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Organizational AI Readiness: Identifying Capability Gaps through a mixed-method approach using SEM

Master's thesis in Entrepreneurship and Strategy

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A mixed-methods investigation of how staff skills, infrastructure, trust, risk, top management support, and strategy alignment shape AI transformation

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An exploratory mixed-methods study of organizational AI readiness, capability gaps, and the factors that enable measurable value creation.
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SUMMARY
This thesis investigates how a large, decentralized high-tech electronics manufacturer can realize measurable business value from generative and agentic AI by developing Organizational AI Readiness (OAIR). Using an exploratory sequential mixed-methods design, we first conduct a scoping review, ten semi-structured interviews, and an executive questionnaire to identify five capability themes and case-specific gaps in skills, infrastructure, governance, and value logic. These insights inform a PLS-SEM survey study (82 respondents) that operationalizes OAIR through established constructs: Staff Skills and Competency, IT Infrastructure, Trust in Organizational AI, Perceived Risk, Top Management Support, and AI Strategy Alignment. The model shows that AI Strategy Alignment and IT Infrastructure have the strongest positive effects on OAIR, while Perceived Risk significantly undermines Trust in Organizational AI. The study contributes an empirically grounded OAIR framework.

Keywords: Artificial Intelligence (AI), AI transformation, Organizational AI Readiness, AI value realization, generative AI, agentic AI, AI governance, PLS-S

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List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
AISA	AI Strategy Alignment
AVE	Average Variance Extracted
CA	Cronbach's Alpha
CMB	Common Method Bias
CR	Composite Reliability
CFO	Chief Financial Officer
CIO	Chief Information Officer
GenAI	Generative AI
HTMT	Heterotrait-Monotrait Ratio
HR	Human Resources
IT	Information Technology
ITI	Information Technology Infrastructure
KPI	Key Performance Indicator
LLMs	Large Language Models
NLP	Natural Language Processing
OAIR	Organizational AI Readiness
PLS-SEM	Partial Least Squares Structural Equation Modeling
PR	Perceived Risk
Q^2	Predictive Relevance
RQ	Research Question
R^2	Model Explanatory Power
SEM	Structural Equation Modeling
SSC	Staff Skills and Competency
TMS	Top Management Support
TOE	Technology-Organization-Environment
TRU	Trust in Organizational AI
VIF	Variance Inflation Factor

1. Introduction

1.1 Background

A clear trend over the last five years within digital transformation research has been a pivot toward artificial intelligence (AI) as a main driver of change, instead of just one of many technologies within digital transformation (Madan & Ashok, 2023). As AI becomes more widely available, it is no longer seen only as a tool, but as a platform and ecosystem technology (Secundo et al., 2025) or as a strategic, dynamic capability that enables continuous adaptation (van de Wetering, 2026). Dynamic capabilities, defined as the ability to sense, seize, and reconfigure in rapidly changing environments (Teece, 2010), have become critical as AI drives radical transformation across core business activities, intensifying the rate at which firms must adapt (Dias & Lauretta, 2024).

For the sake of this paper, we use the definition by Dwivedi et al. (2021) stating that AI is "non-human intelligence programmed to perform specific tasks." This includes algorithms that are able to make decisions based on, and learn from, a data set, as well as workflows that activate automatically based on a predetermined trigger. Simple AI has been around for a long time, with banking firms, medicine providers, and logistics companies using decision trees and regression models (basic machine learning models); email and phone-plan providers using spam filters to remove unwanted messages; and media platforms using recommender systems to cater to individual customers' needs (Haenlein & Kaplan, 2019). More advanced AI was made popular through pop culture, with books like *I, Robot* by Isaac Asimov and *Neuromancer* by William Gibson, and movies like *2001: A Space Odyssey* and *The Terminator*. Although real-world AI has not yet reached the levels of capability depicted in these fictional worlds, ongoing research continues to push the boundaries of what AI can achieve. What has created the latest wave of excitement in the field, however, is the rapid improvement of generative and agentic models.

Generative AI, or GenAI, stands as one of the primary technological building blocks for the current research. GenAI differentiates itself from traditional AI by creating new patterns and contexts instead of merely offering users a way to recognize and analyze data (Susarla et al., 2023). While GenAI's primary focus is on generating outputs in response to user prompts, agentic AI extends these capabilities by emphasizing the performance of independent, autonomous tasks to achieve complex objectives on behalf of a user or another system without total human intervention (Pati, 2025; Sapkota et al., 2026; N. Sharma & Sikarwar, 2025).

This thesis investigates AI value realization at a high-tech electronics manufacturer, addressed as the "case company" in this report. The case company is a large, decentralized organization that has recently begun their AI adoption, with AI initiatives scattered across global divisions. Despite rapid experimentation with generative AI and agentic AI pilots, the company faces coordination challenges typical of such structures: fragmented efforts, duplicated work, inconsistent evaluation methods, and limited cross-unit learning from outcomes. This point to scaling before being ready, an issue reflected the broader industry. This pattern, where enthusiasm for AI outpaces foundational capabilities, lead many firms to invest prematurely and therefore fail to scale initiatives into measurable financial or operational value. This phenomenon is sometimes referred to as *digital magic*, where small investments are expected to yield miraculous returns in a short amount of time (Lamarre et al., 2024).

The core problem is clear: while AI tools and use cases are abundant, capability gaps such as data fragmentation (Bérubé et al., 2021; Radhakrishnan & Chattopadhyay, 2020), uneven AI competencies (Campos Zabala, 2023; Radhakrishnan & Chattopadhyay, 2020), inadequate governance (Ghosh et al., 2025), and misaligned infrastructure (Dwivedi et al., 2021; Tamburri et al., 2026), all prevent organizations from capturing sustainable business value. The main problems for companies today are no longer a lack of AI tools or use cases, but the capability gaps that hinder companies from creating value from AI tools. The infrastructure for and governance of AI technology is lagging behind due to organizational uncertainty and paralysis of action. Generic transformation roadmaps from consultancies like IBM, Gartner, McKinsey, and Google offer high-level guidance but may not address the unique demands of large, decentralized enterprises (Gartner, n.d., 2025; Google Cloud, 2024; IBM, n.d.; Lamarre et al., 2024; McKinsey & Company, 2024, 2025; Stryker & Kavlakoglu, 2024). Prior literature explains general AI adoption barriers but provides limited empirical insight into how organizations such as the case company structure initiatives for value, identify constraining gaps, or build tailored roadmaps linking capability development to outcomes.

One major goal with this report is therefore to identify what capabilities are needed within the fast-moving world of AI and help the case company realize what they are lacking by identifying their capability gaps. Consequently, and in line with the research gap identified above, while prior research has examined AI capabilities in general, there is a limited understanding empirically of how large, highly decentralized organizations structure generative and other AI initiatives for business value.

1.2 Focus and Aim

This study addresses these gaps through two sequential research questions (RQs). The two research questions build on one another, with the first one being two-parted (a & b). RQ1 aims to first of all map current AI capabilities identified from theory and advisory firms' frameworks and explore if these are present in the case copany. The second part of RQ1 aim to address what the executive team of the case company sees as business value, and how they currently aim to increase business value from their AI transformation. The first research question proposed is:

RQ1a: Which capability gaps and enablers emerge from the qualitative phase as most critical for AI value realization in the case company?

RQ1b: How does the case company evaluate and structure AI initiatives to ensure business value creation?

After establishing how the company currently structures and evaluates business value, the next step is to situate these findings within the broader scholarly and industrial context of effective AI transformation. For RQ2, these findings are compared to leading academic and industry literature on required technological and organizational capabilities for effective AI value realization, using structural equation modeling (SEM) to measure the company's maturity and identify gaps that may constrain the organization's ability to capture value from AI. The second research question proposed is therefore:

RQ2: What technological and organizational capabilities are required for effective AI value realization, and what key capability gaps constrain that realization in the case company?

The thesis delivers an empirically grounded framework of Organizational AI Readiness (OAIR) and recommended initiatives to close identified gaps at the case company. By focusing on a real-world company this work bridges theory and practice to enable measurable outcomes from AI investments.

