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Refining SAARM

Exploring AI Adoption Challenges and Resilience in a Small Swedish IT Consultancy Company Through Thematic Analysis

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Abstract

This study explores the challenges and resilience strategies for artificial intelligence (AI) adoption in small and medium-sized enterprises (SMEs) through a qualitative case study of a micro-sized Swedish IT consultancy, conducted from January to May 2025. Despite AI's transformative potential to enhance efficiency and competitiveness, SMEs face significant barriers, including financial constraints, limited technical expertise, and organizational resistance, with adoption rates below 25% compared to over 60% for large firms (OECD, 2021). To address these, we developed and empirically tested the SME AI Adoption Resilience Model (SAARM), a three-layered framework integrating Diffusion of Innovation, Technology-Organization-Environment, Resource-Based View, Change Management, and Dynamic Capabilities theories. The Inner Layer identifies cognitive, emotional, and behavioral resistance (e.g., fear of job loss, mistrust in AI); the Middle Layer focuses on adaptive strategies (e.g., pilot testing, informal champions); and the Outer Layer emphasizes resilience outcomes (e.g., sustained integration, competitive advantage). Using semi-structured interviews, an online workshop, and on-site observations, thematic analysis revealed a reluctance-resistance feedback loop where leadership hesitation amplifies employee skepticism, alongside novel resistance forms like passive disengagement. Phased adoption strategies, such as task segmentation and peer-led demonstrations, mitigated barriers, while experiential learning and external pressures (e.g., client demands) drove long-term resilience. The refined SAARM incorporates bidirectional feedback loops, informal agency, and direct Inner-Outer linkages, addressing context, resistance dynamics, and change management gaps in SME AI adoption literature. Theoretical contributions include a context-specific model for SMEs, while practical implications offer actionable strategies for managers (e.g., fostering informal champions), employees (e.g., engaging in pilot projects), and policymakers (e.g., supporting training subsidies). Future research should test SAARM across diverse SME sectors and regions, explore identity threats as resistance triggers, and examine external pressures through an institutional lens.

Keywords: Artificial Intelligence, SME AI Adoption, SAARM, Innovation Ecosystem, Resistance Dynamics, Change Management, Resilience, Thematic Analysis, Knowledge Co-creation, Dynamic Capabilities

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Chapter1: Introduction

1.1 Background

Remarkable advances in computing power, cloud technologies, and algorithmic sophistication have driven a transforming period for artificial intelligence (AI) over the past ten years. By changing organizational functions, artificial intelligence has become a key factor in increasing efficiency, supporting decision-making processes, and enhancing service delivery across several industries (Dwivedi et al., 2021). Technologies such as chatbots, advanced demand forecasting, and autonomous systems are no longer cutting-edge concepts but practical tools revolutionizing sectors like IT consulting, manufacturing, and healthcare (Jarrahi, 2018). For instance, predictive analytics enables accurate resource allocation, while AI-driven automation streamlines repetitive tasks, offering significant competitive advantages (Mikalef et al., 2020). McKinsey & Company (2019) underscores that firms leveraging AI as early adopters or fast followers often outperform industry benchmarks, highlighting AI's strategic importance.

Adoption rates show a sharp difference between small and medium-sized businesses (SMEs) and large corporations, despite this potential. According to data from the Organization for Economic Co-operation and Development (OECD, 2021), more than 60% of major corporations in industrialized nations have incorporated AI into their operations, taking use of strong financial resources and technical know-how. In contrast, SMEs struggle to reach even 25% adoption, a gap particularly pronounced in IT consulting, where AI could automate routine tasks like requirements analysis or enhance customer service through chatbots (The Digital Transformation of SMEs, 2021). Jarrahi (2018) argues that AI's seamless collaboration with human decision-making holds immense promise for IT consultancies, yet SMEs face persistent barriers that hinder their ability to harness these benefits.

Several factors contribute to this lag. Financial constraints limit SMEs' capacity to invest in AI infrastructure or skilled personnel, while technical expertise remains scarce in smaller firms reliant on legacy systems (OECD, 2021). Sharma (2023) notes that European SMEs, in particular, grapple with additional challenges such as regulatory uncertainties around data privacy, further complicating adoption. Moreover, organizational resistance, rooted in fears of job displacement or distrust in AI reliability, slows progress, especially in SMEs with less flexible cultures (Mikalef & Gupta, 2021).

The pressure is intense for SMEs, as AI adoption is increasingly a determinant of competitiveness. Brock and Von Wangenheim (2019) emphasize that clarifying AI's potential could unlock operational efficiencies for SMEs, yet the lack of accessible frameworks leaves them at a disadvantage. (Lee & See, 2004) add that adaptive strategies are critical for SMEs to transition to AI-driven models, particularly in resource-scarce environments. In IT consulting, where client demands for innovation are rising, SMEs must embrace AI to remain relevant (Badghish & Soomro, 2024). This background underscores the urgency of addressing the adoption disparity, setting the stage for examining the specific challenges and gaps that hinder SMEs' integration of AI technologies.

1.2 Problem Statement

Three main obstacles stand in the way of small and medium-sized businesses' (SMEs') adoption of artificial intelligence (AI): lack of infrastructure and technological know-how, financial limitations, and change aversion. While practical, these issues are firmly based in theoretical dynamics, revealing major research needs.

First Challenge: Financial Constraints

SMEs often lack the capital to invest in AI infrastructure, skilled personnel, or training (OECD, 2021). From a Resource-Based View (RBV) perspective (Barney, 1991), this scarcity of financial resources limits SMEs' ability to build valuable, rare capabilities, unlike large firms with dedicated budgets. The Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) further highlights how this technological disadvantage, lacking funds for advanced systems, creates a context-specific barrier, as SMEs cannot leverage the same economies of scale as larger firms. This suggests a *context gap*: existing research focuses on resource-rich large organizations, neglecting how SMEs navigate such constraints.

Second Challenge: Technical Expertise and Infrastructure

A major obstacle is the lack of machine learning knowledge, data science abilities, and contemporary IT infrastructure (Jarrahi, 2018). Although SMEs frequently rely on outdated systems incompatible with AI solutions, TOE recognizes technological readiness as crucial (OECD, 2021). Because SMEs cannot readily test AI without a significant upfront investment, the Diffusion of Innovation (DOI) theory (Rogers, 2003) adds that this complexity and lack of trialability discourage adoption. Although few studies examine how these dynamics are revealed in resource-constrained environments, this technical gap feeds resistance dynamics as leaders and employees believe AI is not feasible.

Third Challenge: Resistance to Change

Employees who are afraid of losing their careers or managers who are hesitant to invest are examples of both individual and organizational resistance (McKinsey & Company, 2019). While DOI observes that late adopters' skepticism displays this reluctance, change management theories, such as Kotter's 8-Step Model (1996), contend that this results from a failure to establish urgency or convey benefits. Since adaptive strategies suited to small businesses are still understudied, this change management gap is made worse in SMEs by inflexible cultures and a lack of leadership capability (Mikalef & Gupta, 2021). AI integration is delayed by this cycle of resistance and reluctance, in which employee resistance is strengthened by the caution of the leadership. Analysis of these issues using the RBV, TOE, DOI, and Change Management lenses reveals three gaps that hinder the adoption of AI by SMEs: context, resistance dynamics, and change management. These gaps lay the groundwork for additional discussion in the following section.

1.3 Research Gaps & Rationale

Three major gaps in the literature on SME AI adoption are identified by the theoretical discussion in Section 1.2. These gaps are all related to the particular difficulties that SMEs encounter and call for a fresh strategy to close them:

- The gap in context: Most of the current research focuses on the adoption of AI in large organizations with a wealth of financial and technical resources, underrepresenting SMEs, which are known for having limited resources (Jarrahi, 2018). SMEs must self-manage with little external assistance, a dynamic that is ignored in mainstream studies, while large firms benefit from formal innovation processes and dedicated AI teams, according to The Digital Transformation of SMEs (2021). The adoption landscape of European SMEs differs from that of larger firms due to additional contextual pressures, such as regulatory uncertainty, according to Sharma (2023). This gap necessitates research that is specific to the operational and environmental contexts of SMEs.
- Resistance Dynamics Gap: Despite widespread recognition of opposition to AI, there has been little systematic research on feedback mechanisms, particularly the reluctance-resistance cycle in which employee skepticism is reinforced by leadership caution, particularly in SMEs with limited resources (Badghish & Soomro, 2024). According to Mikalef and Gupta (2021), the small size of SMEs heightens these dynamics because mistrust and uncertainty are increased by informal communication.

- Change Management Gap: Although it is advised to use change management strategies to lessen resistance, little is known about how they can be applied in SMEs as flexible, iterative procedures (Brock & Von Wangenheim, 2019). Unlike the standardized approaches appropriate for large firms, Lee and See (2004) contend that SMEs need flexible strategies to address resource constraints and cultural rigidity. According to OECD (2021), SMEs are unable to implement formal change programs or comprehensive training, but there are few models specifically designed to facilitate this transition, which restricts the availability of useful advice.

All these gaps (context, resistance dynamics, and change management) block a comprehensive understanding of SME AI adoption and imply that current frameworks are inadequate in meeting the unique requirements of SMEs. I suggest that these gaps may be filled by creating an integrated model that combines resilience tactics, adaptability mechanisms, and adoption drivers. According to industry insights, such a model would leverage well-established theories (e.g., Rogers, 2003; Tornatzky & Fleischer, 1990; Barney, 1991) to provide a structured, SME-specific approach that would help firms overcome obstacles and achieve sustainable AI adoption (McKinsey & Company, 2019).

1.4 Purpose

The goal of this study is to create and test empirically an integrated model that addresses resource scarcity and resistance to AI adoption in SMEs while building resilience for long-term competitive advantage.

Chapter 2: Theoretical Framework

2.1 Introduction

In Chapter 1, we introduced the growing importance of AI adoption for small and medium-sized enterprises (SMEs), particularly in resource-limited contexts like micro-sized IT firms. We identified three major challenges that hinder adoption: limited financial and technical resources, employee resistance, and a lack of effective change management strategies. These issues revealed key gaps in existing research, which often overlooks the unique needs of SMEs. To address this, we proposed the SME AI Adoption Resilience Model (SAARM), a new framework designed to help SMEs navigate AI adoption more effectively. In this chapter, we present the theoretical foundations of SAARM by integrating established models such as Diffusion of Innovation, Technology-Organization-Environment, Resource-Based View, Change Management, and Dynamic Capabilities. Each theory contributes to a specific layer of the model, helping explain how resistance can be reduced, adaptation can be supported, and long-term resilience can be built. Chapter 3 will then outline the research methods we used to test and refine this model through a case study of a Swedish IT consultancy.

2.2 SME AI Adoption Resilience Model (SAARM)

To tackle the challenges and gaps outlined in Chapter 1, this study introduces the SME AI Adoption Resilience Model (SAARM), a theoretically grounded framework designed to guide SMEs toward sustainable AI adoption. SAARM integrates five established perspectives Diffusion of Innovation (DOI) (Rogers, 2003), Technology-Organization-Environment (TOE) (Tornatzky & Fleischer, 1990), Resource-Based View (RBV) (Barney, 1991), Change Management (Kotter, 1996; Lewin, 1951), and Dynamic Capabilities (Teece et al., 1997)—into a circular, three-layered structure: the Inner Layer (Adoption Drivers and Barriers), the Middle Layer (Dynamic Capabilities for Adaptability), and the Outer Layer (Resilience for Sustainable AI Adoption).The Digital Transformation of SMEs (2021) highlight the importance of these integrative models for SMEs with limited resources, while Baghdadi and Soomro (2024) stress the necessity of such models to address feedback loops in resistance. By offering a rational, doable approach to overcoming monetary, technological, and cultural obstacles, SAARM promotes long-term resilience (Badghish & Soomro, 2024).

2.2.1 Inner Layer: Understanding AI Adoption Barriers and Drivers

The Inner Layer forms the foundation of SAARM by identifying and addressing the core barriers and enablers of AI adoption in SMEs, drawing on four complementary theories:

Diffusion of Innovation (DOI): According to Rogers (2003), adoption is a process that is impacted by trialability, observability, complexity, compatibility, and relative advantage. Adoption in SMEs is hindered by complexity and limited trialability because of resource limitations, especially for late majority employees who are afraid of losing their jobs (Jarrahi, 2018). Tech-savvy managers and other early adopters can show the advantages of AI (e.g., chatbots for customer service), but (Mikalef, Krogstie, Pappas , & Pavlou, 2020)et al. (2020) point out that concrete results are essential to changing attitudes.

By presenting the "threat of AI" (such as worries about job security) as a crucial element in workplace adoption, go beyond Rogers' (2003) traditional attributes and show that it has a long-term effect on attitudes, especially among workers who have previously held unfavorable opinions. This threat intensifies emotional resistance, including job loss fears, which are relevant to SMEs where close-knit relationships may intensify these worries. Similarly, as Jarrahi (2018) points out, technological complexity creates integration and skill challenges in IT companies, leading to skepticism and resistance among staff members who are not used to sophisticated systems like artificial intelligence.

Technology-Organization-Environment (TOE): According to Tornatzky and Fleischer (1990), adoption is influenced by organizational (such as skill shortages), environmental (such as regulatory uncertainty), and technological (such as legacy system incompatibility) factors. Badghish and Soomro (2024) cite regulatory issues such as data privacy laws as external barriers, while The Digital Transformation of SMEs (2021) contend that SMEs' inadequate infrastructure makes these limitations worse.

Resource-Based View (RBV): Barney (1991) asserts that competitive advantage stems from leveraging scarce resources. SMEs’ lack of financial capital and expertise limits their AI capabilities, but Brock & Von Wangenheim (2019) suggest incremental strategies (e.g., pilot projects) can optimize existing resources, addressing TOE-defined constraints.

Change Management: Lewin's 3-Stage Model (1951) and Kotter's 8-Step Model (1996) provide organized methods for reducing resistance. Mikalef and Gupta (2021) point out that SMEs' inflexible cultures necessitate customized interventions to "refreeze" new processes, while Brock and Von Wangenheim (2019) stress short-term wins, like successful AI pilots, to build process.

Theories of change management provide useful solutions for overcoming these obstacles. A self-reinforcing downward trend in AI attitudes is highlighted by Mikalef and Gupta (2021), who also suggest that leadership hesitancy can extend a cycle of reluctance and resistance. This dynamic is relevant to SMEs where informal influence is powerful. Lewin's (1951) unfreezing phase and Kotter's (1996) urgency step can break this cycle by proactively addressing fears, while Jarrahi (2018) stresses the importance of transformational leadership and a supportive culture in lowering resistance. By using early adopters as advocates (Jarrahi, 2018) and clearly communicating AI's advantages (Mikalef & Gupta, 2021), a Swedish IT consultancy SME could overcome resistance from the leadership and gain momentum in line with Kotter's quick wins. These theories interact: TOE defines barriers that DOI deems complex, RBV optimizes resources to support DOI adoption, and Change Management reduces resistance, creating a cohesive foundation for SMEs to address adoption challenges.

2.2.2 Middle Layer: Dynamic Capabilities for AI Adaptation

Building on the Inner Layer, the Middle Layer employs Dynamic Capabilities (Teece et al., 1997) to enable SMEs to adapt to AI challenges:

Sensing: Leadership identifies opportunities, such as low-cost AI tools (e.g., predictive analytics), aligning with TOE's resource constraints (Mikalef & Gupta, 2021)

Seizing: SMEs pilot AI projects to test feasibility, addressing DOI's trialability barrier and reducing resistance through Kotter's short-term wins(Lee & See, 2004)

Reconfiguring: Continuous adjustments refine AI strategies, leveraging RBV's resource optimization to ensure flexibility (Mikalef et al., 2020).

2.2.3 Outer Layer: Resilience for Long-Term AI Sustainability

The Outer Layer solidifies AI adoption as a sustained advantage:

Sustained AI Integration: Ongoing training and system upgrades, supported by Change Management, ensure long-term use (McKinsey & Company, 2019).

Organizational Flexibility: Leadership embeds AI into strategies, using Dynamic Capabilities' reconfiguring to adapt to changes (Mikalef & Gupta, 2021).

Competitive Advantage: Enhanced efficiency and decision-making, enabled by Inner Layer barrier mitigation, provide a strategic edge (Badghish & Soomro, 2024). This layer ensures SMEs evolve beyond initial adoption, achieving resilience through iterative improvement and strategic alignment.

Change Management and Dynamic Capabilities theories underpin SAARM's Outer Layer by ensuring sustained AI integration, adaptability, and competitive advantage in SMEs. Stefanova (2023) emphasizes Change Management's role in overcoming AI adoption barriers like employee resistance, proposing practices such as trust-building and training investments to maintain use overtime. For instance, fostering a climate of trust and providing emotional support Stefanova (2023) aligned with Kotter's (1996) steps of creating urgency and empowering action, ensuring employees embrace AI long-term in a Swedish IT consultancy SME. Similarly, Teece et al. (1997)

highlights Dynamic Capabilities' role in adapting to changes, defining them as the capacity to modify resources, supported by traits like a culture of change and customer engagement. This enables SMEs to reconfigure AI strategies as market needs evolve, sustaining competitiveness.

Empirical evidence further validates these theories' synergy. Kolb (1984) identifies continuous learning (e.g., competency training) and reciprocal relationships as adaptive practices that sustain Dynamic Capabilities ensuring AI skills endure and stakeholder support resilience. Li (2024) confirms this in IT-driven SMEs, finding significant relationships between AI adoption acceptance and a culture of innovation, suggesting that Dynamic Capabilities maintain AI use while driving competitive edge through adaptability (Teece et al., 1997). Together, Change Management secures human buy-in for sustained AI use, while Dynamic Capabilities enable ongoing resource reconfiguration, aligning SAARM with the Swedish SME's need for long-term success in a dynamic tech landscape

Empirical insights from Rogers (2003) suggest that observability, making AI's benefits visible, enhances attitudes among employees with prior negative views, a strategy vital for SMEs to sustain adoption. Workshops showcasing pilot successes, as proposed by Durge et al. (2024), can reinforce this visibility, ensuring long-term resilience by embedding AI into workflows and countering initial resistance through social modeling

2.3 Research Questions

Having developed SAARM with its three layers, this study reformulates its purpose (Section 1.4) into the following research questions to guide the deductive case study of a Swedish IT consultancy SME. Each question corresponds to a SAARM layer, ensuring theoretical coherence and empirical focus:

1. *How can SAARM help reduce different types of resistance—such as doubts, fears, or reluctance to use AI, among employees in a Swedish IT consultancy SME, and how does it address the cycle where leadership hesitation leads to more employee resistance?* (Inner Layer)

   This question tests the Inner Layer's ability to mitigate cognitive, emotional, and behavioral resistance (Mikalef & Gupta, 2021) and break the reluctance-resistance cycle (Badghish & Soomro, 2024) using DOI and Change Management insights.

