results with colleagues, which limited opportunities for team learning and visible success stories. As a result, many employees found it difficult to recognize or appreciate the potential value these tools could offer. Despite some interest, this limited perceived usefulness resulted in minimal engagement with AI tools. Without clear examples of how AI could meaningfully enhance their specific work tasks, the perceived usefulness of AI tools remained low, and early experimentation risked becoming isolated and fragmented, limiting the potential for broader AI adoption despite localized experimentation. Beyond structural isolation, cultural dynamics further shaped these patterns. Teams accustomed to valuing simplicity, autonomy, and fast decision-making often saw AI tools, especially those requiring upfront learning or producing opaque outputs, as introducing complexity or disrupting established workflows.

This reveals an important aspect often overlooked in technology adoption models. Individual-level frameworks like TAM and UTAUT focus on perceived usefulness and ease of use, while organizational frameworks like TOE emphasize leadership support. Both assume that favorable conditions lead to successful diffusion. However, these findings show that even with grassroots enthusiasm, successful AI adoption relies on building legitimacy and cultural reinforcement. In this case, the lack of peer validation and visible success stories hindered broader adoption, as early user enthusiasm remained isolated without strong peer support for sustained momentum.

These examples show intense bottom-up curiosity, but the lack of reinforcement or integration between departments raises questions about scalability, which will be explored further in the next section.

6.2 Organizational Processes: Missing Feedback Loops

Despite top management's strategic interest in AI and employees' curiosity about its potential, these do not align in practice. The gap is not due to a lack of willingness at either level but stems from the absence of structured feedback and open dialogue. This missing feedback loop - an iterative exchange between strategic direction and operational practice - prevents insights from grassroots AI experimentation from informing leadership decisions and, in turn, stops top-down initiatives from being meaningfully adapted to local needs.

Foundational security concerns further shaped this environment, constraining which tools were available for experimentation. Strict internal guidelines, rooted in security priorities, created a risk-averse climate where even motivated employees felt limited in their ability to explore and innovate. While necessary from a risk management perspective, these constraints reinforced a cautious organizational atmosphere, narrowing the scope for bottom-up experimentation.

At the ground level, motivated individuals who engaged in AI experimentation often did so in isolation, which prevented experimentation from contributing to broader organizational adoption. As discussed in Section 5.5, several super users faced challenges sharing successes, building peer learning, or gaining managerial attention. Their initial enthusiasm struggled to grow without structured opportunities to showcase best practices and without acknowledgment or reinforcement from leadership, innovation momentum frequently stalled. Over time, this risks declining motivation, as employees investing personal effort and resources see limited organizational impact or reward.

Traditional technology adoption models such as TAM, TAM2, UTAUT, and the TOE framework highlight leadership support, infrastructure readiness, and positive user perceptions as key adoption enablers. However, these models often assume widespread adoption will naturally follow once favorable conditions occur. The findings of this study challenge that assumption. While strong leadership signals, technical readiness, and individual openness are necessary, they do not appear to be sufficient alone. Organizations must establish active internal structures for successful adoption, including mechanisms supporting grassroots experimentation, encouraging peer learning, and connecting bottom-up insights with strategic priorities. Without these dynamic, reinforcing mechanisms, even the most promising innovation efforts risk remaining isolated and failing to generate meaningful, scalable impact.

Importantly, the barriers identified in this study were not tied to specific AI tools or individual tasks but reflected deeper gaps between strategic goals and operational realities. Despite positive attitudes at both ends of the hierarchy, this persistent disconnect between strategic vision and daily practice points to a deeper organizational hesitation, setting the stage for the paradoxes discussed in Section 6.4.

6.3 Middle Management as the Bridging Layer

The findings in 5.3 show middle managers' crucial role in translating top-level AI ambitions into daily practice. While leadership vision and individual attitudes matter, this meso layer often determines whether ambitions become routines or stall. Without effective bridging, organizations risk fragmentation and missed opportunities in AI adoption.

Because emotional, cultural, and structural factors intersect, successful integration depends on coordinated action across frontline staff, middle management, and senior leadership. Neglecting the role of middle managers can oversimplify the challenges of technology adoption. Middle managers shape local norms through subtle but powerful signals, such as whether they openly use AI tools, encourage experimentation, or prioritize innovation in team discussions. Employees often take behavioral cues from their immediate manager to judge whether AI use is supported or discouraged. When role modeling and encouragement are absent, grassroots experimentation tends to stall, reinforcing cautious behavior. In this way, middle managers serve as cultural gatekeepers, influencing whether employees feel psychologically safe to explore new tools and ways of working.