1.3 Outline

The thesis follows a logical progression from context and theory to empirical analysis and recommendations. Chapter 1 introduces the background on AI as a transformative force, defines the case company's challenges with fragmented AI pilots, and states the research questions related to capability gaps and value realization.

Chapter 2 introduce the relevant theory from AI evolution within a disruptive environment, resorce-based view and dynamic capability theories, both with and without AI, and context for business value realization. Chapter 3 develops the constructs and hypotheses that defines Organizational AI Readiness (OAIR), that connects the variables; Staff Skills and Competency, IT Infrastructure, Trust in Organizational AI, Perceived Risk, Top Management Support, and AI Strategy Alignment; to literature. The method chosen for the thesis is a mixed-methods design combines qualitative exploration with quantitative validation for rigor, explained in chapter 4. Here, the two phases used in this study are introduced and explored in depth, where phase 1 uses thematic analysis of documents, interviews, and executive questionnaires; and phase 2 applies PLS-SEM to a survey of 82 respondents testing the conceptual model. The results from both phases are presented and analyzed in chapter 5, and qualitative themes are presented and validated by interviews, quantitative measurement and structural model results. The hypothesis are tested and evaluated. The results are further discussed in chapter 6, where the autors interpret the results and discuss implications for future research and the case company. Lastly, chapter 7 summarizes the OAIR framework and findings.

2. Theoretical Framework

This chapter presents the theoretical foundations that guide this study's understanding of AI transformation, organizational capability, and value realization. It first introduces AI as an evolving transformative technology, explores aspects of business value before outlining the main organizational theories used to explain how firms adopt, integrate, and scale AI-related change. The chapter then develops the logic linking capabilities, readiness, and business value, providing the conceptual basis for the constructs and hypotheses introduced in the following chapter.

2.1 Intelligence as a transformative technology

Artificial intelligence (AI) has been discussed in academic research for more than half a century, and the definition of the term has evolved alongside advances in computing and data availability. Since Alan Turing first proposed the idea of thinking machines in 1950 and John McCarthy coined the term "artificial intelligence" in 1956, scholars have debated what constitutes intelligence, learning, and understanding in machines (David, 2025). While parts of this literature engage in philosophical discussions about the nature of intelligence, this study adopts a pragmatic and organizationally oriented definition. For the purposes of this thesis, AI is defined as "non-human intelligence programmed to perform specific tasks" Dwivedi et al. (2021). In organizational contexts, AI systems have been used for decades in relatively narrow applications, such as decision trees and regression models in finance and healthcare, spam filtering in communication services, and recommender systems in digital platforms (Haenlein & Kaplan, 2019). These applications illustrate that AI is not a new phenomenon, but rather a technology whose scope and impact have expanded significantly over time.

2.1.1 From narrow AI to generative AI to agentic AI

The term "artificial intelligence" is a broad and frequently used in a loose or imprecise manner, especially following the rapid increase in public and organizational interest after the release of OpenAI's ChatGPT in November 2022 (He et al., 2025). In contemporary discourse, what is commonly referred to as AI often corresponds to large language models (LLMs), which are trained on extensive text datasets to understand and generate human-like language. These systems rely on natural language processing (NLP), a set of techniques that enable computers to analyze, interpret, and generate human language. Similar technologies underpin widely adopted digital assistants such as Apple's Siri and Amazon's Alexa. Despite their advanced capabilities, such systems fall under the category of narrow AI, meaning they are designed to perform specific tasks rather than exhibit general intelligence (David, 2025). The recent wave of AI adoption differs from earlier applications primarily due to the emergence of generative AI (GenAI). Unlike traditional AI systems that focus on prediction or classification, GenAI systems are capable of generating new content, patterns, and contexts rather than merely analyzing existing data (Muralimanohar, 2025; Susarla et al., 2023). GenAI is commonly defined as "a system based on a foundation model that generates digital artifacts based on natural user instructions" (He et al., 2025). These capabilities have significantly lowered the barrier for interacting with AI and expanded its potential use across organizational functions. Its ability to generate new documents, texts, and images based on user prompts has made it a great tool for many organizational use cases, and with the advancements made to the largest office system provider, Microsoft, the use of AI within organizations is rapidly increasing.

While GenAI primarily focuses on producing outputs in response to user prompts, recent research highlights the emergence of agentic AI as a further step in AI capability development (Schneider, 2025). Agentic AI systems extend generative capabilities by emphasizing autonomous goal pursuit and task execution on behalf of users or other systems, often with limited human intervention (Pati, 2025; Sapkota et al., 2026; N. Sharma

& Sikarwar, 2025). Agentic AI has been defined as a "system based on a foundation model that performs tasks potentially yielding artifacts based on natural user instructions, where the system is able to conduct and express complex reasoning including planning and reflection to solve tasks that require interaction with an environment or elaborate tool use." (Pati, 2025). Such systems are increasingly discussed in relation to organizational processes, as they shift AI from a supportive role toward more autonomous participation in workflows and decision-making.

2.1.2 AI beyond IT: enterprise capability and organizational value

In the current organizational context, AI is no longer viewed as a simple isolated project within the IT function, but rather as an integrated enterprise-wide capability that fundamentally alters how organizations function and make decisions across multiple organizational levels and functions (Hirtranusi et al., 2026). As AI systems become embedded across multiple functions, their impact extends beyond individual tasks to influence coordination, decision-making, and organizational learning. Hence, as per Jöhnk et al. (2021), the assessment of AI readiness is a key step in the process since it enables organizations to identify potential gaps proactively, reduce uncertainity, and helps in increasing the probability of successfull implementation of AI. Jöhnk et al. (2021) have stressed further that AI readiness is to be seen as not just a precursor to AI adoption but as a foundational element throughout the entire AI adoption process Despite these technological advances, research consistently shows that the adoption of AI alone does not guarantee performance improvements. Hradecky et al. (2022) demonstrate that successful AI adoption depends on organizational readiness factors such as data quality, leadership alignment, and cross-functional collaboration. Realizing value from AI therefore requires its integration into strategic frameworks and the development of complementary organizational capabilities and governance mechanisms instead of treating AI as a plug-and-play technology (Neiroukh et al., 2024). When such integration fails, organizations risk underutilizing their technological investments. This is a phenomenon commonly referred to as the digital magic, or *AI paradox*, where substantial investments in AI do not translate into proportional performance gains despite widespread adoption (Kuzmin et al., 2025). In enterprise settings, these contextual factors also determine whether AI initiatives remain isolated pilot projects or achieve scalable organizational impact (Hughes et al., 2026).

Understanding AI as an enterprise-wide capability rather than a standalone technology shifts analytical attention from adoption decisions toward the organizational processes and capabilities through which AI-enabled capabilities are developed, coordinated, and scaled. This perspective aligns with dynamic capabilities theory, which emphasizes the firm's ability to sense opportunities, seize them through coordinated action, and reconfigure resources in response to technological change (Teece, 2010; van de Wetering, 2026). From this viewpoint, AI does not create value independently, but rather through the organizational capabilities that enable its effective deployment and integration over time.

This perspective reflects a broader socio-technical and complementarity logic, in which the value of advanced technologies depends on their alignment with organizational structures, routines, skills, and governance mechanisms. AI therefore operates not as an isolated artifact, but as part of an interdependent system of technical and social elements that must co-evolve to enable sustained value creation.

2.2 Business value and value realization

Business value is a central but conceptually contested construct in research on digital and AI-enabled transformation. Across the literature, terms such as business value, firm performance, organizational performance, and firm value are often used interchangeably, despite referring to partially distinct phenomena. In this thesis, business value is treated as an umbrella concept capturing both measurable performance outcomes and immeasurable capability-based effects that enable longterm competitive advantage. This aligns with Enholm et al. (2022), where business value refers to "the extent to which a firm's resources and capabilities contribute to improved outcomes relative to strategic objectives". These outcomes may be financial, such as profitability or cost efficiency (tangible outcomes), but may also include operational, learning-related, or strategic effects that are not immediately reflected in financial indicators (intangible outcomes). Prior research on digital and AI technologies consistently shows that technology investments rarely translate directly into firm performance (Enholm et al., 2022; Islami et al., 2025; Ramos et al., 2025); instead, value emerges through the organizational capabilities that enable technologies to be effectively deployed, integrated, and scaled (Enholm et al., 2022; Mariani & Mancini, 2025).