2. *How does SAARM use strategies from existing theories to overcome barriers like limited resources, lack of skills, and organizational challenges in an SME, and how does it support adaptability during AI adoption?* (Inner and Middle Layers)

This bridges the Inner Layer's barrier analysis (TOE, RBV) with the Middle Layer's adaptability mechanisms (Dynamic Capabilities), exploring practical strategies as per Lee and See (2004)

3. *How does SAARM help an SME achieve lasting success with AI adoption by building resilience, such as maintaining use over time, adapting to changes, and gaining a competitive edge?* (Outer Layer)

This evaluates the Outer Layer's focus on sustained integration and competitive advantage, drawing on McKinsey & Company (2019) and Badghish and Soomro (2024).

These questions operationalize SAARM's theoretical constructs, providing a deductive framework to assess its applicability and refine its components based on empirical findings from The Company.

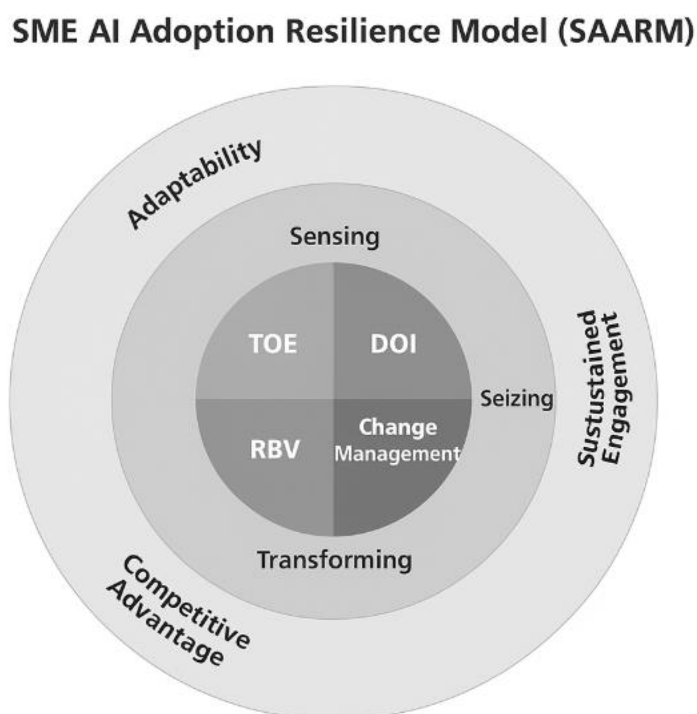


Figure 2. SME AI Adoption Resilience Model (SAARM)

Chapter 3: Methodology and Method

3.1 Introduction:

In Chapter 2, we developed the SME AI Adoption Resilience Model (SAARM), a theoretical framework that brings together multiple well-established theories—including Diffusion of Innovation, Technology-Organization-Environment, Resource-Based View, Change Management, and Dynamic Capabilities. This model was designed to explain how SMEs can overcome resistance to AI, adapt to new technologies, and build long-term resilience. In this chapter, we move from theory to practice by explaining how we applied and tested SAARM in a real-world setting. In this chapter, we outline the methodological approach used to investigate AI adoption in a small Swedish IT consultancy SME and to test and refine the SME AI Adoption Resilience Model (SAARM). Following Saunders et al. 's (2009) research "onion" framework, we detail our philosophical stance, research design, literature review process, data collection methods, data analysis procedures, and measures for quality and ethics. The study was conducted from January to May 2025 at The Company's Stockholm office. To ensure clarity, key concepts such as SAARM alignment and methodological rationales are revisited across sections, with cross-references to maintain conciseness.

Figure 3.1 illustrates our research design within the research onion context (philosophy through data collection layers).

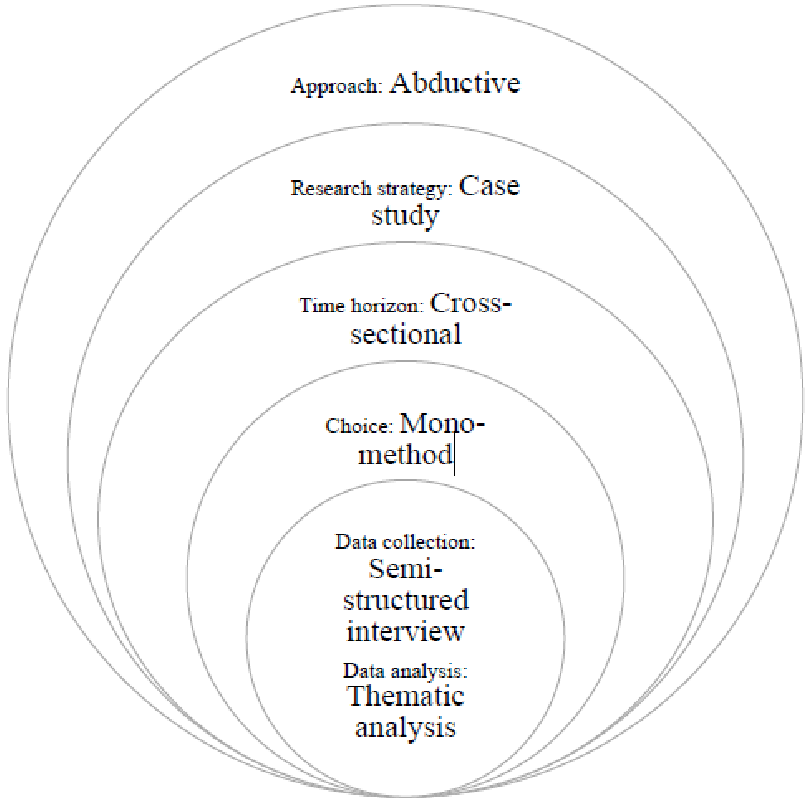


Figure 3.1 Research onion, adapted from Saunders et al. (2009)

3.2 Ontology and Epistemology: Interpretivism/Constructivism

Our research is grounded in an interpretivist paradigm. Ontologically, we adopt a *subjectivist* view that reality in this case, the reality of AI adoption in SMEs is socially constructed by individuals and groups rather than objectively given. We view the phenomena of resistance, adaptability, and resilience as emerging from the perceptions and interactions of the SME's members. Epistemologically, we align with *constructivism*, assuming that knowledge is formed through interpreting these subjective experiences in context. In practice, this means we as researchers seek to understand the meanings that The Company's employees attribute to AI and its adoption, rather than measure AI adoption as an external object. This philosophical stance implies that our role is to interpret and make sense of participants' narratives and behaviors, co-constructing knowledge with them (Saunders et al., 2015). By declaring this interpretivist ontology and epistemology upfront, we clarify the lens through which the research was designed, and data were interpreted.

3.3 Research Design: Qualitative Research

Given our interpretivist stance and exploratory aim, a qualitative research design was chosen. Below we elaborate on the key design decisions, the role of theory in our approach, the nature of the study, the overall strategy, and the time horizon and how these decisions align with our research purpose and questions. Table 3.1 summarizes how these choices align with SAARM layers and research questions, providing a concise overview to guide the following subsections.

Table 3.1: Alignment of Methodological Choices with SAARM Layers and Research Questions

Component	Choice	SAARM Layer	RQ Addressed	Justification
Philosophy	Interpretivism/Constructivism	All	RQ1–RQ3	Captures subjective experiences of resistance, adaptability, and resilience
Approach	Deductive–Inductive	All	RQ1–RQ3	Tests SAARM while refining it based on empirical data
Strategy	Single Case Study	All	RQ1–RQ3	Provides contextual depth into SME-specific dynamics
Time Horizon	Cross-Sectional	All	RQ1–RQ3	Captures a snapshot during a critical phase of AI adoption
Data Collection	Interviews	Inner/Middle	RQ1, RQ2	Offers insights into individual resistance and adaptation
Data Collection	Workshop	Middle	RQ2	Reveals group-based adaptability strategies and social dynamics
Data Collection	Observation	Inner/Outer	RQ1, RQ3	Captures behavioral evidence of resistance and emerging resilience
Analysis	Thematic Analysis	All	RQ1–RQ3	Links qualitative data to SAARM concepts and themes across all layers

3.3.1 Role of Theory: Deductive–Inductive

Our approach to theory is primarily deductive but with important abductive elements. (Dubois & Gadde, 2002). At the outset, we developed SAARM as a theoretical framework based on existing theories (Diffusion of Innovation, Technology-Organization-Environment, Resource-Based View, Change Management, Dynamic Capabilities, etc.). This provided a deductive structure: each of the three SAARM layers (Inner, Middle, Outer) comes with expected factors (e.g., resistance drivers and barriers, adaptability mechanisms, and resilience outcomes) drawn from literature. We designed our research to test and illustrate these theoretical constructions in the context of The Company. For example, we anticipated certain resistance factors (fear, mistrust, etc.) from theory and looked for them in the data. However, we also remained open to unexpected insights, iterating between theory and data in an abductive manner (Dubois & Gadde, 2002). As data were collected and analyzed, we allowed the theory (SAARM) to evolve adding new codes or adjust definitions when empirical findings did not fit the initial model. This hybrid deductive-abductive stance prevented us from being blinded by the initial framework. For instance, while SAARM initially framed "resistance" in a particular way, we were willing to refine this concept if participants revealed new dimensions of resistance. In summary, theory guided our inquiry (deduction) but did not constrain it; iterative reflection on data led to theory refinement (abduction). This approach is appropriate for our study because AI adoption in SMEs is a relatively underexplored phenomenon where some theoretical guidance exists, yet flexibility is needed to capture context-specific nuances.

3.3.2 Nature of Research: Qualitative Exploratory Case Study

Reflecting our interpretivist stance, this study is exploratory and qualitative. We seek to understand *how* and *why* AI adoption challenges unfold in an SME context, rather than to quantify phenomena. The research is explanatory in linking the SAARM framework to real experiences, and exploratory because SME AI adoption is under-researched. Qualitative methods ((Workshop, April 5, 2025; Appendix 2), allow deep insight into participants' perspectives, emergent issues, and the SME's unique context. We intentionally aim to identify patterns and themes rather than statistically generalize across firms.

3.3.3 Strategy: Single Case Study

We employed a single-case study strategy, focusing on one organization (Yin, 2014). A case study was ideal because our research questions require examining AI adoption within its real-life organizational context. The case of The Company – a micro-sized IT consultancy with fewer than 10 employees – was purposefully selected due to its information-rich nature. It serves as an exemplary case (Yin, 2014) where the dynamics of interest (resistance, adaptation, resilience in AI adoption) are transparently observable. The Company met specific criteria that made it a compelling case: (i) it was actively exploring AI integration in its operations (providing a live instance of adoption process), (ii) it has a small, tight-knit team typical of many SMEs (where individual attitudes can strongly influence outcomes), (iii) its adoption process was constrained by limited resources (a context where resilience mechanisms would be truly tested), and (iv) it operates in a competitive sector (IT consulting) where failing to adopt innovations like AI could impact survival. By focusing on this single case, we gained depth of insight – capturing interactions and changes over time in a way that a multi-case or survey approach could not. The unit of analysis is the organization and its members as they undertake an AI adoption initiative. Within the case study, we used multiple data sources (described in Section 3.4) to enable triangulation and a holistic understanding of the phenomenon. This single-case design does trade off breadth for depth – generalizability is limited – but the rich within-case analysis allowed us to refine SAARM and generate insights that could inform theory and practice for similar SMEs. See Table 3.1 for how this strategy addresses RQs 1–3.

3.3.4 Time Horizon: Cross-Sectional

Our research has a cross-sectional time horizon, examining The Company's AI adoption at a particular period (January–May 2025) rather than over many years (Saunders et al., 2015). We effectively captured a "snapshot" of the adoption process during its critical early phase. This timeframe was chosen due to practical constraints (the thesis project duration) and because it aligned with The Company's active experimentation with AI tools in spring 2025. A longitudinal study could have provided insights into how adoption and organizational resilience evolve over a longer term; however, within our cross-sectional approach we still incorporated some temporal elements by observing changes and reflections over the few months of engagement. For example, interviews and observation captured employee attitudes at different points in the adoption initiative (initial introduction, a few weeks in, etc.), giving us a mini trajectory of change within the spring 2025 window. The cross-sectional design suits the exploratory nature of our study – it allowed us to intensely study the current challenges and strategies in play, which was sufficient to address our research questions about immediate barriers (RQ1, RQ2) and early signs of resilience (RQ3).

3.4 Literature Review Processes

Developing the background and theoretical foundation for this study involved two distinct literature review processes: one to problematize and contextualize the research problem (informing Chapter 1 introduction and Chapter 2 problem formulation), and another to build the theoretical framework (SAARM) that guides this study (Webster & Watson, 2002). Both processes were conducted systematically to ensure a comprehensive understanding of existing knowledge and gaps.

3.4.1 Problematization and Industry Context Literature

For the problematization stage, we reviewed literature to establish the practical and scholarly need for our research. This involved surveying industry reports, policy papers, and recent studies on AI adoption rates and challenges, with a focus on SMEs. Key sources included reports by organizations like OECD (2021) and McKinsey (2019) that highlighted the adoption disparity: whereas over 60% of large firms have integrated AI, SME adoption rates linger below 25%. Such sources underscored real-world concerns, for example financial constraints, skill gaps, and cultural resistance as primary barriers for SMEs (OECD, 2021; Mikalef & Gupta, 2021). We also gathered examples of AI's potential benefits in similar contexts (Jarrahi, 2018) to illustrate what SMEs might gain if these barriers are overcome. This phase of the literature review was broad in scope, blending academic findings with practitioner insights, to frame our problem statement around the resilience gap in SME AI adoption. By the end of this stage, we had clarified the central challenges (lack of resources, expertise, and change resistance in SMEs) and the consequent knowledge gap: how can SMEs effectively navigate these challenges to adopt AI successfully? These findings justified our research purpose and the need to investigate adoption through a new lens (SAARM).

3.4.2 Theoretical Framework Development (SAARM)

Building the theoretical framework (SAARM) required a targeted literature review focusing on relevant theories and concepts. We adopted an integrative strategy (Webster & Watson, 2002)to identify theories that could explain different facets of AI adoption in SMEs. First, we examined technology adoption theories: Rogers' Diffusion of Innovations (DOI) to account for individual and cultural factors affecting adoption (perceptions of AI's complexity or relative advantage), and the Technology-Organization-Environment (TOE) framework to consider organizational readiness and external pressures. Next, recognizing the resource limitations in SMEs, we incorporated the Resource-Based View (RBV) to address how internal capabilities (or lack thereof) impact AI adoption. We then looked at change management and organizational behavior literature to cover human and processual aspects of implementing new technology – for instance, theories on resistance to change (self-efficacy, fear of job loss) and leadership's role in change (Kotter, 1996; Armenakis et al., 1993). We also included Dynamic Capabilities theory (Teece,1997) to capture how firms sense opportunities, seize them (through pilot projects), and reconfigure routines to sustain innovation, which is crucial for adaptability (the middle layer of SAARM). Finally, to address long-term success, we drew on concepts of organizational resilience and competitive advantage, referencing works that link adoption of innovation to performance (e.g., McKinsey & Company, 2019; Badghish and Soomron, 2024).

Our search process for this theoretical review involved querying academic databases (Scopus, Google Scholar) with keywords like "AI adoption SME", "technology adoption barriers SME", "SME dynamic capabilities AI", "organizational resilience technology". We filtered for recent publications (primarily 2018–2024) to capture up-to-date perspectives, and we traced key references within those works (backward and forward snowballing) to ensure classic theories (e.g., Barney, 1991 for RBV; Rogers, 2003 for DOI) were included. We also leaned on meta-analyses and review papers (e.g., Dwivedi et al., 2021 on AI in organizations) to not miss important variables. Through iterative comparison of these bodies of literature, we synthesized SAARM as described in Chapter 2: an inner layer addressing individual/organizational resistance factors (informed by change management, DOI), a middle layer capturing adaptation strategies and enabling factors (dynamic capabilities, some TOE and RBV elements), and an outer layer focusing on resilience and sustained benefits (RBV, competitive advantage, resilience theory). Each research question (Section 2.5) was then formulated to correspond to one or more SAARM layers, ensuring our theoretical review directly informed what we sought to investigate empirically. In summary, the literature review for the frame of reference was comprehensive and theory-driven, providing a robust foundation for SAARM and situating our study in the context of existing knowledge.

3.5 Data Collection

Building on the case context in Section 3.2.3, we employed a multi-method qualitative data collection strategy to capture AI adoption at The Company, leveraging its small, dynamic team. Specifically, we employed three complementary methods: semi-structured interviews, an online workshop, and on-site observation. Using multiple sources of evidence allowed for triangulation, enhancing the credibility of our findings by cross-verifying insights across different contexts and forms of data (Yin, 2014).

3.5.1 Semi-Structured Interviews

Interviews were the cornerstone of our data collection, employing a semi-structured format for its balance between guidance and flexibility (Saunders et al., 2015). This approach suited our exploratory study, ensuring key topics derived from SAARM and our research questions (RQs) were covered while allowing participants to elaborate on significant issues. In a small, knowledge-intensive firm adopting new technology, we anticipated diverse experiences, and the semi-structured format enabled deep probing of unexpected concerns without a rigid script (Saunders et al., 2015). The conversational nature fostered rapport and trust, crucial for discussing sensitive topics like fear of job loss or management critiques, creating a safe space for candid reflections on AI adoption's positive and negative aspects.

We developed an interview guide aligned with SAARM layers to address each RQ (Saunders et al., 2015). For the Inner Layer (Resistance, RQ1), we asked, "What concerns or uncertainties do you have about using AI in your work?" to uncover emotional or cognitive resistance. For the Middle Layer (adaptability, RQ2), we inquired, "What small-scale changes or supports could make AI easier to use in your tasks?" to explore adaptation strategies. For the Outer Layer (Resilience, RQ3), we posed, "What would help ensure AI becomes a sustainable, beneficial part of your work in the long run?” to elicit future-oriented insights. These open-ended questions encouraged storytelling, grounding data in concrete experiences (see Appendix A). The guide was reviewed by our supervisor and pilot-tested with a colleague for clarity.

Using purposive sampling, we selected participants across roles and seniority at The Company to capture diverse perspectives, such as those of newcomers versus leaders (Saunders et al., 2009). Table 3.2 summarizes participants. We contacted them via email, explaining the study purpose and ensuring confidentiality, and all agreed to participate. Informal scoping conversations in early March 2025 with key informants Payam (senior IT consultant) and Sara (junior consultant) provided context and refined our questions to match the company’s language.

The main interviews occurred between March 11 and April 5, 2025, lasting 60–90 minutes, conducted either in-person at the Stockholm office or via Zoom, accommodating participants’ preferences (Saunders et al., 2015). We reaffirmed the research purpose and confidentiality (using aliases) and obtained consent to record, emphasizing no right or wrong answers to set a relaxed tone. One researcher led while another took notes, following the guide flexibly, covering initial reactions, adoption challenges, adaptation strategies, and future expectations (Saunders et al., 2015). We probed for examples linking sentiments to incidents and noted non-verbal cues in-person to ensure comfort.