The effectiveness of middle managers as change agents depends on organizational support, including clear mandates, recognition for innovation, and formal feedback structures that allow two-way communication between levels. Without these, middle managers can become bottlenecks, unintentionally reinforcing organizational limbo and fragmented innovation efforts. These insights align with Heyden et al. (2018), who argue that middle managers' involvement in innovation hinges on their ability and willingness to perform extrarole activities such as translating strategy, sensemaking, and informal coordination. Without clear mandates and supportive conditions, middle managers can block top-down innovation goals from taking root at the operational level.

This study refines the TOE framework by emphasizing the critical role of middle managers as a meso layer within the organizational system. Their local legitimacy and influence shape how employees engage with technology, enabling or constraining adoption depending on how well they are supported. Furthermore, the findings extend UTAUT by showing that facilitating conditions are not just organizational or technical features, but are actively mediated by middle managers, who translate formal support into local legitimacy and practical encouragement. Recognizing this bridging role adds relational and multi-level depth to our understanding of the dynamics driving (or stalling) organizational digital transformation.

6.4 Organizational Paradoxes Revealed

This section highlights two key organizational paradoxes that explain the challenges in effective AI adoption, even when conditions seem favorable. These contradictions reveal the deeper, systemic dynamics of organizational change. In organizational theory, paradoxes represent persistent tensions between interdependent elements, leading to behavior patterns over time (Smith & Lewis, 2011). In this study, paradoxes stem from structural, relational, and cultural misalignments that hinder progress subtly, rather than through overt resistance or lack of intent. These patterns emerged through abductive reasoning during iterative analysis, as unexpected data tensions led to the paradoxes' conceptual development.

6.4.1 The Organizational Limbo Paradox

The first paradox - Organizational Limbo - describes how mutual hesitation between hierarchical levels leads to stalled innovation. Leadership expresses a clear interest in AI-driven transformation and expects bottom-up experimentation to emerge, while employees look upward, waiting for explicit direction, practical guidance, and visible role modeling. As neither side moves decisively, good intentions remain suspended in a state of inaction, creating a *vertical waiting game* where neither top-down nor bottom-up efforts are effectively activated.

6.4.2 The Fragmented Engagement Paradox

The second paradox - Fragmented Engagement - highlights a *horizontal disconnect* between teams. In this case, enthusiastic superusers engage in grassroots AI experimentation. Still, their efforts often remain isolated or overlooked due to a lack of formal structures for sharing, scaling, or legitimizing their innovations. Crucially, this paradox produces cross-team consequences: local innovations stay confined within departmental silos, resulting in redundant efforts, missed opportunities to build collective knowledge, and blocked peer learning.

6.4.3 Bringing the Paradoxes Together

While the Organizational Limbo Paradox reflects a vertical misalignment between hierarchical levels, the Fragmented Engagement Paradox reveals a horizontal disconnect where local experimentation fails to spread or gain traction without peer reinforcement and cross-functional integration. Together, these paradoxes show that overcoming barriers to AI adoption requires more than setting strategic ambitions or ensuring technical readiness. Instead, organizations must coordinate efforts across structural, relational, and cultural dimensions. This includes empowering middle managers as bridges between strategy and practice, aligning new ways of working with local cultural values, and creating feedback loops that connect top-down vision with bottom-up experimentation. At the same time, cross-team mechanisms are needed to support horizontal learning, reduce redundant efforts, and promote shared innovation.

This analysis extends existing models like TAM, UTAUT, and TOE by showing that technology adoption is not only shaped by individual-level perceptions of usefulness and ease of use or by organizational-level structural enablers but also by the organization's ability to navigate multi-level tensions and contradictions. While these frameworks capture critical enablers and barriers, they largely overlook the persistent, intertwined paradoxes that arise when structural, relational, and cultural dynamics pull in competing directions.

These findings further align with the extended TOE framework proposed by Awa et al. (2017), which integrates task and individual contexts as distinct drivers of technology adoption. Their research highlights that organizational and task-related factors, such as task complexity, interdependence, and managerial support, often outweigh purely technological considerations. While Awa et al. emphasize the importance of these dimensions, this study shows how their interplay can generate paradoxical tensions that disrupt innovation scaling. Rather than adding new categories, it contributes by revealing how contradictions between strategy and practice, and between individuals and organizational systems, constrain adoption in real-world settings. This supports the insight that adoption efforts must consider how individuals interact with their tasks and environments, and how formal structures and informal norms shape those interactions. In doing so, the study offers a more holistic understanding of how innovation unfolds in large, multi-level organizations.