In the context of artificial intelligence, this distinction is particularly important. AI technologies are widely accessible and increasingly commoditized, which limits their ability to generate sustainable competitive advantage in isolation. Empirical evidence shows that AI adoption alone does not guarantee improved firm performance and may even lead to negative outcomes when complementary organizational resources are absent (Enholm et al., 2022; Lamarre et al., 2024). Rather, AI creates business value when firms develop an AI capability, defined as the ability to select, orchestrate, and leverage AI-specific resources such as data, infrastructure, skills, and coordination mechanisms (Jöhnk et al., 2021; Mariani & Mancini, 2025; Mikalef & Gupta, 2021). This capability-oriented view aligns with the resource-based logic (Priem & Butler, 2001) that performance differences arise from how resources are combined and embedded in organizational processes, rather than from the resources themselves (van de Wetering, 2026). Business value is therefore best understood as a multi-dimensional and temporally distributed construct. Systematic evidence from digital capability research shows that the strongest and most consistent performance effects of digital capabilities are observed in internal process efficiency and learning outcomes, which subsequently influence financial performance over time (Ayoub & Sopuru, 2026; Secundo et al., 2025). These findings suggest that business value realization often follows an indirect pathway, where early gains in efficiency, coordination, or decision quality act as precursors to later financial results. This helps explain why executives frequently struggle to evaluate AI initiatives using traditional return-on-investment metrics, particularly in early stages of adoption.

Dynamic capability theory further clarifies this relationship by emphasizing that firm performance depends on the organization's ability to sense opportunities, seize them through coordinated action, and reconfigure resources in response to change (Teece, 2007). In AI-intensive contexts, value creation is not a one-time outcome but an ongoing process driven by continuous learning and adaptation (Mariani & Mancini, 2025). Recent research demonstrates that AI-enabled value creation is closely tied to interactional mechanisms such as human-AI teaming, trust development, and mutual learning, which operate at the team and process level rather than at the level of individual technologies (Samsuden et al., 2024). These mechanisms enable AI capabilities to evolve dynamically and to influence performance beyond isolated use cases. Taking these articles into consideration, this thesis conceptualizes business value as the realization of performance effects enabled by organizational AI capabilities, rather than as a direct output of AI systems themselves. Business value may manifest as tangible and intangible outcomes, where intangible effects are particularly relevant in decentralized organizations and value is often distributed across units. Consequently, assessing AI-related business value requires a capability- and process-oriented lens that extends beyond short-term financial metrics.

2.3 Organizational theories underpinning AI transformation

This section covers the core theories relevant for AI transformation at scale. The theories goes from broad to narrow, starting with digital and AI transformation, followed by capability theories, learning processes and the TOE framework. Together these theories build toward understanding readiness as the key linking mechanism during an AI transformation.

2.3.1 Digital transformation and AI transformation

Digital transformation is the organization-wide integration of digital technologies to change how value is created, delivered and captured. It can be seen as a blueprint that guides how organizations adopt, integrate and govern digital technologies (Matt et al., 2015). Digital transfomration extends regular IT strategies that focus on systems or infrastructure by incorporating a business-centric focus and emphasize innovation and customer facing digital activities. However, a digital business strategy does more than describe future digital opportunities. It also provides a practical roadmap for managing the transformation process itself and for moving from the current to the future state. (Lamarre et al., 2024; Matt et al., 2015).

AI transformation can be understood as a specific instantiation of digital transformation in which AI acts as the primary enabling technology. AIT refers to the "systematic integration of artificial intelligence into an organization's core operations, decision processes, and value creation logic, with the aim of building continuously learning, data-driven systems" (Lamarre et al., 2024). For AI to transform an organization's way of working, data, architecture, scalable technology platforms, operating model redesign, and talent development needs to be combined. Lamarre et al. (2024) explores the capabilities required for AI transformation and emphasizes continuous improvement through feedback loops, where models evolve based on real-world data, thereby creating compounding performance gains. In this sense, AI transformation shifts firms from static, rule-based operations toward adaptive, learning-oriented systems. This shift, however, is contingent on the development of underlying AI capabilities, which determine an organization's ability to effectively build, deploy, and scale such systems (Lamarre et al., 2024).

2.3.2 AI capability and the resource-based view

AI capability is a term that seems to have had a change of definition in the last couple of years. Early definitions conceptualize AI capability as a property of the technology itself: "AI capability is the ability of a machine-based system to perceive its environment, interpret data, reason, learn, and take autonomous or semi-autonomous actions to achieve specific, human-defined goals" (European Commission, High-Level Expert Group on Artificial Intelligence, 2018). More recent research, however, adopts an organizational perspective: "the ability of a firm to select, orchestrate, and leverage its AI-specific resources" (Mikalef & Gupta, 2021), or "an AI capability is the ability to orchestrate resources (data, technology, and talent) to deploy AI applications that improve efficiency and innovation. This includes: Data Readiness, Technical Infrastructure, Human Talent." (Enholm et al., 2022). Some researchers address the inconsistent definition by distinguishing between firm-level and organization-level AI capability. The modern definition by Mikalef and Gupta (2021) states that AI capability builds upon three formative constructs: tangible resources (data, techology, basic resources), human resources (technical AI skills, business skills) and intangible resources (inter-departmental coordination, organizational change capacity, risk proclivity). This indicates that even the newer frameworks are grounded in older ones like resource based theory.

When discussing capabilities it is hard not to stumble upon resource-based view (RBV) (Priem & Butler, 2001). RBV serves as a core theoretical lens in capability research, and emphasizes that competitive advantage arises from valuable, rare, inimitable, and non-substitutable (VRIN) resources, and capabilities emerge through the building of complementary resources. From an RBV perspective, AI technologies are rarely valuable or rare on their own, which helps explain why AI adoption alone often fails to generate sustained competitive advantage.

2.3.3 Dynamic capabilities theory and AI-enabled dynamic capabilities

Dynamic capability theory (DCT) by Teece (2007) is "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments." DCT has become a core theory in a lot of AI transformation and AI adoption research, since AI technologies evolve rapidly and require organizations to continuously adapt their strategies, structures, and resource configurations (Ångström et al., 2023; Ayoub & Sopuru, 2026; van de Wetering, 2026). van de Wetering (2026) further explored how AI can act as an enabler for dynamic capability, by using AI technology for sensing (identifying environmental change, risk and opportunity), shaping (translating sensed insights into strategic plans) and shifting (reconfiguring resources, processes and structures to execute transformation). The articles confirm a positive correlation between AI and the ability to act to rapid change in the organization's environment, often referred to as AI-enabled dynamic capabilities (AIDC). Priem and Butler (2001) underlines that the technology alone does not bring competitive advantage, something all AIDC, DCT and AI transformation research confirm once more.

2.3.4 Organizational learning and knowledge transfer in AI transformation

Due to the speed of development in the field of AI, as well as the availability of tools, the knowledge of how to use said tools become valuable. In order to strengthen dynamic capabilities, foster innovation, and better navigate complexity, van de Wetering (2026) stresses the importance of learning and using knowledge and know-how. Experimental learning (learning by doing) becomes far cheaper and easier than grafting (acquiring external knowledge via hiring), since the skills of the talent pool is still underdeveloped from the technology being so new. The transfer of knowledge between people in an organization has therefore become more important (Feser, 2023).

Knowledge sharing or knowledge transfer occurs in different ways and learning mechanisms positively affect dynamic capabilities, which positively affect business value (van de Wetering, 2026). Organizational learning is a core mechanism of DCT and occurs through repetition and experience, experimentation and feedback, and social and collective processes (Teece, 2007). The learning embeds knowledge into routines and allow organizations to be resilient in disruptive environments (Gupta & George, 2016). In multinational and increasingly decentralized organizations, effective knowledge sharing becomes particularly challenging yet critical. Empirical evidence from a large multinational firm shows that dispersed units and high autonomy across locations often lead to fragmented knowledge flows, making informal, people-to-people transfer and shared routines essential complements to digital systems (Nyberg & Vasileva, 2024). Consequently, fostering organizational learning across boundaries in multi-national companies requires deliberate managerial support and time allocation to ensure that locally developed AI know-how is integrated and leveraged at the organizational level (Nyberg & Vasileva, 2024).