Post-interview, we recorded observations in a research journal, capturing tone and key points within 10–15 minutes, aiding later analysis (Gibbs, 2007).Interviews were transcribed verbatim shortly after, preserving dialogue richness for interpretive analysis. They offered profound knowledge about resistance like Sara’s fear: “*I was scared that if I used the AI and it worked well, it might prove I’m not needed”* (Sara, Interview, March 14, 2025; Appendix 2), adaptation strategies (e.g., Payam’s task breakdown), and future expectations, informing RQ1, RQ2, and RQ3, respectively, and forming the foundation for triangulation with workshop and observation data.

Table 3.2: Interview Participants

Interviewee	**Name**	**Role**	**Interview Date**
Interviewee 1	Payam	Senior IT Consultant	March 10, 2025
Interviewee 2	Sara	Junior IT Consultant	March 14, 2025
Interviewee 3	John	Junior IT Consultant	March 17, 2025
Interviewee 4	Edvard	CEO	April 2, 2025
Interviewee 5	Alex	Senior Marketing Lead	April 3, 2025
Interviewee 6	Caroline	Junior HR Specialist	April 3, 2025

3.5.2 Online Workshop

On April 5, 2025, we conducted a two-hour online workshop via Zoom to explore group dynamics and collective brainstorming around AI adoption at The Company, complementing individual interview data with an interactive setting (Saunders et al., 2015). The workshop's format allowed participants to exchange ideas and co-create solutions, revealing insights like peer influence and team negotiations not easily captured in one-on-one settings. An online format suited the company's remote collaboration norms, was easily scheduled, and, being part of digital transformation, aligned with AI adoption's context, while also reducing hierarchy by displaying participants in equal-sized Zoom boxes to encourage contributions from junior staff. We invited three participants using purposive sampling for diversity: two junior new hires, one senior member (Payam, a semi-moderator), and ourselves as researcher-facilitators, excluding the CEO to ensure open dialogue. We obtained consent to record the session, starting with introductions to establish a friendly tone.

The workshop had two parts: a 20-minute AI tool demonstration by Payam, showcasing its capabilities like candidate screening and report drafting, followed by a moderated discussion using prompts tied to SAARM layers. The demo demystified the technology, sparking curiosity—e.g., a junior HR staff member noted, “That could be useful for my role”—and surfaced reactions feeding into the discussion. Prompts included: “What concerns do people have about trusting the AI’s recommendations?” (Inner Layer, RQ1), “What could help everyone get more comfortable and skilled with this AI tool?” (Middle Layer, RQ2), and “Imagine a year from now with AI as part of your work—what does success look like?” (Outer Layer, RQ3). An interactive exercise asked participants to share one hope and one worry. Discussions revealed trust issues “How do we know it’s not making mistakes?”—and adaptation strategies like human-in-the-loop checks, with peers normalizing concerns and suggesting solutions. A new hire proposed, “Maybe we can do a one-week trial where we all use the AI for one task,” a pilot testing idea embraced by the group, informing RQ2 on adaptability.

The collegial dynamic allowed even reserved participants to contribute via chat, with Payam facilitating peer learning by sharing tips, such as past pilot tests. By the end, a shared purpose emerged participants set up a Slack channel to continue AI experimentation, indicating resilience (RQ3). The recorded session, transcribed with chat logs, captured insights like shifting attitudes “more comfortable giving it a try now”—and unresolved concerns like “Who will train us further?” The workshop enriched RQ2 by highlighting strategies (e.g., peer demonstrations, pilot testing) and social dynamics (peer influence), validated interview themes like trust issues, and provided RQ3 evidence of a shared vision for AI’s role, forming a foundation for triangulation with interviews and observations.

3.5.3 On-Site Observation

On April 8, 2025, we conducted an on-site observation at The Company’s open-plan office to capture authentic employee interactions with a new AI tool, complementing self-reported data from interviews and workshops (Saunders et al., 2015). This method, aligned with our interpretive approach, allowed us to observe behaviors like hesitations and peer interactions in their natural context, addressing RQ1 (resistance behaviors) and RQ3 (early resilience signs) as per Table 3.1. We informed all 8 employees a week prior, ensuring transparency that we were observing AI usage, not performance, and obtained written consent, minimizing the observer effect by emphasizing anonymity and familiarizing ourselves with the team beforehand (Saunders et al., 2009). Our observation protocol focused on AI tool usage frequency, resistance signs (e.g., avoidance, manual overrides), peer interactions, leadership involvement, and general mood shifts, targeting SAARM’s Inner, Middle, and Outer Layers.

Two researchers observed from 9 am to 5 pm, positioned unobtrusively at spare desks, taking handwritten notes without recording to maintain natural behavior. Initially, we noted resistance: a junior consultant avoided the AI for CV screening, stating, “Not sure I trust it for this—I’ll do it the usual way," reflecting distrust and manual overrides (April 8, 2025). Another employee hesitated while drafting a report with AI, showing frustration, "not great"—indicating skepticism of quality, corroborating Inner Layer resistance themes (RQ1). By midday, adaptive behaviors emerged, driven by peer influence: Caroline, after observing Payam use AI for scheduling, began using it for CV screening, illustrating peer modeling's role in reducing resistance, a Middle Layer adaptation strategy (RQ2) linked to DOI theory (Rogers, 2003). We also saw peer support—two consultants collaborated to improve AI prompts, sharing positive results and concerns, fostering a cooperative atmosphere.

Leadership engagement was evident: CEO Edvard checked in casually, asking, "How's it going with the tool today?" and responds supportively "It's okay if it's not perfect yet, we'll figure it out"—fostering psychological safety, crucial for adaptation and resilience (Kotter, 1996). By late afternoon, AI use normalized: three employees integrated it into tasks, discussing outputs casually and even joking about the tool, indicating familiarity. Field notes, time-stamped and consolidated post-observation, captured these shifts. The data enriched triangulation, confirming RQ1 resistance (e.g., avoidance, distrust) seen in interviews, revealing RQ2 adaptation through peer modeling—a new insight—and showing RQ3 resilience signs like consistent AI engagement and shared norms, such as referring to it as "our tool," suggesting early integration into workflows (Saunders et al., 2015)

3.6 Data Analysis

Our data analysis followed a thematic analysis approach (Braun & Clarke, 2006) to identify patterns related to resistance, adaptation, and resilience in the collected data. We chose thematic analysis for its flexibility and suitability in synthesizing insights from diverse qualitative sources (Observation, April 8, 2025; Appendix 2). Given that our study was guided by the pre-existing SAARM framework, we employed a blend of deductive coding (looking for themes informed by SAARM and theory) and inductive coding (allowing new themes to emerge from the data). This balanced approach aligns with our abductive stance – using SAARM's concepts as an initial guide while remaining open to modifying the model based on empirical evidence. We also applied triangulation during analysis: comparing findings across methods to ensure consistency or explain differences, thereby strengthening credibility.

To structure the analysis systematically, we adhered to the six phases of thematic analysis outlined by Braun & Clarke (2006): familiarization, coding, theme development, theme review, defining/naming themes, and reporting. Throughout these phases, we were mindful of SAARM's layered perspective, which helped organize codes and interpret themes in light of our research questions. We drew inspiration from Esmaeilzadeh and Blanco (2020) in distinguishing between individual-level factors and structural (organizational) factors during coding, since our data spanned personal feelings to organizational practices. Qualitative data was managed and coded using Microsoft Excel, which facilitated the organization of codes and extraction of themes, with Graphy used to generate thematic heatmaps across data sources for visualization.

The analysis process is detailed below, with each phase and key decisions explained:

- Phase 1 – Familiarization: we Both immersed ourselves in all data (interview transcripts, workshop transcript, observation notes). We read and re-read the texts, making notes of striking passages. For instance, we noted Sara's fear ("I was scared… I'm not needed"), John's observation that senior consultants "avoided the chatbot," and a CEO's supportive check-ins. We also highlighted recurring ideas such as mistrust in AI and references to resources or training needs. By the end of this phase, initial patterns (e.g., fear, peer influence, leadership role) were evident.
- Phase 2 – Coding: We iteratively coded the data in Excel. We combined deductive codes (from SAARM and theory) with inductive codes (emerging from the data). For example, we applied codes like "resistance – fear," "adaptation – training," and "outcome – efficiency gain" based on SAARM. Simultaneously, we added new code when needed. For instance, Caroline's remark *"it didn't apply to my role"* (Caroline, Interview, April 3, 2025; Appendix 2), led to a new code "cognitive irrelevance." We also coded concrete actions: Payam's strategy, "I broke their daily tasks into smaller ones," was labeled as "task segmentation." (Payam, Interview, March 10, 2025; Appendix 2). Multiple codes could apply to a single quote: "I was scared… I might prove I'm not needed," (Sara, Interview, March 14, 2025; Appendix 2) we coded it both as "fear of job loss" and "avoidance of AI." In total, we identified 40 distinct codes, (illustrated in table 3.3) covering expected barriers (e.g., mistrust, complexity) and novel ones (e.g., departmental silos, personal initiative).

- Phase 3 – Theme Development: Codes were grouped into five themes aligned with SAARM's layers, reflecting resistance triggers, adaptability challenges, adaptive strategies, and resilience outcomes. Themes were developed by clustering related codes and examining their interactions, such as how structural barriers amplified resistance and adaptive strategies mitigated it. The themes are:

Theme	SAARM Layer	Codes	Description
Cognitive and Emotional Resistance	Inner Layer	fear of job replacement, mistrust in AI, personal disengagement, cultural risk aversion	Encompasses codes like "fear of job replacement," "mistrust in AI," "personal disengagement," and "cultural risk aversion," capturing individual and cultural resistance drivers.
Leadership-Employee Hesitation Cycle	Middle Layer	lack of clarity, leadership hesitation	Includes "lack of clarity" and "leadership hesitation," describing a self-reinforcing cycle bridging individual (Inner) and organizational (Middle) factors, were management's ambiguity fuels employee resistance.
Organizational Constraints	Middle Layer	resource constraints, departmental silos, peer influence	Groups "resource constraints," "departmental silos," and "peer influence," highlighting structural and social barriers to adaptability, inspired by Esmaeilzadeh and Blanco's (2020) governance codes.

Theme	SAARM Layer	Codes	Description
Phased Adoption Strategies	Middle Layer	task segmentation, peer-led demonstration, pilot testing, personal initiative	Covers “task segmentation,” “peer-led demonstration,” “pilot testing,” “personal initiative,” and others, reflecting incremental efforts to build trust and capability (Dynamic Capabilities’ development).
Long-Term Benefits	Outer Layer	efficiency gains, competitive edge, client-centric advantage, industry alignment	Includes “efficiency gains,” “competitive edge,” “client-centric advantage,” and “industry alignment,” denoting sustained outcomes post-resistance.

- Phase 4 – Reviewing Themes: We were cross-checked against the dataset for coherence. For example, “Organizational Constraints” was validated by Caroline’s silo concerns, Payam’s resource limits, and workshop trust gaps. The “Leadership-Employee Hesitation Cycle” was clarified as spanning Inner (employee fears) and Middle (leadership ambiguity) layers to preempt confusion about its scope. Overlaps, like “visible results” (Middle) and “efficiency gains” (Outer), were resolved by positioning “visible results” as a strategy outcome in “Phased Adoption Strategies.” This ensured distinct, data-driven themes.
- Phase 5 – Defining and Naming Themes: Themes were defined with clear, accessible titles to avoid jargon and reflect SAARM’s framework:

Theme	Description	Theoretical Connection
Cognitive and Emotional Resistance	Individual fears (e.g., job loss, linked to Change Management’s human factors), mistrust (e.g., AI reliability, tied to DOI’s complexity/observability), and cultural hesitancy resisting AI use.	Change Management (Kotter, 1996), DOI (Rogers, 2003)
Leadership-Employee Hesitation Cycle	A self-reinforcing cycle where unclear leadership communication amplifies employee reluctance, delaying adoption (Sochor et al., 2018), and creates feedback loops.	(Sochor et al., 2018) systems thinking
Organizational Constraints	Structural (e.g., silos, resource limits including expertise gaps) and social (e.g., peer dynamics) barriers hindering adaptability.	Resource-Based View (Barney, 1991), Organizational Theory (Scott, 2003)
Phased Adoption Strategies	Incremental, peer-driven efforts (e.g., task breakdown, coaching) foster trust and capability, reflecting agile change principles.	Agile change principles
Long-Term Benefits	Sustained outcomes like efficiency, competitiveness, and client/industry alignment, enhancing SME resilience.	Dynamic Capabilities (Teece et al., 1997), Strategic Management (Porter, 1985

- Phase 6 – Reporting: We prepared the final write-up by selecting illustrative quotes and linking themes to theory. Each theme was connected to its research question and SAARM layer. For instance, Theme 1 (inner resistance) was tied to RQ1, and Theme 4 (adoption strategies) to RQ2. We also mapped how themes interlinked: e.g., how small-scale trials reduced fear and fed into long-term adoption (Outer Layer). Figure 3.2 illustrates the explicit linkage between each theme, its corresponding research question, and the SAARM layer.

Table 3.3 Reporting Cods and Theme

First-Order Code	Subtheme/ Type	Theme	SAARM Layer	Theoretical Link
Fear of Job Replacement	Emotional	Cognitive & Emotional Resistance	Inner (Resistance)	Change Management
Avoidance of AI	Behavioral	Organizational Constraints	Inner (Resistance)	Change Management
Mistrust in AI	Cognitive	Cognitive & Emotional Resistance	Inner (Resistance)	Diffusion of Innovation
Manual Override	Behavioral	Cognitive & Emotional Resistance	Inner (Resistance)	Change Management
Preference for Human Judgment	Cognitive	Cognitive & Emotional Resistance	Inner (Resistance)	Diffusion of Innovation
Complexity Perception	Cognitive	Cognitive & Emotional Resistance	Inner (Resistance)	Diffusion of Innovation
Irrelevance Perception	Cognitive	Cognitive & Emotional Resistance	Inner (Resistance)	Diffusion of Innovation
Skepticism of AI Reliability	Cognitive	Cognitive & Emotional Resistance	Inner (Resistance)	Diffusion of Innovation
Skepticism of LLM Accuracy	Cognitive	Cognitive & Emotional Resistance	Inner (Resistance)	Diffusion of Innovation
Collective Doubt Normalization	Emotional	Cognitive & Emotional Resistance	Inner (Resistance)	Change Management
Hesitancy in AI Use	Behavioral	Cognitive & Emotional Resistance	Inner (Resistance)	Change Management
Passive disengagement	Behavioral	Cognitive & Emotional Resistance	Inner (Resistance)	Meyer & Allen (1991)
Excessive Verification	Behavioral/Strategy	Cognitive & Emotional Resistance	Inner (Resistance)	Change Management
Verbalized Distrust	Behavioral	Cognitive & Emotional Resistance	Inner (Resistance)	Change Management
Task Segmentation	Strategy	Phased Adoption Strategies	Middle (Adaptability)	Dynamic Capabilities
Peer-Led Demonstration	Strategy	Phased Adoption Strategies	Middle (Adaptability)	Diffusion of Innovation
Visible Results	Outcome/Strategy	Phased Adoption Strategies	Middle (Adaptability)	Diffusion of Innovation
Pilot Testing	Strategy	Phased Adoption Strategies	Middle (Adaptability)	Diffusion of Innovation Dynamic Capabilities
Informal Champions	Dynamic Capability	Phased Adoption Strategies	Middle (Adaptability)	Sense Making
Lack of Clarity in Communication	Barrier	Phased Adoption Strategies	Middle (Adaptability)	Change Management
Leadership Hesitation	Barrier	Phased Adoption Strategies	Middle (Adaptability)	Change Management
Sensing Opportunities	Dynamic Capability	Phased Adoption Strategies	Middle (Adaptability)	Dynamic Capabilities
Seizing Through Testing	Dynamic Capability	Phased Adoption Strategies	Middle (Adaptability)	Dynamic Capabilities

First-Order Code	Subtheme/ Type	Theme	SAARM Layer	Theoretical Link
Coaching Support	Strategy	Phased Adoption Strategies	Middle (Adaptability)	Change Management
Phased Implementation	Strategy	Phased Adoption Strategies	Middle (Adaptability)	Change Management
Human-in-the-Loop Checks	Strategy	Phased Adoption Strategies	Middle (Adaptability)	Change Management
External Pressure	Outcome	Phased Adoption Strategies	Middle (Adaptability)	Socio-technical Integration
Peer-Influenced Adoption	Strategy	Phased Adoption Strategies	Middle (Adaptability)	Diffusion of Innovation
Resource Constraints	Barrier (Structural/Social)	Organizational constraints	Middle (Adaptability)	TOE Framework
Efficiency Gains	Outcome	Sustained AI Integration	Outer (Resilience)	Resource-Based View
Competitive Edge	Outcome	Sustained AI Integration	Outer (Resilience)	Resource-Based View
Sustained Integration	Outcome	Sustained AI Integration	Outer (Resilience)	Change Management
Process Documentation	Outcome	Sustained AI Integration	Outer (Resilience)	Change Management
Realistic Expectations	Outcome	Sustained AI Integration	Outer (Resilience)	Change Management
Experiential Learning	Outcome	Sustained AI Integration	Outer (Resilience)	Experiential Learning Theory
Shared Purpose	Outcome	Sustained AI Integration	Outer (Resilience)	Change Management
Success Metrics Planning	Outcome	Sustained AI Integration	Outer (Resilience)	Change Management
Consistent AI Engagement	Outcome	Sustained AI Integration	Outer (Resilience)	Resilience (routinization and sustained engagement)
Collective Troubleshooting	Outcome	Sustained AI Integration	Outer (Resilience)	Organizational Learning
Continuous Improvement	Outcome	Sustained AI Integration	Outer (Resilience)	Change Management

For clarity, the analysis (method) phrases above describe *how* we processed the data. Table 3.4 summarizes the key codes and themes identified through the six-phase thematic analysis process, illustrating the outcome of Phases 3 to 5 (theme development, review, and defining/naming) by organizing them according to SAARM layers and research questions. These findings, which emerged from the iterative coding and clustering of data as described, are presented here as a preview, with detailed interpretations and theoretical connections to be explored in Chapter 4.