6.5 Managerial Implications

This section outlines actionable managerial strategies based on key findings to help the organization turn innovation goals into lasting practice. It draws on established technology adoption frameworks while focusing on the specific dynamics and challenges identified in the research.

Tackle Organizational Limbo through Middle Manager Empowerment

To address the Organizational Limbo paradox, the organization must empower middle managers as critical bridges between top-level strategy and operational practice. This involves providing clear mandates, structured feedback loops, and formal mechanisms to highlight and support grassroots initiatives. Importantly, this bridging process must function as a two-way dialogue: middle managers should communicate strategic goals downward and channel upward frontline insights, ensuring real-world experiences inform leadership decisions. Regular feedback mechanisms (such as innovation forums or listening sessions) enhance alignment, boost engagement, and improve the organization's capacity to adapt. These actions address vertical structural and psychological barriers by creating clarity, trust, and a sense of shared purpose, essential for innovation and change readiness.

Overcome Fragmented Engagement through Cross-Team Integration and Peer Learning

To address the Fragmented Engagement paradox, the organization must go beyond individual-level encouragement and create formal cross-team mechanisms that enable horizontal learning and reduce redundant efforts. This includes setting up spaces for superusers and grassroots innovators to showcase their experiments, share successes and failures, and build peer learning networks. Visible support from managers and peer influencers is critical to counteract cultural anxieties, such as fears that AI tools might undermine professional credibility or signal "cheating." The organization can transform isolated initiatives into collective momentum by normalizing experimentation and establishing lateral diffusion channels, fostering scalable innovation across departments.

Address Cultural Misalignment by Tailoring Adoption to Local Contexts

In a large retail organization with diverse departments and units, AI adoption strategies must account for differences in cultural values, workflows, levels of AI maturity, and use cases. The study showed that various parts of the organization - creative departments versus operational teams - perceive AI's relevance and usefulness (PU) differently, depending on their specific tasks, goals, and previous exposure to AI tools. Leaders should therefore tailor change tactics to fit these local realities, adjusting communication styles, framing, and engagement approaches accordingly. In creative teams that value hands-on expertise, managers can emphasize how AI supports craftsmanship by handling routine tasks, freeing time for creative exploration. In contrast, in operational or analytical units with higher AI maturity, strategies may focus on deepening integration and expanding advanced use cases.

Strengthen Innovation and Change Readiness through a Multi-Level Support System
Finally, successful AI adoption requires more than isolated projects; it needs a lasting, company-wide system that supports continuous innovation. This integrated support model responds to the Organizational Limbo Paradox and the Fragmented Engagement Paradox by connecting strategic ambitions with local execution and facilitating learning across teams. This means embedding structural supports (e.g., cross-functional innovation teams, dedicated time and budget for experimentation), relational reinforcements (e.g., leadership encouragement, peer recognition), and cultural norms (e.g., valuing prudent risk-taking and learning from failure). Leadership should establish formal groups or innovation councils that regularly oversee progress, track results, and help remove barriers as they arise. This ensures that top-down ambitions and bottom-up experiments are aligned and that cross-team sharing is consistently reinforced.

Additionally, fostering a climate of psychological safety is critical: employees must feel safe voicing concerns, asking questions, and sharing feedback without fear of blame or ridicule. Managers can nurture this by openly acknowledging challenges and inviting collaborative problem-solving, thus enhancing engagement and innovation capacity across the organization. Managers can unlock greater engagement and sustained innovation across teams by fostering trust and emotional safety.

7. Conclusion

7.1 Summary of Main Findings

This study set out to answer the research question: *What factors influence the adoption of AI tools for internal processes within a retail organization?* The findings show that a dynamic interplay between individual perceptions and organizational conditions shapes AI adoption. Many employees were open to experimentation. However, factors such as credibility anxiety, unclear signals from managers, and isolated innovation often limited their engagement.