2.3.5 From capabilities to organizational readiness

The construct of readiness has long been recognized in organizational change research. Scaccia et al. (2015) describe readiness as the extent to which an organization is both willing and able to implement a particular innovation, while earlier work treats readiness as distinct from resistance (Clarke et al., 1996; Holt, Armenakis, Harris, & Feild, 2007). Other recent studies in sectors such as healthcare reinforce this, defining readiness through the lens of institutional preparedness, financial commitment, specialist staffing, and infrastructure development (Fan et al., 2025).Weiner (2009) further conceptualize organizational readiness as a multi-level, multi-faceted state in which members are behaviorally and psychologically committed to change and possess the efficacy needed to implement it. In the context of digital transformation, readiness is shaped by culture, leadership, resource endowments, and structural arrangements (Lokuge et al., 2019). Taken together, these perspectives show that readiness is not a single condition, but a broader organizational capability that influences whether transformation efforts can be implemented successfully. This readiness perspective also aligns with the business value logic discussed next, where AI outcomes depend on organizational conditions rather than technology alone.

This theoretical grounding is relevant for the present study because AI transformation depends on more than technical deployment alone. As AI becomes increasingly embedded in organizational processes, the ability to coordinate resources, manage change, and align structures with strategic goals becomes central to value creation. For that reason, this thesis uses Organizational AI Readiness (OAIR) as the focal construct in the following chapter, where it is defined and operationalized in more detail.

2.3.6 TOE-framework

The Technology-Organization-Environment (TOE) framework provides a comprehensive structure for understanding organizational technology adoption by integrating three key dimensions: technological characteristics, organizational capabilities, and environmental pressures. Originally developed by Drazin et al. (1991), TOE argues that adoption decisions are rarely driven by technology alone, but emerge from the interplay between internal readiness and external context-making it particularly relevant for complex technologies like AI where outcomes vary widely across firms. In AI research, TOE has been widely applied to explain why some organizations successfully scale AI while others remain stuck at the pilot stage (for example, (Hirtranusi et al., 2026; Hughes et al., 2026; Sánchez et al., 2025)). Yang et al. (2026) used TOE with structural equation modeling to show that technological readiness, organizational support, and competitive pressure jointly determine AI adoption levels, though their variance-based approach may miss the asymmetric effects that characterize real-world implementation. Similarly, Hughes et al. (2026) applied TOE to GenAI adoption and found that within organizations, factors like technological complexity, trust perceptions, risk concerns, and adaptability matter more than the TOE framework's traditional assumptions might predict. Externally, regulatory uncertainty and industry trends further shape whether firms experiment with or fully commit to AI deployment.

The framework's continued relevance is confirmed by recent reviews showing TOE as the dominant lens for AI readiness studies due to its ability to capture both internal capabilities and external drivers (Hirtranusi et al., 2026). For this thesis, TOE is particularly valuable because it structures the multi-dimensional challenges of AI transformation in decentralized firms, where technological infrastructure must align with organizational competencies under competitive and regulatory pressures.

3. Research Constructs and Hypotheses

This chapter presents the theoretical grounding of the constructs used in the quantitative part of this study and develops the hypotheses that guide the empirical analysis. Building on the theoretical framework outlined in the previous chapter, this chapter explains how each construct is conceptually defined, how it has been operationalized in prior research, and why it is appropriate for the research context of this study. Rather than providing a broad narrative review of the literature, the focus of this chapter is on the selection and application of established constructs and theory-driven hypothesis formulation. No new constructs or measurement scales are developed; instead, all constructs included in the structural equation model are adopted from prior research and have been previously validated in empirical studies.

3.1 Organizational AI Readiness (OAIR) - Endogenous Variable

Organizational readiness in change management literature, described by Scaccia et al. (2015) as "the extent to which an organization is both willing and able to implement a particular innovation." Early work by Weiner (2009) further defined it as a multi-level state where members are behaviorally and psychologically committed to change, possessing the "change efficacy" required to execute it. In the context of digital transformation, Lokuge et al. (2019) operationalized this as a formative construct comprising culture, leadership, resource endowments, and structural arrangements.

When transitioning these concepts to the AI domain, researchers have sought to bridge general digital readiness with the specific demands of AI. While "digital readiness" is broadly defined as the degree to which an organization is prepared to digitally transform (Nguyen et al., 2019), AI readiness focuses specifically on the preparedness to implement AI-driven applications (Alsheibani et al., 2018). A notable conceptualization by Jöhnk et al. (2021) views AI readiness as a "holistic organizational chassis" composed of resources, strategic alignment, knowledge, culture, and data-arguing that readiness is not a one-off precondition but an integral foundation for the entire adoption process.

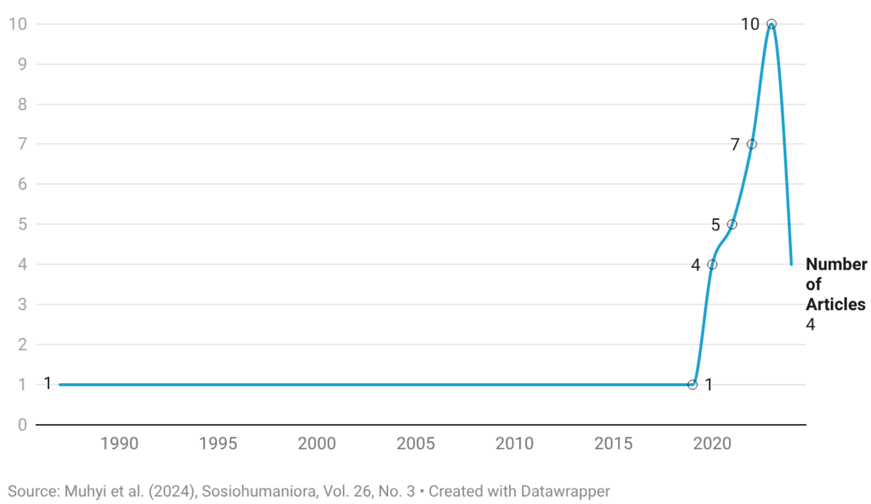


Figure 1: Publications on Organizational readiness for AI

Despite this growing interest, scholars such as Muhyi et al. (2024) highlight that the field still lacks conceptual clarity and rigorous theory development. As *Figure 1* illustrates the published articles on organizational readiness for AI between 1987-2024. The scholarly interest in this area is rising, yet definitions often vary among authors (Ek & Ström, 2021). To maintain consistency, this research adapts the term Organizational AI Readiness (OAIR). As the outcome variable, OAIR is modeled as the combined result of the study's five antecedent constructs: Staff Skills and Competency (SSC), IT Infrastructure (ITI), Top Management Support (TMS), AI Strategy Alignment (AISA), and Trust in Organizational AI (TRU). Together, these constructs reflect the organizational capabilities and contextual conditions necessary to transform AI potential into realized business value.

3.1.1 Staff Skills and Competency (SSC)

SSC: The technical understanding and subject knowledge that enable the employees to carry out their role to the best of their ability (Hughes et al., 2026). It is also understood as organization-wide AI literacy, the ability to apply generative and agentic AI in work tasks, deeper technical capabilities, and continuous training.

Staff skills and competency (SSC) have been identified as a key construct for technology adoption, technology use, and AI implementation by multiple scholars. Hughes et al. (2026) determine that upskilling and internal capability-building are the most critical indicators of whether AI projects become meaningful and scale beyond initial adoption. Their findings suggest that improving employees' skills leads to more informed decision-making and more effective application of these skills, ultimately resulting in better organizational outcomes. Building on this, Gupta and George (2016) identify technical IT skills as a crucial resource for overcoming the technology productivity paradox, showing that staff technical competencies are directly correlated with a company's value realization. .