Table 3.4: Coding and description Summary by SAARM Layer

Code (Phase 1)	Description	Theme (Phase 2)	SAARM Layer	RQ	Theoretical Link
Fear of Job Replacement	Employee fear of redundancy	Cognitive/Emotional Resistance	Inner	RQ1	Change Management (fear of change)
Mistrust in AI	Doubts about AI reliability	Cognitive/Emotional Resistance	Inner	RQ1	DOI (low observability)
Complexity Perception	AI perceived as complex	Cognitive/Emotional Resistance	Inner	RQ1	DOI (complexity)
Perceived Irrelevance	Personal disengagement	Cognitive/Emotional Resistance	Inner	RQ1	DOI (low compatibility)
Lack of Clarity	Unclear leadership communication	Leadership-Employee Hesitation Cycle	Inner/Middle	RQ1	Change Management
Leadership Hesitation	Management cost consensus	Leadership-Employee Hesitation Cycle	Inner/Middle	RQ1	Change Management
Resource Constraints	Limited time/budget	Organizational Constraints	Middle	RQ2	TOE (organization)
Departmental Silos	HR exclusion	Organizational Constraints	Middle	RQ2	TOE (organization)
Task Segmentation	Breaking tasks into smaller steps	Phased Adoption Strategies	Middle	RQ2	Dynamic Capabilities (seizing)
Pilot Testing	Small-scale AI trials	Phased Adoption Strategies	Middle	RQ2	DOI (trialability)
Peer-Led Demonstration	Peer-driven AI showcases	Phased Adoption Strategies	Middle	RQ2	DOI (observability)

Code (Phase 1)	Description	Theme (Phase 2)	SAARM Layer	RQ	Theoretical Link
Coaching Support	One-on-one guidance	Phased Adoption Strategies	Middle	RQ2	Change Management (training)
Efficiency Gains	Faster task completion	Long-Term Benefits	Outer	RQ2	RBV (performance)
Competitive Edge	Quicker client responses	Long-Term Benefits	Outer	RQ2	RBV (advantage)
Sustained Integration	Routine AI use	Long-Term Benefits	Outer	RQ2	Change Management (institutionalization)
Shared Purpose	Collective commitment to AI	Long-Term Benefits	Outer	RQ2	Resilience (culture)

Note: This table lists key codes; descriptions and theoretical links (*additional codes are available in Appendix B)*

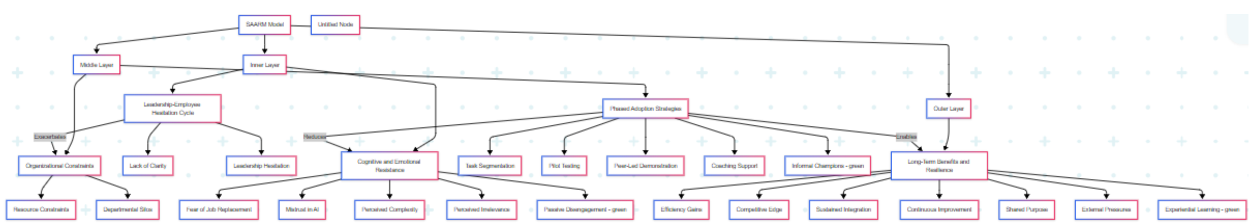


Figure 3.2 hierarchical overview of the themes

Figure 3.2 provides a hierarchical overview of the themes, and their associated codes identified through the thematic analysis visually structuring the findings across SAARM's three layers

Inner, Middle, and Outer, as a complement to the interconnections explored in Section 3.5 It illustrates how themes such as Cognitive and Emotional Resistance (Inner Layer, Section) with codes like Fear of Job Replacement and Mistrust in AI, Organizational Constraints and Phased Adoption Strategies (Middle Layer) with codes like Resource Constraints and Task

Segmentation, and Long-Term Benefits and Resilience (Outer Layer) with codes like Efficiency Gains and Sustained Integration, are organized, highlighting abductive refinements (e.g., Passive Disengagement, Informal Champions, Experiential Learning) in green to reflect data-driven insights that enhance the deductive framework.

3.7 Ethical Considerations

This section outlines the ethical principles guiding our qualitative study on AI adoption at The Company, a small Swedish IT consultancy SME, ensuring the research process respected participants' rights and well-being while maintaining academic integrity (Saunders et al., 2015). We adopted five key principles of research ethics, adapted from Saunders et al. (2015), which were applied throughout the study, from design to dissemination, as summarized in Table 3.4. These principles were particularly critical given the sensitive nature of AI adoption topics, such as fears of job displacement (Section 4.2), and the interpretive approach described in Sections 3.1 to 3.5.

Table 3.5: Ethical Principles Applied in the Study

Principle	Description	Application in This Study
Informed Consent	Participants must be fully informed about the study's purpose, risks, benefits, and their rights, ensuring voluntary participation with the option to withdraw at any time.	All eight employees at The Company were provided with a detailed introduction (Appendix A) before participating in interviews (Section 3.4.1), the online workshop (Section 3.4.2), and on-site observation (Section 3.4.3), conducted between March 11 and April 8, 2025. Written consent was obtained, emphasizing voluntary participation and the right to withdraw without consequences.
Confidentiality	Participants' identities and data must be protected through anonymity and secure storage to prevent unauthorized access.	Participants were anonymized using aliases (e.g., Payam, Sara) in transcripts and field notes, and all data (recordings, transcripts, notes) were stored on encrypted devices accessible only to the research team, as noted in Sections 3.4.1 to 3.4.3.
Minimizing Harm	The study must avoid causing physical, psychological, or emotional harm, allowing participants to opt out of sensitive topics.	We avoided pressuring participants on sensitive topics like job displacement fears, ensured a relaxed tone during interviews by stating "no right or wrong answers" (Section 3.4.1), and adjusted our approach if discomfort was observed, such as during the observation on April 8, 2025 (Section 3.4.3).
Transparency and Integrity	Research must be conducted honestly, with accurate reporting and proper citation to avoid misrepresentation or plagiarism.	We maintained a reflexive journal to document our assumptions (Section 3.6), ensured accurate transcription of interviews and workshop data, and cited all sources properly in the thesis, completed on May 19, 2025, to uphold academic integrity.
Data Usage	Data should be used only for the stated research purpose, with participants informed of its intended use.	Participants were informed that data would be used solely for academic purposes to refine the SAARM framework (Section 1.4), and findings were reported in anonymized form (Sections 4.2–4.4), with the final thesis shared with The Company for reciprocity.

By adhering to these principles, we ensured ethical conduct throughout the research process, fostering trust with participants and maintaining the credibility of our findings on AI adoption dynamics at The Company.

Chapter 4: Empirical Findings and Thematic Analysis

4.1 Introduction

In Chapter 3, we presented the methodological approach used to explore AI adoption within a small Swedish IT consultancy. This included the use of a single-case study design and a multi-method data collection strategy involving interviews, an online workshop, and on-site observation. These methods were chosen to provide rich, contextual insights into how the SME navigated AI-related challenges and to test and refine the SAARM framework introduced in Chapter 2. In Chapter 4, we present empirical findings from the case study, structured around the three layers of the SAARM model: the Inner Layer (resistance), the Middle Layer (adaptation), and the Outer Layer (resilience). Thematic analysis reveals both expected and novel patterns that deepen our understanding of the AI adoption process in SMEs.

This chapter presents the empirical findings from our case study of a small Swedish IT consultancy SME, analyzed through the SME AI Adoption Resilience Model (SAARM). The Chapter is structured by SAARM's three layers—Inner, Middle, and Outer—each addressing a research question (RQ1–RQ3). For each layer, we present the themes identified in Chapter 3, supported by codes and specific data (quotes, observations), followed by abductive refinements and theoretical connections. Tables summarize themes, codes, descriptions, and theoretical links, while simplified models (Table 4.1, Table 4.2, and Table 4.3) visualize the refined SAARM. The story combines proof from existing themes that support SAARM and new ideas based on data to give a clear look at how AI is being adopted. narrative weaves deductive validation (themes confirming SAARM) and inductive enhancements (data-driven refinements) to provide a detailed analysis of AI adoption dynamics.

4.2 Inner Layer: Navigating Resistance to AI Adoption (RQ1)

The Inner Layer addresses RQ1: In this section, we present two key themes that answer RQ1: (1) **Cognitive and Emotional Resistance** and (2) **The Leadership–Employee Hesitation Cycle**. These themes are presented in the following section using the coding resulting from our analysis as presented in table 4.1

Table 4.1 Coding for the inner layer

Theme	Code of Inner Layer	Description	Connection to Framework
Cognitive and Emotional Resistance	Fear of Job Replacement	Anxiety that AI will replace roles, leading to avoidance.	Change Management (Kotter, 1996)
	Mistrust in AI	Skepticism about AI's reliability due to opaque logic.	DOI (Rogers, 2003)
	Perceived Complexity	AI seen as unintuitive, deterring use.	DOI (Rogers, 2003)
	Perceived Irrelevance	Personal disengagement	DOI (Rogers, 2003)
	Passive Disengagement	Apathy is due to perceived irrelevance of AI.	Meyer & Allen (1991)
Leadership–Employee Hesitation Cycle	Lack of Clarity	Unclear leadership communication	Change Management (Kotter, 1996)
	Leadership Hesitation	Management cost consensus	Change Management (Kotter, 1996)

4.2.1 Theme 1: Cognitive and Emotional Resistance

This theme explores the individual, perception-based challenges that shaped employees' responses to AI, revealing how emotional, cognitive, and relational factors intertwined to create resistance.

As we see, Employees at The Company faced significant resistance to AI, driven by cognitive and emotional barriers. Such resistance is first visible in what we can refer to as Fear of Job Replacement. This emotional resistance was frequently cited in interviews. Employees feared that AI might replace them and felt anxiety around using the tool. Such fear was prominent, with junior IT consultant Sara confessing:

> *"I avoided using the AI for a whole week... I was scared that if I used the AI and it worked well, it might prove I'm not needed."* (Sara, Interview, March 14, 2025; Appendix 2).

> *"I was scared that if I used the AI and it worked well, it might prove I'm not needed."* (Sara, Interview, March 14, 2025; Appendix 2)

> *"Senior consultants avoided the chatbot*." (John, Interview, March 17, 2025; Appendix 2)

This fear led to avoidance behaviors, such as manually reviewing CVs despite the availability of AI tools (Observation, April 8, 2025; Appendix 2), aligning with Change Management's focus on fear of change (Kotter, 1996). Indeed, Kotter identifies the failure to create a sense of urgency as the first and most critical barrier to successful change. When employees feel that new technologies might make their roles redundant and no clear reassurance is provided by leadership, fear easily translates into subtle forms of resistance. In this case, the lack of a compelling vision or transparent communication around the role of AI likely intensified insecurity. According to Kotter's 8-Step Model, without early steps like urgency, vision creation, and empowerment, employees are left in an emotional limbo, which Kotter warns can stall transformation efforts altogether. In line with this theoretical framing, this aligns with our data, where the AI tool was available but underused, not due to capability limitations, but due to unresolved emotional tension around job security. From our opinion, this moment reveals that emotional resistance, particularly fear of job loss, is not just a peripheral concern but a core inhibitor of technological change. In a small SME context, where teams are tightly knit and individual roles highly visible, the fear of being replaced may be even more pronounced than in large corporations. Therefore, we interpret this behavior not as irrational, but as a rational response to ambiguity. It underscores that digital transformation in SMEs cannot succeed through tools alone, it must be paired with intentional emotional reassurance. Leadership must actively engage in transparent dialogue, frame AI as a tool for augmentation rather than replacement and foster psychological safety if they hope to move past this invisible barrier.

In addition to this fear-based response, another barrier emerged in the form of mistrust, which further compounded employees' hesitation to engage with the tool. For example, employees' experiences highlighted Mistrust in AI. This mistrust further deepened resistance, with senior consultants asserting as shown below.

> *"I'd rather trust my own brain than some machine"* (Edvard, Interview, April 2, 2025; Appendix 2).
> *"What if AI misses a good candidate just because they didn't use the right words?"* (Sara, Interview, March 14, 2025; Appendix 2).

> This empirical evidence aligns with theory, as this reaction aligns with Rogers' Diffusion of Innovation (DOI) framework, specifically the concept of low observability (Rogers, 2003). Observability refers to how easily users can see and interpret the results of an innovation. When the logic or output of a system is vague—as is often the case with AI—users cannot verify its decision-making process, leading to skepticism. As Rogers argues, innovations with low observability tend to face slower and more hesitant adoption. In this case, because employees could not see how the AI evaluated candidates, they questioned

its ability to make fair and accurate recommendations, ultimately undermining trust. From our perspective, Sara's comment reveals a deeper issue of accountability and psychological ownership. In small teams where individuals are closely tied to outcomes, trust must be earned—not just functionally, but emotionally. When AI tools are introduced without mechanisms for explanation or user feedback, they feel disconnected from the decision-making culture of SMEs. Thus, I interpret this mistrust not as reluctance to change, but as a call for systems that are transparent, interpretable, and aligned with human judgment. In environments where resources for training are scarce, and informal learning dominates, AI tools must communicate their reasoning in ways that foster trust and shared responsibility. Otherwise, mistrust will persist—not due to flaws in the technology itself, but due to a lack of meaningful connection between users and the system.

Alongside this issue of trust, employees also reported challenges related to how user-friendly the AI system can be for their work, which introduced a third barrier: perceived complexity. The mentioned barrier also deterred use, as HR consultant Caroline noted, this comment reflects how the AI system's interface and logic were perceived as misaligned with the relational, fluid nature of HR tasks. Despite being introduced to support efficiency, the tool was seen as more of a burden than a benefit, leading to hesitation and minimal engagement.

"It felt clunky—not very intuitive for the people-centric work we do" (Caroline, Interview, April 3, 2025; Appendix 2)
"It seemed very complex to implement." (Payam, Interview, March 10, 2025; Appendix 2)

Theoretically, this finding resonates with Rogers' Diffusion of Innovation (DOI) theory, particularly the concept of complexity (Rogers, 2003). Complexity refers to the extent to which an innovation is perceived as difficult to understand or use. Rogers argues that higher perceived complexity reduces the likelihood of adoption, particularly in environments with limited technical support. In SMEs—where training is often informal and capacity stretched thin—tools that are not immediately intuitive can quickly generate frustration. Caroline's experience illustrates how a lack of design-user fit reinforces this barrier: although the AI may have been functionally capable, it failed to match the workflows and mental models of HR professionals, thus violating DOI's principle that innovations must align with users' cognitive frames and task realities to succeed. We argue that from our perspective, this case highlights how AI adoption is not just a matter of functionality, but of perceived compatibility with existing ways of working. The perception of inefficiency speaks to more than usability—it suggests a mismatch between technology's logic and the social nature of HR work. In small teams like this SME, where roles are closely tied to client experience and trust, tools that feel rigid or vague can unintentionally undermine human judgment. Therefore, we interpret this as a reminder that perceived complexity is not only a design issue but also a cultural and relational one. In such contexts, human-centered design and co-creation during implementation may be necessary to lower complexity and increase buy-in. If SMEs hope to integrate AI meaningfully, adoption strategies must account for how the tool "feels" to the user, not just what it does. However, even beyond complexity, another significant form of obstacle arose—rooted in doubts about AI's relevance to specific roles. Perceived Irrelevance / Apathy also shaped employees' interaction with AI. Some staff questioned whether AI was relevant to their role at all. This sense of disconnect led to personal disengagement. This was not resistance in the traditional sense, but a quiet withdrawal: a decision not to engage. Observational and workshop data confirmed that HR staff gravitated toward traditional methods, signaling a lack of perceived relevance. Instead of actively rejecting AI, some employees simply ignored it, choosing familiarity over exploration.

> *"I wasn't against AI, but... I wasn't sure if it applied to my role"* (Caroline, Interview, April 3, 2025; Appendix 2), *while Sara shared, "I prefer human judgment—I feel like I can understand a candidate's potential better"* (Sara, Interview, March 14, 2025; Appendix 2).
> *"They saw it as completely unrelated to HR."* (Payam, Interview, March 10, 2025; Appendix 2).

Theoretical grounding for this pattern comes from Rogers' Diffusion of Innovation (DOI) theory, specifically the attribute of compatibility (Rogers, 2003). Compatibility refers to how well an innovation fits with existing values, experiences, and needs of potential adopters. When a technology is seen as misaligned with a user's role or professional identity, adoption is unlikely—even if the tool itself functions well. In this case, the perception that AI lacked emotional nuance or domain-specific judgment made it seem unsuitable for human-centric tasks like recruitment or people management. As DOI suggests, innovations that fail to resonate with users' existing practices or self-concepts tend to face passive resistance, a more subtle but equally damaging barrier to adoption. From our point of view, this disengagement highlights a critical but often overlooked form of resistance: apathy grounded in perceived irrelevance. Employees did not oppose AI ideologically; rather, they struggled to see its personal or professional value. In SMEs—where job roles are fluid and deeply identity-driven—if a new tool does not clearly enhance an individual's daily contributions, it is likely to be sidelined. Thus, we interpret this as a sign that meaningful adoption must be preceded by relevance-building. Simply introducing AI is insufficient; leadership must explicitly connect the technology to each team's purpose and workflows. Otherwise, innovation risks becoming invisible—not due to technical failure, but because it never found a meaningful place in the user's mental model.

Taken together, these four dimensions—fear of replacement, mistrust, complexity, and irrelevance—reveal a multifaceted and deeply human pattern of resistance which connect to the theoretical framework as presented. They also help us with the introduction of a subtler, abductively refined barrier that further enriches our understanding of resistance within this SME context.

passive disengagement—which emerged as an abductive refinement. Unlike overt resistance or vocal skepticism, this behavior reflected apathy rather than objection—a quiet withdrawal from engagement without open opposition. Staff did not actively reject AI, but neither did they incorporate it, reflecting a deeper issue of psychological detachment.

> *"I wasn't against AI but... I wasn't sure if it applied to my role"* (Caroline, Interview, April 3, 2025; Appendix 2)*, while observational data revealed HR staff continuing to use traditional processes, quietly sidelining the AI tool* (Observation, April 8, 2025; Appendix 2).

Theoretically, this dynamic corresponds with Organizational Commitment Theory, particularly affective commitment as proposed by Meyer & Allen (1991). Affective commitment refers to the emotional attachment employees feel toward organizational goals or innovations. When this connection is weak—as in cases where employees feel an innovation is irrelevant or externally imposed—they may show low optional effort, choosing to passively avoid rather than resist. In this case, disengagement occurred not from fear or complexity, but from a perceived lack of emotional or professional alignment. This insight contributes to theoretical refinement, as the abductive emergence of this code refines SAARM by pointing to the importance of perceived meaningfulness in shaping employee behavior. From our analytical perspective, Passive Disengagement may be the most difficult barrier to detect—and the most dangerous. Unlike fear or mistrust, which often provokes conversation or concern, apathy can remain invisible until adoption fails. In small firms like this SME, where each team member's engagement significantly impacts outcomes, this silent opting-out can undermine even well-designed implementation efforts. Therefore, I interpret this code as a sign that emotional resonance and role relevance must be intentionally cultivated during AI rollouts. Simply offering access to a tool is insufficient; employees need to understand how it empowers their specific contributions. Addressing passive disengagement requires not just training or persuasion, but co-creation of meaning—ensuring employees see AI not as a foreign system, but as a relevant, empowering extension of their role.