At the individual level, adoption was influenced by perceived usefulness, ease of use, and emotional and social dynamics, including trust, peer pressure, and fear of appearing incompetent. Managers' lack of visible role modeling reinforced these concerns, leading to cautious, delayed engagement. At the organizational level, leadership communication, middle management involvement, and mechanisms for cross-functional learning emerged as key enablers. Two paradoxes were identified. The Organizational Limbo Paradox describes a vertical standstill in which top management expresses interest in AI. Still, it offers limited guidance, while employees hesitate to act without clear support, resulting in mutual inaction. The Fragmented Engagement Paradox captures a horizontal disconnect where local experimentation remains isolated due to the absence of formal structures for sharing, scaling, or legitimizing grassroots efforts.

Together, these findings suggest that successful AI adoption depends not only on individual perceptions or organizational structures, but also on how these two levels interact. While grounded in a large retail organization, the insights may hold broader relevance for companies operating in similar sectors. The study also offers actionable managerial implications, including empowering middle managers, fostering psychological safety, and establishing formal mechanisms for sharing and scaling grassroots experimentation. Applying a paradox lens contributes to a new perspective, revealing how hidden tensions between strategic ambition and local practice can silently stall adoption, even under seemingly favorable conditions. Ultimately, this study advances our understanding of how organizations can align strategic ambition with actual adoption by illuminating the multi-level dynamics that shape internal engagement with AI tools.

7.2 Theoretical Contribution

By extending established theoretical frameworks and addressing the lack of qualitative, employee-centered research on internal AI use in retail, this study contributes new perspectives to the academic discourse on technology adoption. It surfaces emotional and identity-based dynamics and structural tensions often overlooked in existing models.

The findings refine TAM and UTAUT, which traditionally emphasize perceived usefulness, ease of use, and social influence (Davis, 1989; Venkatesh et al., 2003). While these constructs remain relevant, this study highlights barriers such as credibility anxiety, peer signaling, and perceived professional risk. These insights build on Shin's (2020, 2021) work by showing that trust and causability are not only technical or interpretive conditions for AI adoption, but also emotionally mediated, particularly when professional identity feels threatened. They also extend Dabbous et al.'s (2022) findings by demonstrating that self-image and social dynamics can act as barriers rather than facilitators, as credibility anxiety and fear of negative peer judgment lead some employees to avoid AI use despite general openness.

The study refines the TOE framework at the organizational level by introducing two paradoxes: the Organizational Limbo Paradox and the Fragmented Engagement Paradox. These concepts explain how AI adoption can stall despite formal enablers such as top management support or technical readiness. Specifically, the findings illustrate how vertical misalignment between strategic ambition and local action and a lack of horizontal knowledge-sharing structures undermine efforts to scale AI use. This complements prior work on organizational barriers (e.g., Enholm et al., 2021; Ångström et al., 2023) by emphasizing the importance of cultural alignment, peer learning, and middle manager activation. It also aligns with Awa et al.'s (2017) extended TOE framework, which incorporates individual and task-level factors. While this study does not apply their complete taxonomy, it supports their claim that organizational conditions, such as communication and role relevance, can outweigh purely technical factors.

Finally, the study contributes empirically by offering a qualitative, interpretive account of how employees in a large retail organization engage with AI in their daily work. While previous research has primarily focused on consumer-facing technologies or relied on large-scale surveys (Heins, 2023; Vogelsang et al., 2013), this study addresses a gap by exploring how internal users perceive, resist, and adapt to AI tools in their local context. The findings confirm the importance of trust and employee engagement in digital transformation (Robertson et al., 2025; Shrestha et al., 2019), but also challenge the assumption that technical readiness and strategic ambition are sufficient conditions for adoption. This study shows that concerns about credibility, peer judgment, and professional identity can significantly shape employees' willingness to engage with AI. By highlighting these social and emotional dimensions, the findings offer a deeper understanding of the organizational realities that influence AI adoption in practice.

7.3 Limitations & Future Research

While the case-based approach provided rich, context-specific insights, focusing on a single Swedish fashion retailer may limit generalizability. Variations in industry, size, or national context may yield different dynamics, which future research could explore. Additionally, the study reflects a specific point in time. As AI strategies, tools, and organizational structures evolve, so will employee perceptions and practices. This research offers a snapshot during an unfolding adoption process rather than a complete view of long-term integration.

Future research should pursue longitudinal studies to examine how adoption unfolds across phases, from experimentation to formalization. Comparative case studies across industries, firm sizes, and national settings would further illuminate how external factors such as regulation, market pressure, or digital maturity shape adoption dynamics.