Additional literature further reinforces SSC as a key indicator of Organizational AI Readiness. For instance, the ability of teams to apply analytical techniques and translate insights into business value highlights the importance of both technical and interpretive skills within the workforce (Garmaki et al., 2023). Moreover, drawing on the RBV and technology adoption theory, internal workforce competencies are identified as foundational enablers of AI adoption, directly influencing organizational performance outcomes (Frikha, 2025). Furthermore, organizational transformation requires employees to continuously update and generate knowledge, enabling innovation and adaptation to emerging challenges, which further underscores the importance of SSC in dynamic AI environments (Jewapatarakul & Ueasangkomsate, 2024).

Similar endogenous variables in prior studies, such as AIDC, have been measured using technical and business skills, which together constitute human resources as a core construct (Ayoub & Sopuru, 2026). Dynamic capabilities emphasize the ability to adapt to change, and Hughes et al. (2026) confirm that organizations with high levels of technical literacy, AI familiarity, or prior experience with automation technologies are more likely to engage in experimentation, customization, and integration of GenAI tools. Recent studies further echo the importance of upskilling and technical literacy for AI readiness, particularly in rapidly evolving fields such as GenAI (Hughes et al., 2026). These findings, combined with the conducted literature review, position SSC as a strong potential construct for OAIR. This suggests that SSC plays a central role in Organizational AI Readiness, which helps formulate the following hypothesis:

> **H1:** Staff Skills and Competency (SSC) has a significant positive effect on Organizational AI Readiness (OAIR).

3.1.2 IT Infrastructure (ITI)

ITI: Data infrastructure and core IT capability for AI (data accessibility, interoperability, scalability, and integration) (Hughes et al., 2026; Jöhnk et al., 2021).

IT Infrastructure (ITI) is widely recognized as a foundational component for enabling AI adoption and value realization within organizations. Prior research highlights that technological context plays a crucial role in shaping the adoption of emerging technologies. For instance, within the TOE framework, Hughes et al. (2026) identify key technological factors such as complexity and relative advantage as central determinants influencing the adoption of GenAI. These factors emphasize that organizations must possess robust and adaptable IT infrastructures to effectively manage technological complexity while leveraging the relative benefits of AI systems.

Building on this, advancements in information and communication technologies, alongside increased computational power, have significantly accelerated the development and adoption of AI across various domains (Fosso Wamba et al., 2024). Their findings further suggest that AI infrastructure is not merely supportive but constitutes a critical resource in achieving high organizational performance, as different configurations of AI capabilities consistently rely on strong underlying IT systems. Jöhnk et al. (2021) explictly stated IT Infrastructure as one of 18 factors influencing OAIR which streghtens the choice of this construct in measuring the readiness variable.

Moreover, as AI matures, it increasingly becomes embedded within standard organizational infrastructure rather than serving as a standalone innovation. Islami et al. (2025) note that AI is gradually transitioning from a differentiating enhancement to a core component of technological environments, thereby raising expectations for what defines an innovative and supportive workplace. This shift reinforces the necessity for scalable, interoperable, and well-integrated IT infrastructures capable of sustaining continuous AI deployment and evolution.

Taken together, these findings position ITI as a critical construct for OAIR, as it underpins the organization's ability to adopt, scale, and derive value from AI technologies. Based on the above, the following hypothesis is proposed:

> **H2:** IT Infrastructure (ITI) has a significant positive effect on Organizational AI Readiness (OAIR).

3.1.3 Trust in Organizational AI (TRU)

TRU: The confidence and reliance employees and stakeholders place in an AI system to operate safely, ethically, and reliably.

Trust in Organizational AI (TRU) has been identified as a critical factor influencing organizational adoption and use of AI technologies. Prior research shows that technological factors such as trust, Perceived Risk, and complexity often play a more decisive role in AI adoption than traditional frameworks, such as TOE, may fully capture (Hughes et al., 2026). Within organizations, Trust in Organizational AI is closely linked to perceptions of reliability, transparency, and ethical considerations, including concerns related to privacy, bias, misinformation, and accountability. These factors shape employees' willingness to engage with AI systems and integrate them into their daily work practices.

Weisz et al. (2024) highlight that trust and information sharing form core dimensions of AI-enabled collaboration, where both are necessary for realizing the value of AI capabilities. Their framework demonstrates that across different stages of AI adoption, trust in AI technology evolves alongside the organization's ability to share and utilize information effectively. Importantly, Weisz et al. (2024) extend traditional notions of interpersonal and interorganizational trust by introducing trust in AI as a distinct and necessary dimension in AI-driven environments. Furthermore, their findings suggest that AI capabilities influence trust in AI systems, which in turn affects how successfully these systems are implemented and utilized. This indicates connection between trust and capability, where technological capabilities alone are insufficient unless employees perceive AI systems as reliable and trustworthy. In line with this reasoning, perceived risks and uncertainties surrounding AI can reduce trust for the technology, thereby limiting organizational readiness adoption.

Taken together, these insights position trust as a key mechanism through which AI-related factors influence organizational outcomes. Based on the above, the following hypothesis is proposed:

> **H3:** Trust in Organizational AI (TRU) has a significant positive effect on Organizational AI Readiness (OAIR).

3.1.4 Percieved Risk of AI (PR)

PR: The ambiguity and potential negative consequences associated with a certain product or service as defined by Dang and Erorita (2025). In simple, it is a perceived potential negative outcomes from AI use (decision errors, privacy/security breaches, job loss, misuse), consistent with multi-facet perceived risk theory.

Perceived Risk (PR), has been consistently recognized as a primary constraint of trust in interactions between trust and technology, and AI is no exception. In the context of AI, PR typically conveys some of the main concerns of privacy, security, and performance reliability, which collectively erode individuals' willingness to rely on AI systems. Based on risk-trust theory, higher PR is hence anticipated to damage stakeholders' TRU which in the current study's case understood as employees' and users' confidence that AI applications or initiatives introduced by the organization or in general are reliable and safe (Dang & Erorita, 2025; Kim et al., 2008). In the scholarly work by Dang and Erorita (2025), PR had a strong direct negative effect on TRU and indirect effects via trust, mediating 39.45% of the risk-intention relationship. Similarly, Olaniyi (2025) extends this research on firm-level datasets, showing the outcome as PR displays a negative effect on TRU, along with positive trust effects on ML/AI adoption intention. This analysis provides direct evidence on how risk hinders TRU sysytems like cybersecurity. Zuo et al. (2025) in their research about university teachers' trust in organizational AI tools using SEM on 487 teachers, concluded that PR negatively impacted TRU. Lastly, R. Sharma et al. (2024) explicitly explore the relation between PR and intentions to use AI, with TRU based technologies as a mediator. They confirmed direct effect through trust, which gives strong theoretical basis that the construct is validated for the measurement of OAIR.

Transferring these findings to the current study, organizational members who perceive higher risks connected with AI are less inclined to trust AI applications or services. Contrarily, lower perceived risks should help facilitate the trust formation in organizational AI. Based on the above, following hypothesis is proposed:

> **H4:** Perceived Risk (PR) has a significant negative effect on Trust in Organizational AI (TRU).

3.1.5 Top Management Support (TMS)

TMS: Visible and sustained senior-management behaviors that support AI. This includes company vision, resource provision, championing, and accountability.

Jöhnk et al. (2021) directly identify Top Management Support (TMS) as one of the 18 organizational AI readiness factors within the category of strategic alignment. It is described by the authors as the willingness to commence AI initiatives top-down and to signal support for bottom-up initiatives. Following up on this, they state it is the TMS that enables the strategic relevance of AI to the organization and also provide support in nurturing the AI initiatives. Moreover, it is emphasized how vital TMS is for successful AI adoption, which directly links TMS to a higher order of AI readiness. Jöhnk et al. (2021) theorize that organizational AI readiness as a multi-factor organizational "chassis" that must be developed continously to foster AI adoption. Their model on the other hand, emphasizes that simultaneous improvement of multiple readiness dimensions is an implication of stronger TMS. In parallel, Mustafa et al. (2026) demonstrate in their scholarly work that active support and involvement of top management is critical to facilitate change readiness, and structuaral alignment.