To further consolidate these insights, we now move from a thematic interpretation to a layered analytical synthesis, highlighting how both deductive and abductive reasoning contributed to our understanding of resistance in this layer.

4.2.2 Theme 2: Leadership–Employee Hesitation Cycle

This bridging theme highlights how ambiguous leadership behavior influenced employee adoption patterns and created a circular pattern of hesitation. Employees perceived uncertainty from management, which made them hesitant to use AI. That hesitation then reinforced management's doubts, contributing to a stagnation in adoption momentum.

Several employees described the communication from leadership about AI as vague or lacking in clarity. This ambiguity left employees uncertain about AI's purpose, expectations, or value. Observations during the workshop and follow-up interviews showed that this confusion particularly affected junior staff, who hesitated to engage with the AI tool in the absence of clear guidance. "

> *"They [management] weren't sure if it's worth it, so we weren't sure either"* (Sara, Interview, March 14, 2025; Appendix 2)
>
> *"We didn't know if it was mandatory or optional... nobody said clearly how or when to use it"* (John, Interview, March 17, 2025; Appendix 2)

This observed confusion aligns with Kotter's Change Management Model, particularly Step 4: Communicate the Vision (Kotter, 1996). Kotter emphasizes that even if a vision for change exists, it must be communicated clearly, credibly, and repeatedly to mobilize action. When leadership fails to articulate how a new system fits into daily work, uncertainty spreads—and people default to inaction. As Kotter argues, unclear messaging weakens urgency and prevents alignment, which is crucial during early phases of technological change. Reflecting on this through our lens, from our perspective, this lack of clarity is not just a communication failure, it's a leadership risk that feeds resistance. In small firms, employees often look to leadership for behavioral cues, especially when navigating unfamiliar tools like AI. When that guidance is missing or tentative, it fosters passivity, skepticism, or quiet avoidance. Accordingly, we interpret this behavior as a symptom of low psychological ownership—employees didn't adopt the AI because they didn't feel it was theirs to adopt. This case reinforces our belief that in SMEs, clear, consistent, and participatory communication is not optional.

Closely related to this communication gap was a second leadership behavior: hesitation around commitment, particularly tied to practical concerns such as cost and feasibility. Leadership expressed reluctance to enforce or accelerate AI adoption due to concerns about cost, complexity, and uncertain return on investment. Interview and Observations from the workshop revealed that this leadership hesitation is downward to employees

"My manager said, 'We're not sure if this is worth the cost—we might need to rethink this.' Hearing that made me feel like, if they're not confident, why should I be?" (Sara, Interview, March 14, 2025; Appendix 2)·

"My manager was both for and against it… They thought it was like buying a product… When they encountered the complexities, they realized the cost was much higher, and that's when they started opposing it"

This dynamic is clearly reflected in Kotter's Change Management Model, particularly Step 1: Create a Sense of Urgency (Kotter, 1996). Kotter argues that without strong, visible leadership commitment, organizational change will falter at the starting line. In SMEs, where leadership plays a central symbolic and operational role, any sign of hesitancy—whether due to resource concerns or strategic doubts—can rapidly undermine employee motivation. Kotter emphasizes that early ambiguity from leaders reduces the perceived seriousness of change, allowing resistance or disengagement to take root. From our perspective, this leadership hesitation was more than financial—it was psychological and cultural. It signaled uncertainty, which employees internalized as a lack of importance. In SMEs, where hierarchies are flat and leadership actions are highly visible, mixed messages are amplified. We interpret this situation as a failure to anchor change in confident leadership behavior. When managers delay commitment, they create a climate of doubt that not only slows adoption but also reduces employee ownership. However, this cycle, suggests that visible leadership engagement is one of the most powerful tools for shifting organizational momentum toward

Final Insight for inner layer:

As we can see in chapter 3, we prepared the final articulate by selecting illustrative quotes and linking themes to theory. Each theme was connected to its research question and SAARM layer. For instance, Theme 1 (inner resistance) was tied to RQ1. In chapter 4, in inner layer based on data, theory revealed that employees' resistance to AI was not rooted in a single barrier but emerged from a group of interrelated perceptions. Deductively applying Diffusion of Innovation (Rogers, 2003) and Change Management theory (Kotter, 1996) clarified how emotional resistance (e.g., fear of job loss), cognitive skepticism (mistrust), and perceived misalignment (complexity and irrelevance) worked to suppress engagement. Each of these perceptions lowered the perceived value or safety of AI, leading to avoidance or disengagement. Complementing these deductive findings, an abductive refinement has been introduced as a fifth barrier, an important but less visible pattern of behavior Through a deductive lens, the Inner Layer revealed four key barriers to AI adoption in SMEs: fear of job loss, mistrust in AI, perceived complexity, and perceived irrelevance. Drawing on Rogers' Diffusion of Innovation and Kotter's Change Management, these codes illustrate how emotional and cognitive resistance limit engagement when employees perceive AI as threatening, unclear, or misaligned with their roles. However, through abductive analysis, we identified a significant fifth barrier: passive disengagement. Unlike overt resistance, this form of quiet withdrawal—marked by indifference rather than opposition—emerged when AI felt irrelevant or disconnected from personal purpose (Meyer & Allen, 1991). This refinement highlights that in SME contexts, the absence of emotional resonance can be as limiting as active fear or complexity, underscoring the need for relevance-building and meaningful alignment in AI adoption strategies. Having examined resistance from within the individual dimension, we now shift focus to the interplay between leadership behavior and employee perception—an interaction that forms the basis of the second theme in the Inner Layer.

4.3 Middle Layer: Overcoming Organizational Barriers (RQ2)

The Middle Layer addresses RQ2 by examining organizational barriers and adaptive strategies, focusing on **Organizational Constraints** and **Phased Adoption Strategies**.

Table 4.2 Coding for the Middle Layer

Theme	Code of Middle Layer	Description	Connection to Framework
Organizational Constraints	Resource Constraints	Limited budget and lack of technical expertise hindered AI implementation.	Resource-Based View (Barney, 1991)
	Departmental Silos	Lack of cross-departmental coordination excluded key users from early planning.	TOE Framework – Organizational Context (Tornatzky & Fleischer, 1990)
Phased Adoption Strategies	Task Segmentation	Work broken into smaller tasks to ease AI learning and reduce complexity.	DOI – Complexity & Trialability (Rogers, 2003)
	Pilot Testing	AI trialed in low-risk projects to build confidence.	DOI – Trialability (Rogers, 2003)
	Peer-Led Demonstration	Trusted peers modeled AI use, inspiring others.	DOI – Observability & Social Influence (Rogers, 2003)
	Coaching Support	One-on-one guidance filled skill gaps and built confidence.	Change Management – Empowering Action (Kotter, 1996)
	Informal Champions	Peer-led AI adoption driven by informal leadership.	Sensemaking Theory (Weick, 1995)

4.3.1 Organizational Constraints

The company’s small size posed significant barriers to AI adoption, most notably in the form of resource constraints. “We had limited time and no formal training – it was figure it out as you go.”

(Observation, April 8, 2025; Appendix 2). Observations from April 8, 2025, revealed that employees relied on ad-hoc learning and informal experimentation, with no structured training or onboarding process in place. These constraints were not due to resistance, but rather structural limitations that were feasible within the organization's existing capabilities.

> *We had limited time and no formal training – it was figure it out as you go."* (Observation, April 8, 2025; Appendix 2)
> *"When I saw the cost, I started waffling on pushing the AI project." (Edvard, Interview, April 2, 2025; Appendix 2).*

This scenario aligns conceptually with the Resource-Based View (RBV) of the firm, particularly Barney's (1991) emphasis on how resource scarcity affects strategic implementation. According to RBV, sustainable advantage stems from possessing valuable, rare, inimitable, and interchangeable resources. In contrast, firms lacking in financial, technological, or human capital struggle to convert strategic goals—such as AI adoption—into operational reality. In our case, the absence of both budget and technical knowledge significantly constrained what the organization could execute, regardless of intent. Viewed through our lens, the organization's limitations highlight a common but under-discussed tension in SME innovation: the will to change often exceeds the means to do so. AI adoption in this context wasn't resisted—it was stalled by capacity gaps. Therefore, we interpret this not as a failure of strategy, but a misalignment between ambition and capability. In SMEs, where lean operations are the norm, introducing complex systems like AI without dedicated support or external partnerships can unintentionally burden staff, leading to frustration or inaction.

Complementing these internal capacity limitations, we also observed how organizational structure—particularly in the form of departmental silos—amplified resistance and disengagement. Departmental Silos highlighted how structural exclusion contributed to resistance during AI implementation. This lack of early involvement created a disconnect between the implementation team and other departments, particularly HR—one of the key user groups. As a result, team members felt disengaged and peripheral to the change process, which slowed their adoption and reinforced a sense of misalignment.

> *"HR wasn't part of early planning, so they felt out of the loop later"* (Caroline, Interview, April 3, 2025; Appendix 2).

This structural dynamic directly corresponds with the Organizational Context dimension of the Technology–Organization–Environment (TOE) framework by Tornatzky & Fleischer (1990). TOE highlights how internal organizational structures and processes influence technology adoption. Departmental silos are a prime example of structural fragmentation that weakens coordination, slows knowledge flow, and fosters resistance. From our analytical standpoint, the emergence of this code reflects a deeper governance gap in how change was managed. In SMEs, where roles are often blurred and resources limited, excluding a department—intentionally or not—has not appropriate consequences. In this light, we interpret our case not as a deliberate exclusion but as a lack of structural planning for inclusion. Involving end-users like HR earlier could have ensured the tool's features aligned with practical needs and values. This further supports our view that successful AI adoption is not just technical or strategic, but deeply relational. Without intentional integration of all stakeholder groups, even well-intentioned initiatives risk being perceived as imposed, irrelevant, or misaligned.

Despite these constraints, the organization did not remain stagnant—instead, it pursued several adaptive strategies that enabled progress under pressure, which we explore in the next section.

4.3.2 Phased Adoption Strategies

Despite constraints, The Company adopted AI through gradual strategies:

Task Segmentation captured how breaking work into smaller, manageable components eased AI adoption. This deliberate unpacking of complex workflows allowed employees to experiment with AI in low-risk, focused ways. Rather than confronting the full system at once, staff engaged with it gradually, building comfort and confidence through stepwise exposure.

> *"I broke their daily tasks into smaller ones, and in the end, it showed them how AI could help step by step"* (Payam, Interview, March 10, 2025; Appendix 2).

This practical approach resonates strongly with two dimensions of Rogers' Diffusion of Innovation (DOI) theory—complexity and trialability (Rogers, 2003). Rogers suggests that the perceived complexity of a new tool can prevent adoption, but when users are given a chance to trial it incrementally, their willingness to adopt increases. Task segmentation reduces cognitive overload by minimizing the initial learning curve. It also enhances trialability by creating testable interactions with the tool. Through our lens, Task Segmentation represents a strategically simple but psychologically powerful approach to change. In SMEs, where employees juggle multiple responsibilities and formal onboarding may be minimal, large-scale shifts often feel disruptive. In contrast, introducing AI in bite-sized pieces reframes it as an enabler rather than an obstacle. Therefore, we interpret this technique not just as a practical method, but as a confidence-building tool—one that respects employees' learning pace and preserves their sense of control.

Building upon this gradual engagement, the organization also implemented targeted trials that allowed staff to explore AI in controlled, low-risk environments. Pilot Testing captured how structured experimentation with AI helped reduce uncertainty and build confidence among staff. By isolating AI use to a low-risk task, the team created a safe space for experimentation, learning, and feedback. This reduced the perceived risk of failure and allowed employees to interact with the tool without fear of making irreversible mistakes.

> *"We launched a trial where junior consultants tested AI tools on a small project*(John, Interview, March 17, 2025; Appendix 2) *"We tried it on small tasks first before rolling out fully."* (Alex, Interview, April 3, 2025; Appendix 2)

This strategic choice aligns clearly with Rogers' Diffusion of Innovation (DOI) theory, specifically the attribute of trialability (Rogers, 2003). Trialability refers to the degree to which an innovation can be tested or experimented with before full-scale implementation. Rogers argues that when users are allowed to "try before they commit," their adoption likelihood increases because direct experience reduces ambiguity. From our vantage point, Pilot Testing was a pivotal strategy in overcoming initial resistance. In contrast to top-down mandates or abstract rollouts, this grassroots approach invited participation and framed AI as something to explore—not something to fear. Thus, we interpret pilot testing not only builds user confidence, but it also generates internal success stories that can catalyze wider adoption.

Reinforcing this learning-by-doing approach, adoption was further driven by peer influence—an organic, relational force that helped bridge the gap between skepticism and action. The Peer-Led Demonstration highlighted how peer modeling encouraged adoption. These moments of peer-led influence functioned as informal training, helping bridge the gap between doubt and experimentation through trust-based internal advocacy.

> *"As Senior Marketing Consultant Alex shared, and our observation further confirmed, once IT staff successfully demonstrated AI use, HR consultants began to follow suit"* (Observation, April 8, 2025; Appendix 2).
> *"Payam showed me how AI could draft a newsletter, which convinced me to try it"* (Workshop, April 5, 2025; Appendix 2).

This behavior is well explained by two elements of Rogers' Diffusion of Innovation (DOI) theory—observability and social influence (Rogers, 2003). Observability refers to how visible the outcomes of innovation are to others; when employees see AI being used effectively by peers, it validates the technology's usefulness. Additionally, Rogers emphasizes the power of interpersonal networks in shaping adoption decisions. From our perspective, Peer-Led Demonstration proved to be a low-cost but high-impact catalyst for adoption, especially in a resource-constrained SME setting. Unlike formal training, peer demonstrations offer contextualized, role-relevant examples that feel more attainable and trustworthy. Therefore, we interpret this as a powerful strategy to normalize AI use organically. When someone like Payam takes the lead, it not only transfers knowledge but also builds social permission to try.

Alongside peer modeling, personalized coaching emerged as another form of relational support that empowered hesitant users to participate in the change. Coaching Support captured how personalized guidance helped bridge the skills gap during AI adoption. Rather than relying on formal instruction, this hands-on, peer-based coaching created an immediate support mechanism for employees who were hesitant or unsure how to use the new tools.

> *"I trained them one-on-one whenever someone struggled" (Payam, Interview, March 10, 2025;* Appendix 2).
> *"Payam sat with us and showed us how to use it step by step."* (Observation, April 8, 2025; Appendix 2).

This behavior aligns closely with Kotter's Change Management Model, specifically Step 5: Empower Others to Act on the Vision (Kotter, 1996). Kotter emphasizes that after a vision is communicated, organizations must remove barriers, including skill gaps—that prevent employees from acting. One effective method is through targeted training and support systems. Coaching, in this context, functioned as an empowerment tool: it not only transferred knowledge but also built confidence. In our view, Coaching Support represents a highly adaptive and context-appropriate strategy for SMEs navigating digital change. It reflects relational learning, where trust and familiarity between colleagues make the transfer of complex knowledge more accessible. As such, we interpret this as a key cultural enabler—especially in flat organizations—where traditional training may be too formal, time-consuming, or disconnected from real tasks. Coaching doesn't just fill knowledge gaps; it fosters ownership and inclusion.

Together, these adaptive strategies not only facilitated progress under constrained conditions but also created a foundation for cultural momentum around AI use.

However, it also reveals that individual initiative and cultural dynamics can spark resilience, particularly through the emergence of informal leadership. Informal Champions- An abductive refinement,- emerged through workshop observations where individuals like Payam drove AI adoption through enthusiasm and initiative. This dimension illustrated how informal, peer-led leadership created momentum in a setting where formal structures had not yet taken hold, rather than waiting for top-down direction. As noted during one session, Payam's live demonstration of an AI tool prompted a junior consultant to suggest:

> *"What really helped was when someone from IT—I think it was Payam—started working with us... Doing those small tasks made me see how the AI could help without feeling overwhelmed. It wasn't really a leadership strategy—it was more Payam taking the initiative."* (Sara, Interview, March 14, 2025; Appendix 2).

This behavior strongly reflects Karl Weick's (1995) Sensemaking theory, particularly the concept of bottom-up leadership in ambiguous environments. Weick argues that in loosely structured or uncertain settings—such as SMEs undergoing digital transformation—meaning and action often emerge from localized rather than formal plans. Informal champions help others "make sense" of change by showing how tools work in practice, thereby reducing uncertainty and building collective confidence. From our perspective, Informal Champions were essential in bridging the gap between intention and behavior. In an SME context, where hierarchy is flatter and formal training is limited, enthusiastic individuals become cultural carriers of innovation. Thus, we interpret this dynamic as a powerful, underutilized resource in change management. Unlike formal leadership, informal champions gain trust not from authority, but from credibility and proximity.

This insight completes our understanding of the Middle Layer by connecting adaptive behavior with cultural leadership, showing how resilience emerged not only from strategy, but from people.

Final Insight, Middle Layer:

Baes on theory and data revealed two central dynamics shaping AI adoption: organizational constraints and phased adoption strategies. The first theme, Organizational Constraints, showed how limited resources and departmental silos created structural barriers to implementation. Financial scarcity and lack of technical know-how (Barney, 1991) restricted what was possible, while fragmented communication between departments (Tornatzky & Fleischer, 1990) hindered cohesion. Together, these factors formed a brittle foundation for innovation. In contrast to these limitations, the second theme, Phased Adoption Strategies, illuminated how bottom-up, adaptive behaviors supported incremental progress. Techniques such as task segmentation, pilot testing, peer-led demonstrations, and coaching (Rogers, 2003; Kotter, 1996) helped reduce perceived risk, build confidence, and localize learning. The Middle Layer illustrates how structural limitations constrained adoption.

From the Lense of Deductive, the Middle Layer revealed how organizational constraints, notably resource scarcity and departmental silos, limited AI adoption by undermining capacity and cross-functional alignment. In response, employees developed phased adoption strategies such as task segmentation, pilot testing, peer-led demonstrations, and coaching to ease integration and build confidence. However, through abductive analysis, a deeper enabler emerged: Informal Champions. These individuals, like Payam, catalyzed change from the ground up by modeling use, shaping meaning, and inspiring action.
As these structural and cultural enablers laid the groundwork for wider engagement, the Outer Layer reveals what happens when experimentation evolves into sustained success.

4.4 Outer Layer: Achieving Sustained AI Success (RQ3)

The Outer Layer addresses RQ3 by exploring long-term outcomes, focusing on Long-Term Benefits and Resilience. The storyline depicts a transition from resistance to routine AI use, driven by learning, but tempered by stagnation risks.