Finally, future research could explore and further develop the paradoxes introduced in this study - Organizational Limbo and Fragmented Engagement - in other organizational settings. Investigating whether similar patterns emerge across different industries or cultural contexts could provide a more nuanced understanding of the barriers to internal AI adoption and the conditions under which they can be resolved. Such exploration would contribute to deepening our understanding of the multi-level tensions that often shape organizational technology integration.

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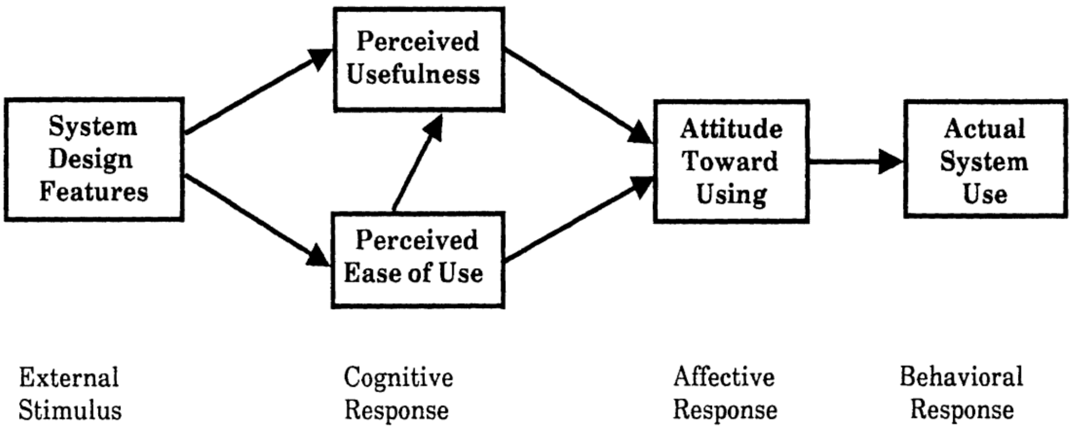
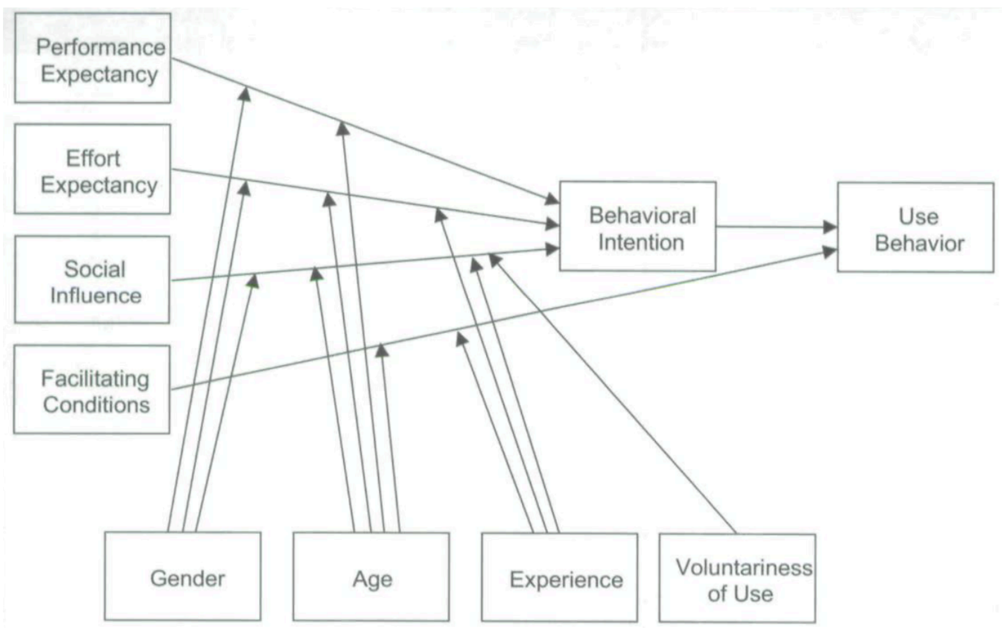
9. Appendix

Appendix 1: Technology Acceptance Model (TAM)



Appendix 2: Unified Theory of Acceptance and Use of Technology Model (UTAUT)



Appendix 3: Interview Guide

Background Information

- Could you describe your role within the company, and which department it belongs to?
- How long have you been working at the company?
- Do you use any AI tools in your work today?

General Perceptions of AI in the Workplace

- How would you describe your experience with AI tools or systems in your current role?
- What benefits does AI bring to your daily tasks and decision-making processes?
- What challenges, if any, have you experienced when using AI tools?