Accordingly, the following hypothesis is proposed:

> **H5:** Top Management Support (TMS) has a significant positive effect on Organizational AI Readiness (OAIR).

3.1.6 AI Strategy Alignment (AISA)

AISA: Alignment of AI initiatives with business strategy, shared understanding across functions, value-based prioritization, and clear decision rights for AI.

AI Strategy Alignment (AISA) is increasingly recognized as a critical factor in enabling organizations to successfully adopt and scale AI initiatives. Prior research shows that a lack of strategic coordination and shared understanding across organizational units can significantly hinder AI development and value realization. For example, Ångström et al. (2023) describe how decentralized data management and inconsistent terminology across units created inefficiencies, limited data accessibility, and increased the risk of errors. To address these challenges, the organization established dedicated structures for data governance and strategic oversight, highlighting the importance of aligning data and AI initiatives with broader organizational objectives.

DCT literature emphasizes that technological capabilities alone are insufficient for generating business value unless they are aligned with strategic priorities. Mariani and Mancini (2025) provide empirical evidence showing that AI capabilities must be supported by organizational processes and strategic investments to effectively contribute to project value creation. Similarly, Frikha (2025) argue that successful AI adoption depends on a combination of technological resources, human competencies, and strong managerial commitment, with management systems playing a key role in ensuring strategic alignment. Their findings further suggest that organizations that integrate AI into core business functions, rather than treating it as an isolated or experimental initiative, achieve superior performance outcomes.

These insights highlight that AISA enables organizations to coordinate resources, reduce fragmentation, and prioritize AI initiatives that deliver tangible business value. By fostering a shared understanding of AI across functions and embedding AI within strategic decision-making processes, organizations are better positioned to scale AI efforts and enhance overall readiness. In this way, AISA acts as a guiding mechanism that ensures AI investments are purposeful, coordinated, and aligned with organizational goals.

Based on the above, the following hypothesis is proposed:

> **H6:** AI Strategy Alignment (AISA) has a significant positive effect on Organizational AI Readiness (OAIR).

3.2 Summary of Hypotheses

The following *Table 1* summarises the hypotheses developed in this chapter. The direction (positive or negative) indicate if the correlation between the constructs, meaning: for (+) if one construct value increases, the other value increases as well, i.e as the skills of the staff increase the readiness of the firm increase. and for (-) if one construct value decreases the other construct value increases, i.e if percieved risk for the technology increases, the trust for that technology decreases.

Hypothesis	Statement	Direction
H1	Staff Skills and Competency (SSC) has a significant positive effect on Organizational AI Readiness (OAIR).	+
H2	IT Infrastructure (ITI) has a significant positive effect on Organizational AI Readiness (OAIR).	+
H3	Trust in Organizational AI (TRU) has a significant positive effect on Organizational AI Readiness (OAIR).	+
H4	Perceived Risk (PR) has a significant negative effect on Trust in Organizational AI (TRU).	-
H5	Top Management Support (TMS) has a significant positive effect on Organizational AI Readiness (OAIR).	+
H6	AI Strategy Alignment (AISA) has a significant positive effect on Organizational AI Readiness (OAIR).	+

Table 1: Summary of Research Hypotheses

4. Methodology

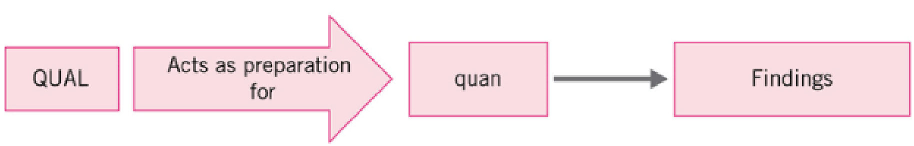
This study employs a mixed-methods research design combining qualitative exploration with quantitative validation to address the two main research questions. Phase 1 uses thematic analysis of interviews and documents to identify critical AI capability gaps within the case company, while Phase 2 applies structural equation modeling (SEM) to test theoretically-grounded hypotheses about organizational AI readiness. This sequential approach leverages the strengths of both methods to provide both contextual depth and empirical rigor.

4.1 Research design - Mixed Methods approach

The term mixed method research following Bell et al. (2022) is "a simple shorthand to stand for research that integrates quantitative and qualitative research within a single project". In the meantime, it is essential to note that mixed methods research is not equivanlent to *multi method* research as distingued by Bell et al. (2022). It is also stated by the author that the term multi-method is applied specifically when methods "cross the two research strategies", this clear distinction is followed and adopted throughout this study.

The current study opts for a mixed method research design, which is combining qualitative and quantitative approaches in an orderly manner. RQ1 has been approached with qualitative method and RQ2 through quantitaive method. The rationale for opting this design is due to the nature of the reasearch questions and the complexity surrounding organizational AI readiness in a multinational decentralized firm. In parallel, a mixed method design allows "the various strengths to be capitalized upon and the weakness offset" of each individual research strategy (Bell et al., 2022). Additionally, according to Holt, Armenakis, Feild, and Harris (2007), the assessment of readiness can be conducted using both qualitative (thematic analysis, interview-based) and quantitative (survey based, statistical) methods. Even though qualitative methods provide extreme change-specific information, quantitative methods are an appropriate supplement, offering unique advantages to managers, organizational development consultants, and researchers in certain settings.

This study follows an exploratory sequential design (refer *Figure 2*), as stated by Bell et al. (2022): Qualitative data are collected first in order to generate constructs and themes, which are then tested with a quantitative phase. The authors also note that this is the dominant pattern in business research. In simple words, qualitative work "typically acts as preparation for the main phase of the mixed methods research which is quantitative in nature. This leads directly onto the structure of this current study: Addressing RQ1 qualitatively and the themes resulting from them make way for the constructs and hypothesis tested in RQ2 (Bell et al., 2022).



Source: Creswell & Clark (2011)

Figure 2: Exploratory sequential design

This adopted design is further justified by two main functions highlighted by Creswell and Clark (2011): *providing hypotheses*, where exploration in qualitative phase generates "hunches that can be then tested using a quantitative research approach" and *aiding measurements*, where in depth insights acquired from qualitative research aid in designing the survey questions for collecting data in quantitative stage. In this study, both functions are applied (Bell et al., 2022).

Data collection followed a sequential stage research design that systematically moved from qualitative exploration to quantitative validation in sequential steps. Initial qualitative phases were used to explore relevant concepts and align them with established theory, which subsequently informed the development of a quantitative questionnaire. The process began with an exploratory scoping review to familiarize the researchers with relevant themes and current trends. This was followed by a semi-structured interview aimed at capturing the current state of the organization and initiating the mapping of existing AI use as well as potential gaps. Next, a self-completion qualitative questionnaire, in accordance with Bell et al. (2022), was administered to members of the executive team via email in order to capture their perceptions of the business value derived from the use of AI. The data generated from this stage informed the analysis addressing the first research question. Third, a targeted literature review was conducted to align identified concepts and themes with established constructs and terminology used in prior research. This review also informed the construction of the questionnaire used in the quantitative phase of the study. The questionnaire consisted of 28 items and was distributed via the organization's intranet and subsequently via email to employees in order to collect responses.

4.1.1 Research Phases Overview

Figure 3 illustrate the two-phase mixed-method research design in which Phase 1 frames the foundation for the concepts and Phase 2 quantitatively tests these concepts. Phase 1 starts with a scoping review, followed by semi-structured interviews; the data from the interviews are analyzed using thematic analysis framework by Braun and Clarke (2006). This informs the development of well-defined constructs. These constructs are then used in a survey questionnaire systematically in Phase 2, refined through literature-based validation, and empirically tested using Structural Equation Modeling (SEM), ultimately leading to an assessment of Organizational AI Readiness (OAIR).