Table 4.3 Coding for the Outer Layer

Theme	Code of Outer Layer	Description	Connection to Framework
	Efficiency Gains	AI improved workflow speed and quality.	Resource-Based View (Barney, 1991)
	Competitive Edge	Faster AI-supported output enhanced client responsiveness.	Resource-Based View (Barney, 1991)
	Sustained Integration	AI became embedded in daily routines and reporting processes.	Organizational Learning / Institutionalization
Long-Term Benefits and Resilience	Continuous Improvement	Iterative adjustments kept AI effective over time.	Dynamic Capabilities (Teece et al., 1997)
	Shared Purpose	Unified commitment toward common goals and values.	Change Management (Kotter, 1996)
	External Pressures	Client expectations and market demands sustained AI use.	TOE – Environmental Context (Tornatzky & Fleischer, 1990)
	Experiential Learning	Learning through reflection on hands-on experiences.	Experiential Learning (Kolb, 1984)

We begin with the most visible indicator of progress—efficiency—before turning to deeper markers of organizational and cultural transformation. Efficiency Gains captured how AI enhanced workflow speed and quality across teams. These statements reflected a shift from tentative experimentation to tangible operational benefit, especially as AI tools began handling repetitive tasks and accelerating decision-making.

> *"AI-generated insights improved efficiency in our workflow"* (John, Interview, March 17, 2025; Appendix 2) *"It's made us faster without sacrificing quality"* (Alex, Interview, April 3, 2025; Appendix 2) *"It's made us faster without sacrificing quality"* (Alex, Interview, April 3, 2025; Appendix 2).

This positive outcome aligns with the Resource-Based View (RBV) of the firm (Barney, 1991), which argues that sustained competitive advantage comes from the strategic use of internal resources that are valuable, rare, inimitable, and non-substitutable. In this context, AI tools—when embedded effectively—became performance-enhancing assets. They improved internal capabilities by enabling faster processing and higher-quality outputs without proportionally increasing costs or effort. From our point of view, these gains signal a turning point in the adoption journey. They reflect not just technical effectiveness, but behavioral integration—where the tool is no longer treated as experimental, but as routine and beneficial. Accordingly, we interpret this dimension as a validation of AI's value only when it becomes embedded in context-specific tasks, not as a generic tool.

Leveraging these operational improvements, AI adoption also began to yield strategic advantages visible to external stakeholders. Competitive Edge emerged through comments highlighting how AI-enhanced responsiveness improved the firm's market positioning.

> *"Our responses to clients are faster than before—that sets us apart"* (Alex, Interview, April 3, 2025; Appendix 2).
> *"It's given us a competitive edge with AI-driven insights for clients"* (Edvard, Interview, April 2, 2025; Appendix 2).

This observation aligns with the Resource-Based View (RBV) of the firm (Barney, 1991), which emphasizes that organizations gain sustained competitive advantage by leveraging internal resources that are valuable, rare, inimitable, and non-substitutable. From the lens of RBV, when such capabilities are embedded and hard to replicate, they differentiate the firm and enhance its resilience in dynamic environments. From our perspective, Competitive Edge signifies a more outward-facing benefit of adoption—where AI's value becomes visible to clients, not just internal teams. Therefore, we interpret this dimension as evidence that AI adoption, when successful, scales from internal efficiency to external advantage. However, true success lies not only in performance gains, but in embedding these gains into the organization's fabric—making AI use part of everyday routines.

> Sustained Integration reflected how AI transitioned from an experimental tool to an embedded part of daily operations.
> *"We now rely on AI for reporting—it's part of the routine"* (Payam, Interview, March 10, 2025; Appendix 2)*, and this was confirmed by consistent usage observed during fieldwork* (Observation, April 8, 2025; Appendix 2).
> *"It's become a co-pilot in my daily work, not an experiment anymore."* (Alex, Interview, April 3, 2025; Appendix 2).

This evolution aligns with concepts from Organizational Learning and Institutionalization theories, which emphasize that true change occurs when new practices are routinized and embedded in organizational norms. Institutionalization marks the shift from individual adoption to collective behavioral change, indicating the organization has absorbed the innovation into its operating DNA. From our perspective, Sustained Integration represents a critical indicator of long-term adoption success. It shows that AI use has moved beyond early champions or specific initiatives and become part of how work gets done. In this sense, we interpret this not just as a technical outcome but as a cultural milestone: when a tool becomes routine, it no longer represents "change”it represents how things are done here, which is the ultimate goal of meaningful digital transformation.

This normalization of use created the conditions for another important development: a shift toward continuous refinement and proactive learning. Continuous Improvement reflected how the organization kept moving forward by continually improving its AI systems, as mentioned in the interview:

> *“When AI tools didn’t work as expected, management refined the algorithm rather than discarding the initiative”* (John, Interview, March 17, 2025; Appendix 2).

This response demonstrated a commitment to learning and adaptation, signaling a resilient approach to implementation challenges. This behavior is well captured by the principles of the Dynamic Capabilities framework (Teece et al., 1997), which emphasizes an organization’s ability to integrate, build, and reconfigure internal competencies in response to a changing environment. Rather than seeing failure as a stopping point, the team used it as a feedback loop to refine their tools and improve performance. From our perspective, Continuous Improvement signals the shift from reactive to proactive learning. In this way, this dimension reveals a cultural turning point: AI adoption was no longer a trial, but a process to be smoothed and sustained. Accompanying this cultural learning process was a deepening sense of shared meaning, as team members began to align around a common purpose.

Shared Purpose reflected a unifying sense of direction that supported sustained AI engagement. Through interviews and workshop discussions, several team members referenced a collective belief that AI could:

> *“It fostered a shared purpose—everyone was on the same page that we want to make AI work for us.”* (Workshop, April 5, 2025; Appendix 2).
> *“Let’s define success metrics like faster placement of candidates, so we know if it’s working.”* (Workshop, April 5, 2025; Appendix 2).

This dimension clearly aligns with Kotter’s Change Management Model, specifically Step 3: Develop a Vision and Strategy (Kotter, 1996). Kotter emphasizes that a shared vision is essential to drive alignment and voluntary engagement during change. When people understand not just what is changing but why, they are more likely to internalize and support the transformation.

From our perspective, Shared Purpose represents a powerful cultural shift. As such, we interpret this dimension as evidence that the alignment of values and vision can foster intrinsic motivation. Shared purpose bridges the gap between organizational intent and individual action, turning AI from a task into a cause, and reinforcing the emotional commitment needed for long-term success.

As internal motivation increased, external pressures also grew, highlighting the role of outside expectations in driving adoption. External Pressures revealed how client expectations played a critical role in sustaining AI adoption. Alex explained,

> *"In our SME, much of what drives internal adoption is client demand. If clients expect smarter insights or faster turnarounds, we adopt."* (Alex, Interview, April 3, 2025; Appendix 2).

. This dimension aligns with the Technology–Organization–Environment (TOE) framework, specifically the Environmental Context dimension (Tornatzky & Fleischer, 1990), which emphasizes how external pressures such as customer demands, industry trends, and competitive forces shape technology adoption. As TOE suggests, even in resource-constrained settings, strong environmental forces can accelerate adoption by creating a sense of urgency that internal dynamics alone might not produce. From our perspective, External Pressures highlight how AI adoption was not purely strategic—it was reactive and relational. Therefore, we interpret this dimension as a reminder that adoption is often pulled by the market as much as it is pushed by leadership. Together, these forces—both internal and external—paint a picture of a firm transitioning from experimentation to maturity in its AI journey.

In sum, The Outer Layer deductively revealed that sustained AI adoption in the SME was driven by a combination of tangible performance outcomes and strategic alignment. Efficiency gains and competitive edge demonstrated clear improvements in workflow and market responsiveness, consistent with the Resource-Based View (Barney, 1991). Sustained integration showed that AI had become routine, while continuous improvement reflected the firm's ability to adapt and refine tools over time (Teece et al., 1997). Additionally, a shared purpose emerged as a unifying vision that motivated engagement across teams (Kotter, 1996), and external pressures—particularly client expectations—reinforced the urgency and value of continued use (Tornatzky & Fleischer, 1990). Together, these factors illustrate that long-term adoption success depended not just on functional benefits, but on the convergence of organizational commitment, learning, and environmental alignment.

Beneath these outcomes was a deeper cultural shift—employees became active participants, not just users, in shaping how AI was used. An abductive refinement, Experiential Learning emerged from a *workshop where employees collectively proposed:*

> *"Yes, the company launched a trial where junior consultants tested AI-powered data analysis tools. This trial phase gave us a chance to experiment without pressure."* (John, Interview, March 17, 2025; Appendix 2).

This observation aligns with Kolb's Experiential Learning Theory (1984), which emphasizes learning as a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation. In our case, employees were not just following instructions; they were shaping the innovation process by testing, evaluating, and iteratively adjusting their use of AI. Kolb's model suggests that such learner-led adaptation fosters deeper engagement and long-term retention of new practices, especially when change is smooth and context-specific. From our perspective, Experiential Learning marks a critical evolution in the adoption journey: employees became not just users, but co-creators of innovation success. In this sense, employees weren't just adapting to AI—they were shaping its trajectory, embedding learning into culture and practice.

This cultural shift provides a powerful lens through which to interpret the broader patterns revealed in the Outer Layer.

Final Insight, Outer Layer:

The Outer Layer deductively revealed that sustained AI adoption in the SME was driven by a combination of tangible performance outcomes and strategic alignment. Efficiency gains and competitive edge demonstrated clear improvements in workflow and market responsiveness, consistent with the Resource-Based View (Barney, 1991). Sustained integration showed that AI had become routine, while continuous improvement reflected the firm's ability to adapt and refine tools over time (Teece et al., 1997). Additionally, a shared purpose emerged as a unifying vision that motivated engagement across teams (Kotter, 1996), and external pressures—particularly client expectations—reinforced the urgency and value of continued use (Tornatzky & Fleischer, 1990). These outcomes reflected a maturing system shaped by both internal learning and external demands. However, through abductive analysis, the emergence of experiential learning refined this view, highlighting how employees actively shaped AI use through trial, feedback, and co-created metrics.

Chapter 5: Theoretical Discussion

5.1 Introduction

In Chapter 4, we presented the empirical findings from our case study of a small Swedish IT consultancy, organized according to the three layers of the SAARM model: resistance, adaptation, and resilience. The thematic analysis revealed how various barriers to AI adoption emerged, how employees and leaders responded through adaptive strategies, and how early signs of resilience began to take shape. These findings provided both validation and refinement of the SAARM framework based on real-world evidence. In Chapter 5, we move into a deeper theoretical discussion. Here, we interpret the findings in light of existing literature and examine how the different layers of SAARM interact with one another. We also highlight the model's theoretical contributions and suggest refinements based on the observed feedback loops, informal agency, and contextual dynamics.

5.2 Layer Interactions and Connections

In this section we analyze how SAARM's layers interact—that is, how Inner-Layer barriers, Middle-Layer processes, and Outer-Layer outcomes influence one another. Rather than treating each layer in isolation, we consider the dynamic linkages uncovered by the empirical data and by related theory.

5.2.1 Inner–Middle Interactions

RQ1: How can SAARM reduce resistance and address the reluctance–resistance cycle in a Swedish IT consultancy SME?

The Inner–Middle interaction is critical, revealing a bidirectional feedback loop where leadership hesitation amplifies employee resistance, and vice versa. Deductively, the Inner Layer's cognitive, emotional, and behavioral resistances such as fear of job replacement, mistrust in AI perceived complexity and perceived irrelevance (Section 4.1)—aligns with DOI's complexity and perceived risk (Rogers, 2003) and Change Management's fear of change (Kotter, 1996). For instance, junior consultant Sara expressed, *"I was scared that if I used the AI and it worked well, it might prove I'm not needed"* (Sara, Interview, March 14, 2025; Appendix 2). This fear was intensified by Middle Layer barriers, notably the CEO's skepticism. The CEO, stated, *"When I saw the cost, I started waffling on pushing the AI project"* (Edvard, Interview, April 2, 2025; Appendix 2), which Sara echoed: *"They [management] weren't sure if this is worth it, which made us unsure too*" (Sara, Interview, March 14, 2025; Appendix 2). This reluctance–resistance cycle, where managerial caution fuels employee skepticism, exemplifies Senge's (1990) reinforcing feedback loops and aligns with Mikalef & Gupta's (2021) findings on SME cultural rigidity.

Middle Layer strategies disrupted this cycle. Transparent communication and peer-led demonstrations, such as Payam's workshop showing AI's practical benefits, reduced perceived complexity. A participant noted, *"Payam showed me how AI could draft a newsletter, which convinced me to try it"* (Alex, Interview, April 3, 2025; Appendix 2). These align with Kotter's (1996) short-term wins and DOI's observability. Conversely, Inner Layer resistance shaped Middle Layer priorities. Persistent distrust, like *"How can a system really understand what a company needs?"* (Sara, Interview, March 14, 2025; Appendix 2), prompted investments in coaching and informal champions, with Payam training colleague's one-on-one: "I trained them one-on-one whenever someone struggled" (Interview, March 10, 2025; Appendix B). These adaptive responses reflect Dynamic Capabilities' sensing and seizing (Teece et al., 1997).

Based on abductive refinement Passive disengagement emerged as a resistance form, where employees avoided AI without overt opposition, e.g., *"I wasn't against AI but... I wasn't sure if it applied to my role"* (Caroline, Interview, April 3, 2025; Appendix 2). This refines SAARM's resistance dynamics, aligning with Meyer & Allen's (1991) low commitment in SMEs, and addresses the resistance dynamics gap by highlighting SME-specific cycles absent in large-firm studies (Badghish & Soomro, 2024).

In summary, Inner Layer fears and Middle Layer leadership hesitation create a reinforcing loop, but strategies like peer mentoring and clear communication mitigate resistance, while employee concerns drive adaptive Middle Layer responses, illustrating a bidirectional dynamic.

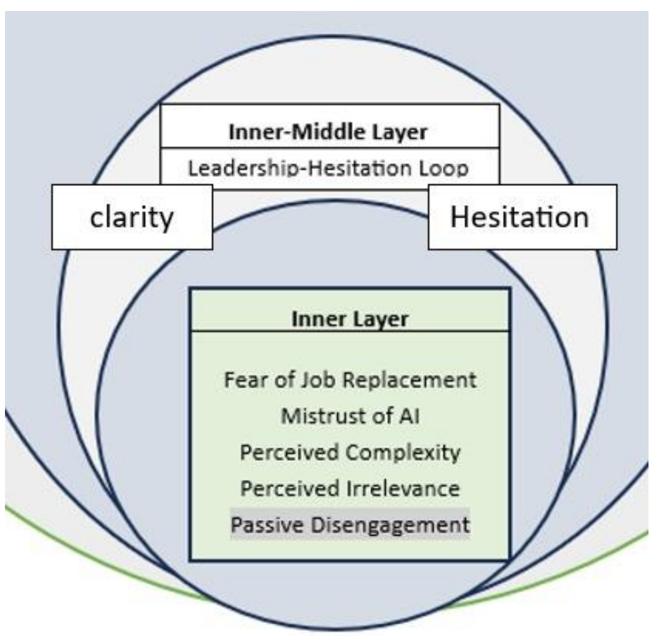


Figure 5.1 Inner-Middle Layer

5.2.2 Middle–Outer Interactions

RQ2: How does SAARM use strategies to overcome barriers and support adaptability in an SME?

The Middle–Outer interaction emphasis how adaptive strategies foster long-term resilience. Deductively, Middle Layer phased adoption strategies—task segmentation, pilot testing, peer led demonstration and coaching support —overcame barriers like resource constraints and departmental silos (Section 4.2), aligning with Dynamic Capabilities (Teece et al., 1997) and DOI's trialability (Rogers, 2003). For example, Payam's task segmentation approach, "*I broke their daily tasks into smaller ones, and in the end, it showed them how AI could help step by step" (Interview, March 10, 2025; Appendix B)*, reduced complexity and enabled Outer Layer efficiency gains. John confirmed, *"AI-generated insights improved efficiency in our workflow" (Interview, March 17, 2025; Appendix B)*, supporting RBV's performance enhancement (Barney, 1991). Pilot testing further drove sustained integration, with John noting, *"We launched a trial where junior consultants tested AI tools on a small project" (Interview, March 17, 2025; Appendix B).*

External pressures reinforced Middle Layer adaptability, aligning with TOE's environmental context (Tornatzky & Fleischer, 1990). Alex stated, "*In our SME, much of what drives internal adoption is client demand. If clients expect smarter insights or faster turnarounds, we adopt"* (Alex, Interview, April 3, 2025; Appendix 2), incentivizing leadership to prioritize AI. The CEO's shift to proactive support, "*Test it on scheduling tasks first, then expand if it works"* (Edvard, Interview, April 2, 2025; Appendix 2), facilitated novel AI-enabled services, enhancing competitive edge: *"Our responses to clients are faster than before – that sets us apart" (Marketing Senior, Interview, April 3, 2025; Appendix B)*.

Based on Abductive Refinement Informal champions, like Payam, emerged as cultural enablers, driving adoption through peer modeling: *"What really helped was when someone from IT—I think it was Payam—started working with us"* (Sara, Interview, March 14, 2025; Appendix 2). This aligns with Weick's (1995) sensemaking, addressing the change management gap by offering SME-tailored leadership solutions. Continuous experimentation, balancing exploration (pilot testing) and exploitation (routine use), supported resilience, reflecting O'Reilly & Tushman's (2013) ambidexterity.

These findings highlight how Middle Layer strategies and external pressures lay the groundwork for Outer Layer resilience, with informal leadership amplifying adaptability in resource-constrained SMEs.

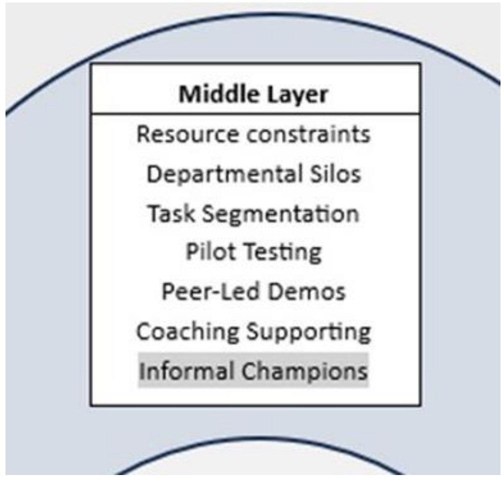


Figure 5.2 Middle Layer

5.2.3 Inner–Outer Interactions

RQ3: How does SAARM help an SME achieve lasting success by building resilience?

Inner–Outer interactions reveal direct links between individual psychological shifts and long-term resilience, bypassing Middle Layer mediation in some cases, refining SAARM's original structure. Deductively, Inner Layer emotional empowerment drove Outer Layer sustained integration. For instance, a marketing senior noted, *"It's become a co-pilot in my daily work, not an experiment anymore" (Interview, April 3, 2025; Appendix B)*, after feeling valued by clients, aligning with Stefanova's (2023) emphasis on trust-building in SMEs. This intrinsic motivation, sparked by time savings and client feedback, fostered consistent AI engagement: "*Noticed continued AI use without prompting by several staff"* (Observation, April 8, 2025; Appendix 2).