Performance Expectancy (PU, belief that AI improves job performance)

- In what ways do you believe AI enhances productivity or efficiency within your team?
- Can you share an example of how AI has positively or negatively impacted your performance?
- How confident are you that AI can help you achieve better outcomes in your role?
- How do managers communicate the benefits of AI to employees? (Leadership)

Effort Expectancy (PEOU, perceived ease of use of AI tools)

- How easy or difficult do you find using AI tools for your tasks?
- What factors make AI tools easier or harder to use?
- How much training or support did you receive when adopting AI tools? Was it sufficient?

Social Influence (Impact of others' opinions on AI)

- How do your colleagues and managers view the use of AI in the organization?
- Do you feel encouraged or pressured to use AI tools? If so, by whom?
- How does the organization promote AI adoption across different departments?
- How do leaders act as role models for AI adoption? (Leadership)

Facilitating Conditions (Organizational and technical support)

- What kind of resources or support does the company provide to help employees use AI or other technology effectively?
- If you encounter difficulties with AI tools, how easy is it to get help or solutions?
- Are there clear guidelines or policies in place for using AI in your role?

Leadership's Role

- How do leaders communicate the company's vision for AI adoption?
- How do managers address employees' concerns or resistance to AI?
- What role do leaders play in promoting trust and confidence in AI systems?
- Have there been situations where leadership decisions regarding AI caused tension or resistance? How were these managed? (Tensions)

Organizational Culture

- How would you describe the company's culture regarding innovation and technology adoption?
- Does the company encourage open discussions about the impact of AI on employees' roles?
- Have you observed any cultural tensions related to AI adoption? If so, how have they been addressed? (Tensions)

Personal Adaptation and Resistance

- Have you ever felt resistant to using AI tools? If yes, what were the reasons?
- What would make you feel more confident and motivated to use AI in your work?

Closing Questions

- In your opinion, what could the organization do to improve AI adoption and acceptance?
- Do you have any additional thoughts on how leadership or culture affects AI adoption?

Appendix 4: Interview Sample

Interviewee	Department	Seniority	Date	Duration
Interviewee 1	Business & Product Development	Senior	4/3-2025	46:51
Interviewee 2	Business Controlling	Senior	5/3-2025	39:46
Interviewee 3	Planning/Buying	Junior	7/3-2025	31:19
Interviewee 4	Tech/Data/Innovation	Senior	12/3-2025	40:38
Interviewee 5	Stores	Junior	13/3-2025	31:36
Interviewee 6	Tech/Data/Innovation	Executive	17/3-2025	47:11
Interviewee 7	Tech/Data/Innovation	Mid	21/3-2025	34:28
Interviewee 8	Design & Product Development	Mid	21/3-2025	41:17
Interviewee 9	Design & Product Development	Senior	7/4-2025	32:57

Appendix 5: AI Disclosure

What artificial intelligence (AI) tools were used and how?	ChatGPT was solely used to refine language by enhancing the academic tone without altering or adding to the content or the research. No empirical data, including interview materials, were input into ChatGPT at any stage. Klang AI was used to support the initial transcription of the anonymized interview audio recordings. All interviews were anonymized before transcription to protect participant privacy and company anonymity. Afterward, all transcriptions and audio recordings were manually reviewed to correct and ensure accuracy.
In what ways have these tools contributed to increasing the quality of the thesis?	Chat GPT was used to increase the quality of the language by rewording the authors' paragraphs. Klang AI was used to improve the efficiency and speed of transcription. Allowing more time for careful coding and analysis of the data.
What potential risks were found using AI, and what measures were taken to Reduce these risks?	A risk of overreliance on AI writing was identified and managed through careful author oversight to ensure that the content remained original and that AI did not alter or add to the research content. Furthermore, to protect participant and company anonymity, no sensitive or identifying data was input into ChatGPT. For Klang AI, potential transcription errors were identified and addressed through manual review and cross-checking with the original audio recordings. Both authors carefully corrected the transcripts for accuracy and consistency, ensuring that the anonymization was preserved.
What are the insights gained from using AI tools in the thesis writing process?	During the process, insights were gained that Generative AI can support academic writing by enhancing the academic tone when it is used carefully and ethically. AI-supported transcription tools can increase the efficiency of the transcribing process by providing an initial draft while still requiring human validation to ensure the accuracy and trustworthiness of the data.