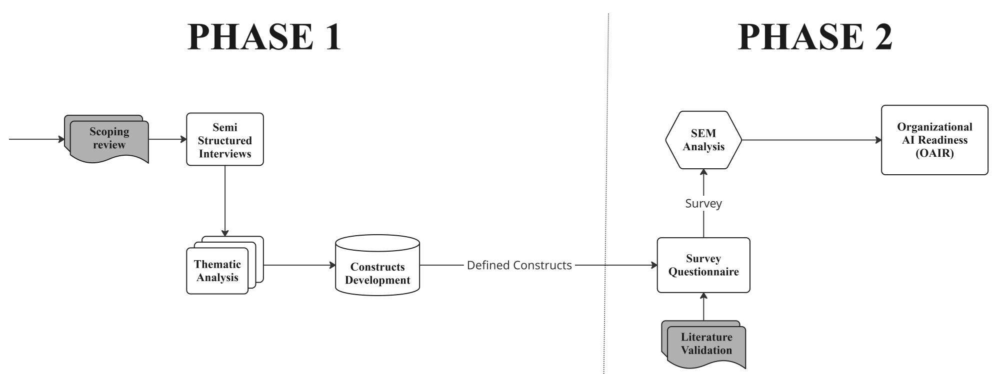


Figure 3: Research design and approach

4.2 Phase 1 - Qualitative Study

Phase 1 is consisted of three complementary data sources: an exploratory scoping review of internal and external documents, semi-structured interviews with employees involved in or affected by AI initiatives, and a self-completion qualitative questionnaire targeting the executive team. The scoping review was used to identify recurring challenges, capability needs, and themes related to AI transformation in both academic and practitioner literature. These themes informed the development of the interview guide and provided an initial analytical framework.

Semi-structured interviews were then conducted to examine whether the literature-derived themes were present within the organizational context of the case company and how they manifested across different roles and units. Finally, the executive questionnaire was used to capture senior-level perspectives on business value, governance, and strategic expectations related to AI. Together, these qualitative data sources enabled triangulation across organizational levels and data types, confirming the empirical relevance of the identified themes and establishing a foundation for aligning them with theoretically validated constructs in the subsequent phases of the study.

4.2.1 Qualitative Data Collection and Analysis

The scoping review consisted of reading and extracting themes and quotes in relation to AI transformation, AI readiness, AI adoption, and capability to use AI to its full potential. During the reading, these topics, or "needs" surrounding a successful AI transformation, was codified and collected in a document for later analysis. The reading material consisted of approximately fifty internal and forty external documents. The internal documents were provided by the case company and included material (ppt, pdf, docx, excel) created by the organization as well as recommendation-documents from the advisory firm Gartner. These consisted of strategic initiatives, educational material, governance-guidelines for AI-related decisions and general guidelines for the incorporation of AI into an organization. The external documents were industry reports, fact sheets about AI and advisory reports from the large consultancy firms. The extracted excerpts and themes were coded using a inductive thematic analysis approach as recommended by Bell et al. (2022) and Braun and Clarke (2006). *Table 3* illustrates the progression from excerpts identified in the scoping review to codes and broader themes that were subsequently used to guide interview design and qualitative analysis. First-order codes were used only as an intermediate analytical step and were not carried forward directly into later stages of the analysis. The resulting five themes are broad and covers many topics by themselves, however, they summarize everything the 90+ articles addresses in order to succeed with an AI transformation and increase a company's capability to use AI proficiently. In order to validate that the five themes were correctly derived, a cross-reference with peer-reviewed academic papers was conducted. This was done on Google Scholar, Springer and ScienceDirect to name a few, with the search terms *AI transformation, AI capabilities, AI-first companies* and *digital capability development*. This confirmed that the themes were correctly identifies, albeit with incorrect naming, something addressed on the next page. The resulting *Table 3* provided the foundation to conduct the semistructured interviews, and created the direction of the report.

The interview guides was informed by established technology adoption literature, including the TOE framework (Baker, 2011; Drazin et al., 1991); however, the framework was not used in subsequent analysis due to limited relevance of the environmental dimension in the case context. The guides was developed in accordance with the guidelines provided by Bell et al. (2022) and shaped by the themes identified in the scoping review. The interview guides covered topics related to ongoing AI initiatives, capability and resource requirements, technology infrastructure, knowledge sharing, and organizational factors affecting AI implementation, *(see Appendix C & D)*. The initial four interview participants were identified as relevant stakeholders by the Chief Information Officer (CIO) at the case company, based on their involvement with AI-related activities. A non-probability sampling strategy, specifically snowball sampling, was subsequently employed to expand the sample by asking participants to recommend additional interviewees from their professional networks. This sampling approach is recommended by Yin (2015) for exploratory semi-structured interviews. It is further described by Bell et al. (2022) as a non-probability sampling approach where initial participants are asked to refer to other candidates who meet the same criteria for inclusion in this study. This type of sampling is useful particularly when target group is hard to access or identify via the conventional methods. Similarly for this study, there was no readily identifiable group involved for the topic of AI initiatives, thus referral based approach suited the best route to technique to reach more professionals. In short, each contact opens a lead to a wider network of participants relevant for this study. Subsequently, the process resulted in the recruitment of six additional participants, leading to a total of ten conducted interviews.

During the initial phase of data collection, the first four interview participants were under the impression that their responses would not be anonymous, which may have influenced the openness of their responses. In light of time constraints and some repetition in these interviews, the interview procedure was subsequently adjusted. For the remaining six interviews, participants were explicitly informed of the anonymity of their responses prior to participation. All interviews were voice-recorded for transcription-purposes. The voice recordings from the interviews were transcribed using a locally hosted AI-based transcription tool (TranscribeX). Hosting the transcription software locally reduced the risk of sensitive data being transferred to external servers while still enabling efficient automated transcription. All transcripts were reviewed against the original audio recordings to ensure accuracy, and minor transcription errors were corrected during the initial coding process. The qualitative data were analyzed using a thematic analysis approach, following the six-phase framework proposed by Braun and Clarke (2006). Given that the study aimed to examine whether themes identified in the initial scoping review were also present within the case company, the analysis was guided by a theoretically informed thematic approach. This approach is often described as deductive or top-down, as it uses predefined themes derived from prior literature as an initial analytical lens (Boyatzis, 1998). Specifically, the five broad themes identified in the scoping review were used as an overarching coding framework. These themes functioned as analytical "umbrella categories" under which more detailed codes were organized. During the coding process, interview excerpts were first mapped to one or more of the predefined themes. Within each theme, a more inductive coding process was then applied, allowing sub-codes to emerge based on how participants described concrete challenges, decisions, and experiences related to AI use. For example, discussions concerning "make-versus-buy decisions for AI solutions" were coded as a sub-category within the broader theme of Data, Technology, and Architecture. This qualitative coding and organization of themes was done by the researchers after first anonymizing the transcripts, and codified in the DelveTool, a dedicated software for thematic analysis and theory development.

This hybrid approach (deductive at the thematic level and inductive within themes) enabled a systematic assessment of whether the literature-derived themes were empirically observable in the case company, while also capturing which aspects of these broader topics were most prominent in practice. Some interview excerpts were relevant to multiple themes and were therefore coded accordingly, reflecting the interconnected nature of organizational capabilities related to AI adoption. In line with the analytic process described by Braun and Clarke (2006), the analysis proceeded through familiarization with the data, initial coding, and iterative refinement of codes and sub-themes. Both thesis authors participated in the coding process, discussing code interpretations and resolving ambiguities collaboratively to enhance analytical consistency. As the analysis progressed, between three and seven sub-themes were identified within each of the five overarching themes. The later phases of the thematic analysis focused on reviewing and refining theme definitions and ensuring conceptual clarity. At this stage, the emphasis was not on generating new themes, but on clarifying and improving the labeling of existing themes. This process involved cross-referencing the empirically identified themes with established terminology in the academic literature. The outcome of this step was a refinement of theme names and definitions to better align with constructs previously validated by prior research. This refinement process (seen in *Table 5*) formed the basis for the subsequent construct selection and hypothesis formulation.

The final stage of the qualitative data collection consisted of a self-completion qualitative questionnaire distributed to the entire executive team of the case company. They included the CEO and six senior vice presidents, each responsible for one division or major functional area (such as finance or HR). The purpose of this data collection step was to capture executive-level perspectives on business value and their expectations regarding what AI can enable within the organization. The questionnaire comprised predefined open-ended questions and was administered via email. The full set of questions is provided in Appendix B.