Conversely, unresolved Inner Layer resistance hinders resilience. A junior consultant's persistent avoidance, *"I wasn't sure if it applied to my role"* (Caroline, Interview, April 3, 2025; Appendix 2), despite training, reflected fear of replacement. This supports Li et al.'s (2024) link between employee perceptions and SME AI adoption outcomes. The CEO's supportive stance, *"It's okay if it's not perfect yet, we'll figure it out"* (Observation, April 8, 2025; Appendix 2), mitigated some resistance but was insufficient for all, highlighting the need for emotional commitment in flat SME structures (Stefanova, 2023).

Based on abductive refinement experiential learning emerged as a resilience driver, with employees shaping AI use through trials: "The trial phase gave us a chance to experiment without pressure" *(John, Interview, March 17, 2025; Appendix 2)*. This aligns with Kolb's (1984) Experiential Learning Theory, refining SAARM's Outer Layer to emphasize user-driven adaptation. Direct Inner–Outer shortcuts, where motivation drove routine use without top-down enforcement, address the context gap, reflecting SME-specific agency in non-hierarchical settings (OECD, 2021).

Figure 5.3 Outer Layer

5.3 Refined SAARM Model

The empirical findings refine SAARM by incorporating bidirectional feedback loops, informal dynamics, and direct Inner–Outer linkages, enhancing its applicability to SMEs. Figure 5.1 presents the updated model, with abductive refinements in green.

The refined SAARM (SME AI Adoption Resilience Model) enhances the original three-layered framework by integrating empirical insights from The Company, making it a tailored guide for small businesses adopting AI. It retains the Inner Layer (employee feelings like fear of job loss, mistrust, and quiet resistance, e.g., *"I wasn't against AI but... I wasn't sure if it applied to my role,"* (Caroline, Interview, April 3, 2025; Appendix 2), the Middle Layer (company strategies such as small steps and employee leaders, e.g., *"What really helped was when someone from IT—I think it was Payam—started working with us,"* (Sara, Interview, March 14, 2025; Appendix 2), and the Outer Layer (long-term success like efficiency and learning by doing, e.g., *"The trial phase gave us a chance to experiment without pressure," (John, Interview, March 17, 2025; Appendix 2).* New additions include two-way cycles (e.g., employee-boss hesitation) and direct Inner–Outer links (e.g., confidence driving AI use), addressing small business challenges, resistance, and change needs. In conclusion, this refined SAARM, with its focus on how feelings, plans, and success connect, offers a clear, practical model for SMEs, showing how to overcome fears and resource limits to achieve lasting AI benefits, as seen in The Company's faster work and client trust, paving the way for Chapter 6's practical tips and future research.

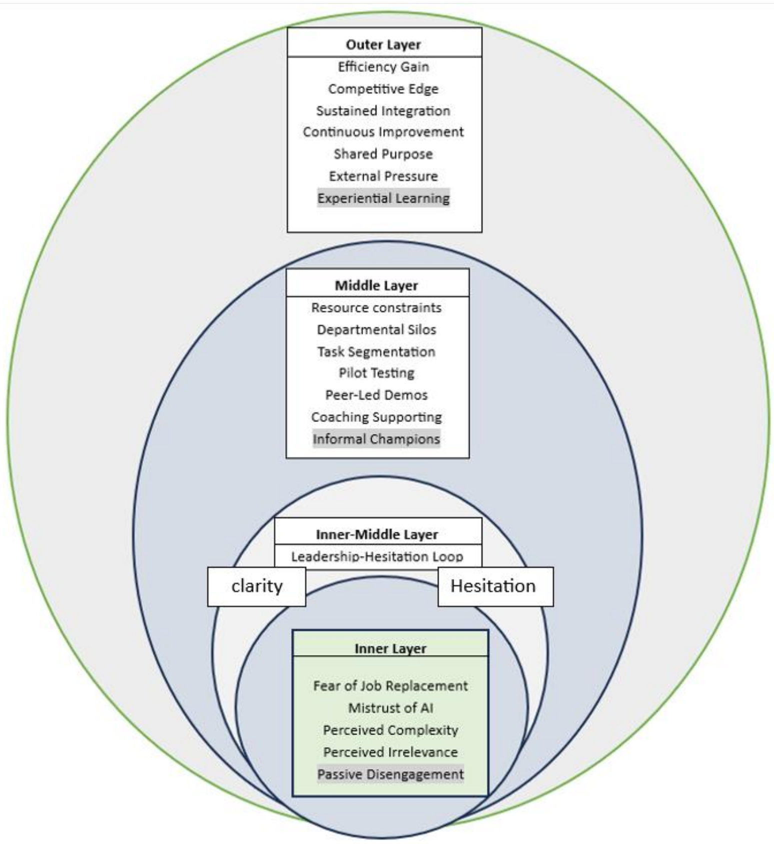


Figure 5.4 Refined SAARM Model

Chapter 6: Conclusion

6.1 Introduction

Our study concludes by summarizing the achievement of the research purpose, outlining the theoretical and practical contributions, and recommending areas for further investigation. The four elements of the discussion, the research purpose, theoretical contributions, practical contributions, and future research—are organized in accordance with Saunders et al. (2015). The study connects empirical findings to the research gaps of context, resistance dynamics, and change management noted in Chapter 1 (Section 1.3) and is based on the enhanced SME AI Adoption Resilience Model (SAARM) presented in Chapters 4 and 5. As a tailored framework for resource-constrained situations, SAARM also addresses the practical challenges small and medium-sized enterprises (SMEs) face while utilizing artificial intelligence (AI). Our research contributes to the body of knowledge by integrating deductive confirmation of existing the study presents hypotheses that incorporate abductive changes based on empirical data and offers practical strategies for the adoption of AI by SMEs.

6.2 Answer to the Research Purpose

The objective of our research was to create and test an integrated model, the SME AI Adoption Resilience Model (SAARM), experimentally solve resource scarcity and SMEs' resistance to adopting AI while building resilience for sustained competitive advantage. Our investigation, which was carried out at a small Swedish IT Consultancy company, from January to May 2025, used a qualitative, single-case study approach. We investigated the dynamics of AI adoption through on-site observation, an online workshop, and semi-structured interviews. The three layers of SAARM, Inner, which focuses on adoption barriers and drivers; Middle, which emphasizes dynamic capabilities for adaptability; and Outer, which targets resilience for sustainable AI adoption, were tested using an interpretivist paradigm, which was guided by a deductive-abductive methodology as described by Dubois and Gadde (2002). The model was then refined based on emergent insights.

The results presented in Chapter 4 and summarized in Chapter 5 demonstrate that SAARM can effectively capture the complexity of AI adoption in SMEs. The Inner Layer exposed behavioral, cognitive, and emotional barriers, as demonstrated by workers' concerns about losing their jobs. For example, one employee wrote, "I was scared... it might prove I'm not needed," which reflects their skepticism about the dependability of AI, as shown by their queries about "How can a system really understand…?" Clear outcomes, such as less time spent writing reports and peer-led demonstrations helped to lessen these obstacles (Chapter 4, Table 4.2). A senior consultant made the following remark, which supports the Middle Layer's identification of organizational barriers: "When managers began to hesitate, so employees thought, 'Why should I be?'" and limitations on resources, including scarce financial resources. Adaptable tactics, such as informal champions and pilot testing, helped overcome these difficulties, with Payam's coaching serving as an example (Chapter 4, Table 4.2). Driven by continuous improvement and external pressures like client demands, the Outer Layer showed resilience outcomes, such as sustained AI integration (one employee referred to AI as “a co-pilot, not an experiment) and competitive advantages (Chapter 4, Table 4.3), such as faster client responses.

The applicability of SAARM was enhanced by cross-layer interactions, especially in the reluctance-resistance feedback loop, where employee resistance was increased by leadership mistrust, further set hesitancy (Chapter 5; Section 5.2; Senge, 1990). Direct Inner-Outer links highlighted the role of individual agency in resilience, such as psychological changes brought about by successful AI use encouraging long-term adoption According to these results, SAARM can overcome organizational obstacles through iterative strategies like task segmentation, reduce resistance through peer influence and obvious benefits, and achieve long-term success through routinization and competitive advantage (Chapter 4, Sections 4.1–4.3). These findings also addressed the research questions outlined in Section 2.2. By offering a theoretically supported, empirically validated framework specifically designed for SMEs, the modified SAARM—which is illustrated in Figure 5.1—fulfills the research goal by integrating feedback loops, informal agency, experiential learning, and external pressures. Our research addresses the theoretical gaps and practical issues of low AI adoption, providing resource-constrained businesses with a systematic method for integrating AI in a sustainable manner (OECD, 2021; Mikalef & Gupta, 2021).

6.3 Theoretical Contributions

This study makes a meaningful theoretical contribution by addressing three key gaps in the literature on AI adoption in small and medium-sized enterprises (SMEs): the context gap, resistance dynamics gap, and change management gap. Through the development and empirical validation of the SME AI Adoption Resilience Model (SAARM), the study offers a new understanding of how small firms adopt AI under constraints.

First, the SAARM model addresses the context gap by offering a framework specifically designed for SMEs. Most existing models—such as the Technology-Organization-Environment (TOE) framework or the Resource-Based View (RBV)—are based on large firms with formal resources and structures. In contrast, SMEs typically operate with limited budgets, fewer technical staff, and informal decision-making. SAARM reflects this reality by integrating external pressures (like client demands) and internal challenges (like lack of expertise), showing how small firms adopt AI not through a top-down strategy, but through flexibility, experimentation, and external collaboration. This makes SAARM a context-sensitive model that better explains technology adoption in smaller, resource-constrained environments.

Second, SAARM contributes to the resistance dynamics gap by revealing that resistance in SMEs is often not direct opposition but dynamic, social, and cyclical. Instead of viewing resistance as a fixed barrier, the model introduces the reluctance–resistance feedback loop, where unclear signals from leadership cause hesitation among employees, which in turn reinforces leadership doubt. This mutual uncertainty can hinder the adoption process. In addition, the study identifies new forms of resistance often overlooked by traditional models, such as *passive disengagement*—where employees simply disconnect from the process. One HR employee, for example, said she "wasn't against AI, but… also wasn't sure if it applied to my role." These insights extend existing theories like Diffusion of Innovation (DOI) and (TOE) by adding emotional and relational dimensions, particularly relevant in SME settings.

Third, SAARM addresses the change management gap by showing how change in SMEs happens through informal and adaptive processes rather than formal programs. Classical change models often assume structured leadership and planned interventions, but SMEs rarely operate this way. This study shows that change is driven by informal champions, peer learning, and small-scale experimentation. For example, pilot projects and peer-led demonstrations helped build trust and reduce resistance in the case study. SAARM also refines Dynamic Capabilities Theory by showing how small firms build resilience through simple, iterative learning, adapting AI tools gradually and aligning them with evolving needs, rather than relying on formal systems.

Overall, SAARM is a novel and integrative framework that brings together multiple theories—DOI, TOE, RBV, Change Management, and Dynamic Capabilities— and tailors them to the SME context. By combining individual emotions, organizational behaviors, and external pressures, the model offers a more complete understanding of how SMEs navigate AI adoption. Rather than applying large-firm assumptions to small firms, SAARM captures the unique challenges and strengths of SMEs, making it a valuable theoretical tool for both researchers and practitioners studying digital transformation in smaller organizations.

6.4 Practical Contributions

Our study offers practical contributions for stakeholders identified in Chapter 1 (Section 1.1), including SME managers, employees, consultants, and policymakers, providing actionable strategies to navigate AI adoption in resource-constrained environments. SAARM translates theoretical insights into a practical roadmap, responding to SMEs' urgent need to adopt AI to remain competitive in innovative sectors like IT consulting, as emphasized by OECD (2021) and McKinsey & Company (2019).

SME managers and employees benefit from SAARM's structured approach to overcoming adoption barriers. Managers should prioritize emotionally intelligent communication to break the reluctance-resistance loop, ensuring clear messaging about AI's benefits, as observed in The Company (Goleman, 1995). Informal champions, such as Payam, who demonstrated AI's value in drafting newsletters (section 4.2.2), enhance observability and trialability, reducing resistance, as supported by Rogers (2003) and Chapter 4, Table 4.3. Employees gain from peer-led coaching and phased implementation, such as small-scale pilots, fostering trust and competence in AI use, as detailed in Chapter 4, Section 4.2. These strategies empower SMEs to leverage limited resources effectively.

For The Company, our study provides a tailored strategy. Formalizing AI processes, such as usage protocols and success metrics like faster candidate placement, ensures sustained integration, as shown in Chapter 4, Table 4.5. External partnerships, such as reliance on consultants, address resource gaps, aligning with Gulati (1998). The workshop's role in fostering shared purpose (Section 4.2.3) suggests regular collaborative sessions to maintain momentum and embed AI into routines.

IT consultants can use SAARM to create AI solutions tailored for small and medium enterprises (SMEs), focusing on affordable, step-by-step methods like pilot testing and working with vendors, as mentioned in Chapter 4, Section 4.2. These ensure compatibility with SMEs' limited infrastructure and expertise, enhancing adoption success, as supported by Gulati (1998).

Policymakers are informed by our study's call for policies supporting SME AI adoption. Subsidies for training and infrastructure upgrades address financial and technical barriers, as noted by OECD (2021). Regulatory clarity on data privacy, a significant obstacle (Sharma, 2023), can reduce hesitancy. Knowledge-sharing networks, inspired by The Company's consultant reliance, can facilitate expertise access, boosting adoption rates, as suggested by McKinsey & Company (2019). These contributions align with the practical problem of SMEs' low AI adoption, offering strategies to enhance competitiveness and resilience in dynamic markets.

6.5 Further Research

6.4 Further Research As mentioned by Saunders et al. (2015), our work suggests three avenues for future research, each with its own foundation, to build on SAARM's insights without challenging the current methods. To further SME AI adoption research, these avenues make use of SAARM's improved model, emerging themes, and outside influences. As described in Chapter 3 (Section 3.2.3), our study validated SAARM in a micro-sized IT consultancy. Future studies might examine how applicable it is to various SME industries, like manufacturing or retail, or geographical areas with different regulatory systems, like Asia or North America. According to the OECD (2021), a survey or research with several examples could explore if the elements of SAARM—the reluctance-resistance loop, experiential learning, and informal champion—are important for larger SMEs or in different cultural environments. Looking at several cases could help determine if the parts of SAARM—the reluctance-resistance loop, experiential learning, and informal champion—apply to larger SMEs or different cultures. multiple cases could investigate whether the parts of SAARM—the reluctance-resistance loop, experiential learning, and informal champion—are relevant to bigger SMEs or different cultural settings. As mentioned in Chapter 1 (Section 1.2), this would close the context gap and increase SAARM's universal relevance. It is necessary to investigate emerging themes, such as identity danger as a trigger for resistance, where AI questioned workers' professional worth (Chapter 4, Table 4.1). SAARM's Inner Layer could be enhanced by looking into how AI affects SMEs' professional identities and creating mitigation plans. According to Dimaggio & Powell (1983), a longitudinal qualitative study that tracks identity growth over time would aid in the literature on organizational behavior and help guide change management procedures, as mentioned in Chapter 5.

One employee stated that "Strong client demand… was a major motivator" Chapter 4 (Section 4.3), indicating that external pressures like client requests emerged as strong adoption drivers. The way that market, regulatory, or competitive factors influence SME AI adoption may be clarified by using an institutional theory lens, as described by DiMaggio and Powell (1983). As stated in Chapter 4, a mixed-methods approach that combines industry analysis and interviews would uncover the responsibilities of external stakeholders in resilience, extending SAARM's Outer Layer and guiding the creation of policies Chapter 4 (Section 4.3). These approaches, which are backed by the OECD (2021) and McKinsey & Company (2019), expand on the empirical and theoretical underpinnings of our work and advance our knowledge of SME AI adoption while meeting academic and practical needs.

Appendix A: Interview Guide

Introduction to Participants

We are Nasim and Sedigheh, master's students in Strategic Entrepreneurship for International Growth. Thank you for agreeing to participate in this interview as part of our thesis research. Our study explores the challenges small and medium-sized enterprises (SMEs) face in adopting Artificial Intelligence (AI), with a specific focus on understanding and overcoming resistance to AI adoption within your Swedish IT consultancy SME. We have developed a preliminary model, the SME AI Adoption Resilience Model (SAARM), which integrates theories across three layers—Inner (barriers and drivers), Middle (adaptability mechanisms), and Outer (resilience outcomes)—to guide our investigation. This interview aims to test and refine SAARM by capturing your experiences and perspectives on AI adoption.

The interview will last approximately 50-90 minutes and will be semi-structured, allowing us to explore your responses in depth while following a set of guiding questions. With your consent, we will record the session to ensure accuracy in capturing your insights, and all data will be anonymized and stored securely. Participation is voluntary, and you may withdraw at any time without consequence. Your insights are invaluable to understanding AI adoption dynamics in SMEs and will contribute to refining a model to support organizations like yours. Do you have any questions before we begin?

Ethical Considerations

Informed Consent: Participants will be provided with this introduction verbally and/or in writing, confirming their understanding and agreement to participate.

Confidentiality: All identifiable information will be anonymized, and data will be stored on encrypted devices accessible only to the research team.

Voluntary Participation: Participants are informed of their right to withdraw at any point, with no impact on their professional standing.

Interview Questions

The questions are organized into five sections, each aligned with SAARM's theoretical framework and layers, designed to elicit detailed narratives on resistance, adaptability, and resilience in AI adoption.

1. Understanding Resistance (Cognitive, Emotional, Behavioral)

Aligned with SAARM Inner Layer: DOI, TOE, Change Management

These questions explore initial perceptions and barriers to AI adoption, focusing on cognitive (understanding), emotional (feelings), and behavioral (actions) dimensions of resistance.

Can you describe your initial thoughts or feelings when AI was introduced in your organization? Were there any concerns about job security, automation, or the technology itself?

Purpose: To capture emotional and cognitive responses (e.g., fear of job loss, excitement) and link to DOI's perceived attributes (e.g., relative advantage, complexity).

How did you or your colleagues perceive the complexity or reliability of AI tools? Did any lack of understanding or mistrust influence your willingness to adopt them?

Purpose: To assess perceived complexity and trustworthiness (DOI), and organizational factors (TOE), influencing adoption intent.

Were there moments when you or others avoided using AI or resisted its implementation? What factors (e.g., fear, preference for human judgment) contributed to this?

Purpose: To identify behavioral resistance and underlying drivers (e.g., Change Management's resistance factors), grounding Inner Layer barriers.

2. Exploring the Reluctance Resistance Loop

Aligned with SAARM Inner and Middle Layers: Change Management, TOE

These questions investigate the interplay between leadership and employee resistance, reflecting SME-specific dynamics and adaptability challenges.

How did leadership's initial hesitation or caution about AI adoption affect your willingness to engage with the technology?

Purpose: To explore leadership influence on employee attitudes, linking to Change Management's urgency and TOE's organizational context.

Did you notice a cycle where leadership delays or uncertainty led to employee resistance, which then reinforced leadership caution? Can you provide an example?

Purpose: To identify iterative resistance loops, a potential refinement for SAARM's Inner Layer, with examples grounding the cycle.

What factors, such as resource constraints or small team dynamics, made this cycle more pronounced in your organization?

Purpose: To contextualize resistance within SME constraints (TOE's environment, RBV's resources), informing Middle Layer adaptability needs.

3. Leadership and Organizational Culture (TOE, RBV)

Aligned with SAARM Inner Layer: TOE, RBV

These questions examine how leadership communication and organizational culture shape resistance, focusing on SME resource and environmental factors.

How did your leaders communicate the purpose and value of AI? Did their approach influence your resistance or acceptance?

Purpose: To assess communication effectiveness (TOE's organization), linking to adoption barriers or facilitators.

What role did your organization's culture—such as openness to change or risk aversion—play in resistance to AI adoption?

Purpose: To explore cultural influences (TOE), identifying facilitators or barriers within the Inner Layer.

Given the limited resources in your SME, how did financial or skill constraints impact resistance, and how were they addressed?

Purpose: To investigate resource constraints (RBV) and mitigation strategies, grounding Inner Layer resource-based barriers.

4. Change Management Strategies (Change Management, Dynamic Capabilities)

Aligned with SAARM Middle Layer: Change Management, Dynamic Capabilities

These questions probe strategies to overcome resistance, focusing on adaptability mechanisms within the SME context.

What specific strategies or actions did leadership take to reduce resistance and encourage AI adoption? For example, were there training programs, pilot projects, or communication initiatives?

Purpose: To identify Change Management interventions (e.g., Kotter's steps), informing Middle Layer strategies.

How did short-term successes or visible results (e.g., pilot projects) influence your or your colleagues' willingness to adopt AI?

Purpose: To assess observability (DOI) and seizing (Dynamic Capabilities), linking to adaptability mechanisms.

Can you describe any iterative or adaptive approaches (e.g., testing AI in phases) that helped your organization overcome resistance over time?

Purpose: To explore iterative testing (Dynamic Capabilities' transforming), refining Middle Layer adaptability processes.

5. Resilience and Outcomes (Dynamic Capabilities, Resilience)

Aligned with SAARM Outer Layer: Dynamic Capabilities, Resilience

These questions evaluate long-term adaptation and outcomes, testing SAARM's resilience focus.

Looking back, how did your organization adapt to challenges like resistance or failed AI implementations? What enabled you to persist and succeed?

Purpose: To examine resilience strategies (Dynamic Capabilities' transforming), grounding Outer Layer persistence.

What changes in your work or the organization's processes resulted from AI adoption, and how do you feel these changes have sustained over time?

Purpose: To identify sustained process changes (Resilience), assessing Outer Layer outcomes.

Can you identify any long-term benefits or competitive advantages your SME gained from overcoming resistance and adopting AI?

Purpose: To evaluate competitive gains (Dynamic Capabilities, Resilience), validating SAARM's Outer Layer focus.

Appendix B:

Table B.1: Codes, Subthemes, and Theoretical Connections by SAARM Layer

Code	**Subtheme**	**Representative Quote (Source)**	**SAARM Layer**	**Research Question**	**Theoretical Link**
Inner Layer					
Avoidance of AI	Behavioral	“I avoided using it for a whole week.” (Sara, Interview, March 14, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (resistance behavior)
Avoidance of AI	Behavioral	“Senior consultants avoided the chatbot.” (John, Interview, March 17, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (resistance behavior)
Collective Doubt Normalization	Emotional	Workshop: “Everyone had their reservations, which made me feel it’s okay to be doubtful.” (General sentiment among participants)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (group dynamics of resistance)
Complexity Perception	Cognitive	“It seemed very complex to implement.” (Payam, Interview, March 10, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (complexity of innovation)
Complexity Perception	Cognitive	“The setup looked like a maze.” (Management/CEO, Interview, April 2, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (complexity of innovation)
Complexity Perception	Cognitive	“It felt clunky — not very intuitive for the people-centric work we do.” (Caroline, Interview, April 3, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (complexity of innovation)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Excessive Verification	Behavioral/Strategy	Observation: "Double-checked every AI output manually before trusting it." (Routine of verifying AI suggestions)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (coping strategy for low trust)
Fear of Job Replacement	Emotional	"I was scared that if I used the AI and it worked well, it might prove I'm not needed." (Sara, Interview, March 14, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (fear of change)
Hesitancy in AI Use	Behavioral	Observation: One employee delayed using the AI tool for a task, opting to do it manually until prompted by a peer.	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (initial inertia)
Irrelevance Perception	Cognitive	"They saw it as completely unrelated to HR." (Payam, Interview, March 10, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (low compatibility)
Irrelevance Perception	Cognitive	"I wasn't against AI but... I wasn't sure if it applied to my role." (Caroline, Interview, April 3, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (low compatibility)
Manual Override	Behavioral	Observation: Junior consultants manually override an AI-generated candidate match instead of accepting it.	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (low trust manifested in action)
Mistrust in AI	Cognitive	"How can a system really understand what a company needs?" (Sara, Interview, March 14, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (perceived risk/low observability)
Mistrust in AI	Cognitive	"What if AI misses a good candidate just because they didn't use the right words?" (Sara, Interview, March 14, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (perceived risk/low observability)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Passive Disengagement	Behavioral	“I wasn’t against AI but... I wasn’t sure if it applied to my role.” (Caroline, Interview, April 3, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Meyer & Allen (1991)
Preference for Human Judgment	Cognitive	“I prefer human judgment — I feel like I can understand a candidate’s potential.” (Sara, Interview, March 14, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (compatibility with existing values)
Preference for Human Judgment	Cognitive	“I’d rather trust my own brain than some machine.” (Management/CEO, Interview, April 2, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (compatibility with existing values)
Skepticism of AI Reliability	Cognitive	“What if it spits out garbage and we look bad to a client?” (Management/CEO, Interview, April 2, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (perceived risk)
Skepticism of LLM Accuracy	Cognitive	Workshop: “I’m skeptical about the LLM’s recommendations being accurate.” (Alex, Workshop, April 15, 2025)	Inner (Resistance)	RQ1 (Reduce employee resistance)	Diffusion of Innovation (uncertainty in results)
Verbalized Distrust	Behavioral	Observation: “I just don’t fully trust the algorithm,” one consultant openly admitted during use.	Inner (Resistance)	RQ1 (Reduce employee resistance)	Change Management (open resistance expression)
Middle Layer					
Coaching Support	Strategy	“Payam sat with us and showed us how to use it step by step.” (Observation note & Interviews)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (training & support; guiding coalition)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Coaching Support	Strategy	"I trained them one-on-one whenever someone struggled." (Payam, Interview, March 10, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (training & support; guiding coalition)
External Pressure	Outcome	"In our SME, much of what drives internal adoption is client demand. If clients expect smarter insights or faster turnarounds, we adopt." (Alex, Senior Marketing, Interview, April 3, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Socio-technical Integration (combining automation with human insight)
Human-in-the-Loop Checks	Strategy	Workshop: "We'll always have a human pre-screen AI output" – consensus to pair AI with human review.	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (ensuring human oversight to build trust)
Human-in-the-Loop Checks	Strategy	Observation: Indeed, AI drafts were reviewed by a person before use.	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (ensuring human oversight to build trust)
Informal Champions	Dynamic Capability	"What really helped was when someone from IT—I think it was Payam—started working with us... Doing those small tasks made me see how the AI could help without feeling overwhelmed. It wasn't really a leadership strategy—it was more Payam taking the initiative." (Sara, Junior Consultant, Interview)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Karl Weick's (1995)
Lack of Clarity in Communication	Barrier	"They just said, 'AI will make your work easier,' but didn't explain how or why." (Sara, Interview, March 14, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (importance of clear vision & communication)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Lack of Clarity in Communication	Barrier	“My shaky pitch to the team didn’t convince them initially.” (Management/CEO, Interview, April 2, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (importance of clear vision & communication)
Leadership Hesitation	Barrier	“When I saw the cost, I started waffling on pushing the AI project.” (Management/CEO, Interview, April 2, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (leadership commitment); RBV (resource investment hesitation)
Leadership Hesitation	Barrier	“They (management) weren’t sure if this is worth it, which made us unsure too.” (Sara, Interview, March 14, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (leadership commitment); RBV (resource investment hesitation)
Organizational Constraints	Barrier (Structural/Social)	“We had limited time and no formal training – it was figure it out as you go.” (General observation from multiple interviews)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	TOE Framework (Organizational context: resource & structural constraints); Change Management (incomplete stakeholder engagement)
Organizational Constraints	Barrier (Structural/Social)	“HR wasn’t part of early planning, so they felt out of the loop later.” (Caroline, Interview, April 3, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	TOE Framework (Organizational context: resource & structural constraints); Change Management (incomplete stakeholder engagement)
Peer-Influenced Adoption	Strategy	Observation: “HR started using AI after observing IT’s success with it” – one department’s use inspired another’s.	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Diffusion of Innovation (social contagion within organization)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Peer-Led Demonstration	Strategy	Workshop: “Our marketing lead changed his mind after seeing an AI-generated draft from Payam’s demo.”	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Diffusion of Innovation (observability via peer examples)
Peer-Led Demonstration	Strategy	“Payam showed me how AI could draft a newsletter, which convinced me to try it.” (Alex, Interview)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Diffusion of Innovation (observability via peer examples)
Phased Implementation	Strategy	Workshop: “Let’s test AI on a small scale, then expand gradually once we trust it.” (Group consensus during workshop)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Change Management (incremental change strategy)
Pilot Testing	Strategy	“We launched a trial where junior consultants tested AI tools on a small project.” (John, Interview, March 17, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Diffusion of Innovation (trialability); Dynamic Capabilities (experimentation)
Pilot Testing	Strategy	“We tried it on small tasks first before rolling out fully.” (Marketing Senior, Interview)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Diffusion of Innovation (trialability); Dynamic Capabilities (experimentation)
Sensing Opportunities	Dynamic Capability	“The idea of launching AI came from me noticing repetitive tasks we could automate.” (Payam, Interview, March 10, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Dynamic Capabilities (sensing opportunities for innovation)
Sensing Opportunities	Dynamic Capability	“I could see potential—automated reporting could free our time.” (Marketing Senior, Interview)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Dynamic Capabilities (sensing opportunities for innovation)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Seizing Through Testing	Dynamic Capability	"We started with a small pilot project to see results before investing more." (Interview)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Dynamic Capabilities (seizing opportunities via pilots)
Seizing Through Testing	Dynamic Capability	"Test it on scheduling tasks first, then expand if it works." (Management/CEO, Interview, April 2, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Dynamic Capabilities (seizing opportunities via pilots)
Task Segmentation	Strategy	"I broke their daily tasks into smaller ones, and in the end, it showed them how AI could help step by step." (Payam, Interview, March 10, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Dynamic Capabilities (seizing opportunities incrementally)
Visible Results	Outcome/Strategy	"Once I saw the AI could find good candidates, I felt less scared." (Sara, Interview, March 14, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Diffusion of Innovation (relative advantage demonstrated)
Visible Results	Outcome/Strategy	"It cut my report writing time by half – that was an eye-opener." (John, Interview, March 17, 2025)	Middle (Adaptability)	RQ2 (Overcome barriers & support adaptation)	Diffusion of Innovation (relative advantage demonstrated)
Outer Layer					
Collective Troubleshooting	Outcome	Observation (April 6, 2025): "Employees gathered to discuss and troubleshoot an odd AI result together" – indicating issues are addressed collaboratively, not causing abandonment of the tool.	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Organizational Learning (adaptive learning culture)

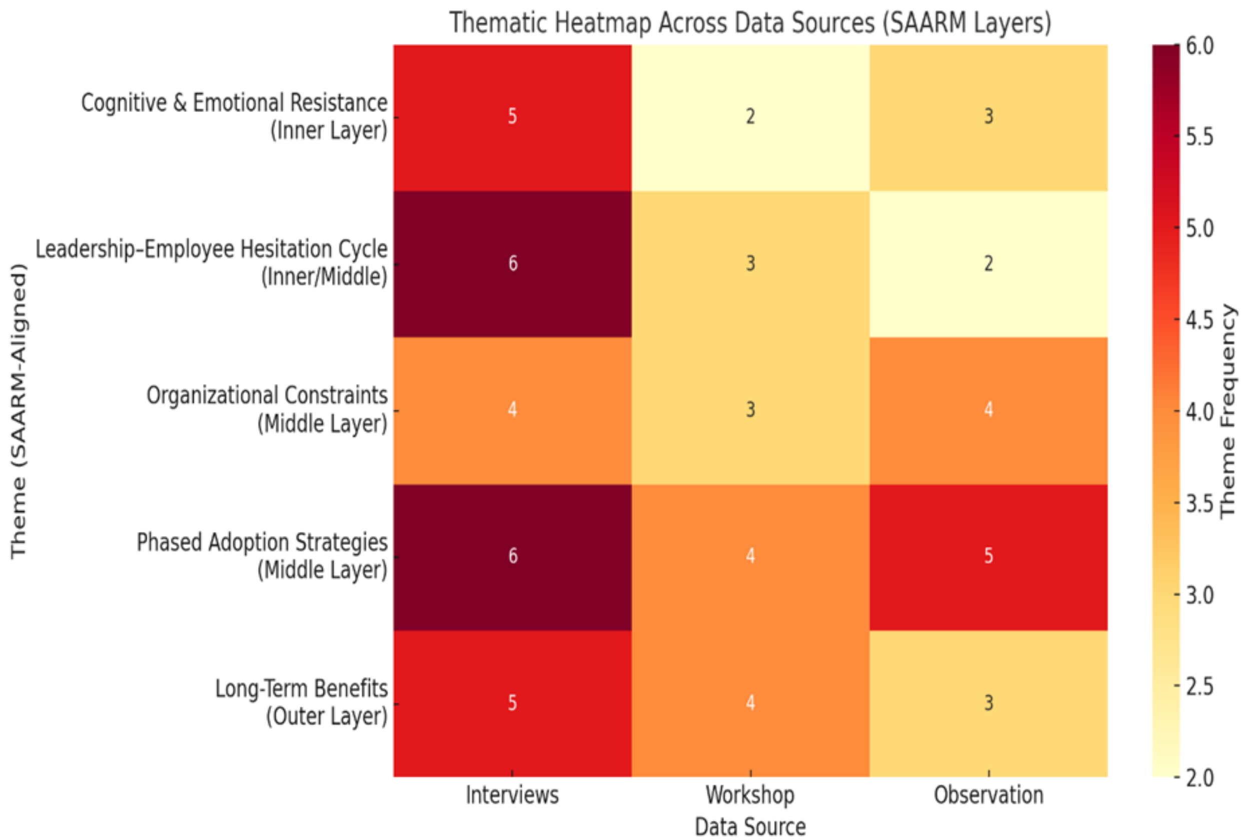
Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Competitive Edge	Outcome	"It's given us a competitive edge with AI-driven insights for clients." (Management/CEO, Interview, April 2, 2025)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Resource-Based View (competitive advantage from AI resource)
Competitive Edge	Outcome	"Our responses to clients are faster than before – that sets us apart." (Marketing Senior, Interview)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Resource-Based View (competitive advantage from AI resource)
Consistent AI Engagement	Outcome	Observation (April 5, 2025): "Noticed continued AI use without prompting by several staff by afternoon" – team members were independently using AI as part of their tasks consistently.	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Resilience (routinization and sustained engagement)
Continuous Improvement	Outcome	"When AI tools didn't work as expected, management refined the algorithm rather than discarding the initiative." (John, Interview, March 17, 2025)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (supportive culture); Organizational Resilience (trust and safety enable adaptation)
Efficiency Gains	Outcome	"It's made us faster without sacrificing quality." (Marketing Senior, Interview)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Resource-Based View (enhanced capability for performance)
Efficiency Gains	Outcome	"AI-generated insights improved efficiency in our workflow." (John, Interview, March 17, 2025)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Resource-Based View (enhanced capability for performance)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Experiential Learning	Outcome	“Yes, the company launched a trial where junior consultants tested AI-powered data analysis tools. This trial phase gave us a chance to experiment without pressure.” (John, Interview, March 17, 2025)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Kolb’s Experiential Learning Theory (1984)
Process Documentation	Outcome	“I documented all the AI usage processes, and we even got a protocol in place.” (Payam, Interview, March 10, 2025)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (institutionalization via formal procedures)
Realistic Expectations	Outcome	“We became more realistic – it’s a tool, not a magic wand. Now we use it where it helps and don’t expect miracles.” (Marketing Senior, Interview)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (refreezing stage – new norms and expectations)
Realistic Expectations	Outcome	“Our expectations evolved into something manageable and practical.” (Caroline, Interview, April 3, 2025)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (refreezing stage – new norms and expectations)
Shared Purpose	Outcome	Workshop: “It fostered a shared purpose—everyone was on the same page that we want to make AI work for us.” (General sentiment post-workshop)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (building a unified vision/culture)
Success Metrics Planning	Outcome	Workshop (April 15, 2025): “Let’s define success metrics like faster placement of candidates, so we know if it’s working.” – the team decided on KPIs to monitor AI impact.	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (reinforcement – measuring and reinforcing gains)

Code	Subtheme	Representative Quote (Source)	SAARM Layer	Research Question	Theoretical Link
Sustained Integration	Outcome	"We now rely on AI for reporting – it's part of the routine." (Payam, Interview, March 10, 2025)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (institutionalization of change in routines)
Sustained Integration	Outcome	"It's become a co-pilot in my daily work, not an experiment anymore." (Marketing Senior, Interview)	Outer (Resilience)	RQ3 (Achieve lasting success & resilience)	Change Management (institutionalization of change in routines)

Note: Codes marked with an asterisk (*) represent abductive refinements derived from data, enhancing the deductive framework of SAARM.

Appendix C:


Thematic Heatmap Across Data Sources (SAARM Layers)
Theme (SAARM-Aligned)
Cognitive & Emotional Resistance (Inner Layer)
Leadership-Employee Hesitation Cycle (Inner/Middle)
Organizational Constraints (Middle Layer)
Phased Adoption Strategies (Middle Layer)
Long-Term Benefits (Outer Layer)
Interviews
Workshop
Observation
Data Source
5
2
3
6
3
2
4
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4
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4
5
5
4
3
Theme Frequency
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0

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