The responses were analyzed and categorized according to perceived business value outcomes. Drawing on the definition of firm performance proposed by Ayoub and Sopuru (2026), business value was operationalized in terms of operational and financial outcomes, consistent with the conceptualization of business value and business performance outlined in the construct development chapter. Within these two categories, the identified outcomes were further differentiated into tangible and intangible value dimensions. Tangible outcomes refer to directly observable or measurable effects, such as efficiency gains, cost reductions, or process improvements (Atasoy et al., 2022; Veblen, 1908). Intangible outcomes capture less immediately measurable effects, including capability development, learning effects, improved decision quality, or enhanced organizational readiness, which are nevertheless expected to contribute to longer-term value creation (Atasoy et al., 2022; Intara & Suwansin, 2024). Responses were coded accordingly and grouped based on the type of value described.

4.3 Phase 2: Quantitative Study

Phase 2 of the study comprised a quantitative investigation aimed at assessing the organization's current level of Organizational AI Readiness and examining the relationships between key organizational, technological, and managerial antecedents identified in prior literature. Building on the insights generated during the qualitative phase, the quantitative phase served a confirmatory and evaluative purpose by translating theoretically validated constructs into measurable indicators and assessing their empirical relationships across the broader organization. A structured questionnaire was developed based on constructs previously validated in academic research and aligned with the themes confirmed during phase 1. The questionnaire was distributed company-wide in order to capture perceptions of AI-related capabilities across multiple organizational units and roles. Structural Equation Modeling (SEM) was employed to analyze the data, allowing for simultaneous assessment of the measurement model and the hypothesized structural relationships between constructs. The quantitative phase provides an empirical basis for identifying capability strengths and gaps related to OAIR, thereby complementing the qualitative findings and enabling a systematic comparison between theoretically ideal capability conditions and the organization's observed state. The results of this phase form the foundation for the integrative analysis and the development of the AI transformation roadmap presented in subsequent chapters.

4.3.1 Conceptual Model and Model Specification

Building on the constructs and hypotheses developed in Chapter 3., the model specifies the relationships between organizational, technological, and managerial capabilities and OAIR, which serves as the endogenous construct. In the model OAIR represents the outcome construct or endogenous variable. Staff Skills and Competency, IT Infrastructure, Top Management Support, AI Strategy Alignment, Trust in Organizational AI, and Perceived Risk are specified as antecedent constructs.

Structural Equation Modeling (SEM) was selected as it allows simultaneous estimation of both the measurement model (relationships between constructs and indicators) and the structural model (relationships between constructs) (Hair et al., 2022), which is appropriate given the multidimensional and latent nature of Organizational AI Readiness. *Figure 4* illustrates the conceptual model used in the quantitative analysis, showing the hypothesized relationships between the capability constructs and Organizational AI Readiness.

4.3.2 Quantitative Data Collection

The quantitative phase was conducted to address the second research question and to provide an empirical basis for the identification of capability gaps related to OAIR. Given that both organizational capabilities and AI readiness represent latent constructs that cannot be observed directly, SEM was selected as the

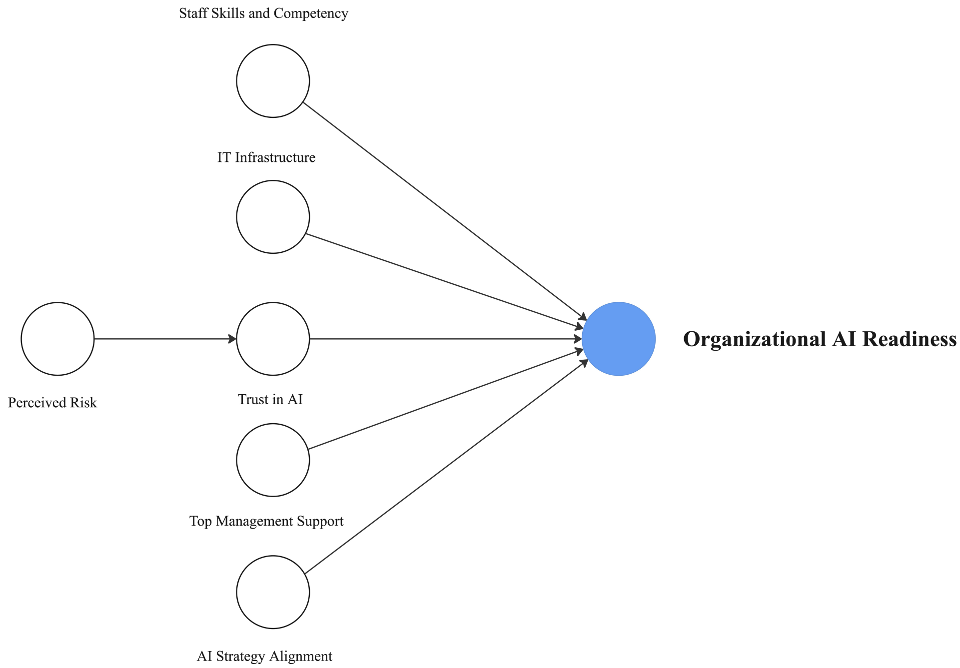


Figure 4: A proposed phase-2 conceptual model

primary analytical approach. Specifically, PLS-SEM (Partial Least Squares Structural Equation Modeling) was selected due to its suitability for prediction-oriented research and complex models with latent variables (Ghasemy et al., 2020; Hair et al., 2021). PLS-SEM is well suited for examining relationships between theoretically grounded but inherently abstract constructs, as it enables the simultaneous estimation of measurement models and structural relationships between latent variables (Chew et al., 2025; Elangovan N., 2015; Hair et al., 2021).

A critical prerequisite for SEM is the use of valid and reliable measurement instruments (Hair et al., 2021). In this study, construct development therefore focused on the selection and reuse of constructs and measurement items that have been previously validated in academic research. The development of entirely new constructs would have required extensive scale development, pilot testing, and validation procedures (Chew et al., 2025), which was considered beyond the scope of the present study. Consequently, established constructs and survey items were adopted to ensure construct validity and methodological rigor. The theoretical justification for the selected constructs is provided in Chapter 3., and the corresponding measurement items are listed in Appendix A. The questionnaire was designed using a seven-point Likert scale and formulated using clear and accessible terminology in order to facilitate comprehension and encourage completion. A Likert scale is a psychometric response scale used in questionnaires to measure respondents' attitudes or levels of agreement with a statement across an ordered set of response categories (Likert, 1932). The survey was implemented in Microsoft Forms, with 28 Likert-scale items set as mandatory, while optional open-ended questions were included to allow respondents to elaborate on their responses if desired. Each construct was measured using four items. At last, ethical approval is secured prior to any data collection as highlighted by Bell et al. (2022).

The decision to present all substantive survey items on a single page was made deliberately and described by Wolf et al. (2016) as one of the ways to increase transparency and reduce respondent fatigue by allowing participants to view the full scope of the questionnaire during completion. Participation was fully anonymous, and only basic demographic information (age, gender, and division) was collected. The final number of items was determined during the construct selection process. One of the initially identified qualitative themes was divided into two separate constructs (Perceived Risk and Trust in Organizational AI) while the overarching outcome construct representing the combined effect of organizational capabilities was defined as OAIR. Each construct was operationalized using four measurement items adopted from prior empirical studies, as recommended by Chew et al. (2025) and Hair et al. (2021).

4.3.3 Structural Equation Modelling (SEM) Analysis

The analysis of the data in the current study is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with SmartPLS V4.1.1.8 software. Structural equation modeling (SEM) enables researchers to answer a set of interrelated research questions in a single, systematic, and comprehensive analysis by modeling the relationships among multiple independent and dependent constructs simultaneously as emphasized in Elangovan N. (2015). The choice of PLS-SEM method is due to its abilty to analyze research models of complex nature, its strength in non-normal data distribution, and also its suitability for comparatively small sample sizes (Hair et al., 2019, 2022; Kock & Hadaya, 2018). Based on the work of Coltman et al. (2008), relfective measurement models were opted since the constructs illustrate primary characteristics that already exist independently and cause the observed indicators, not vice versa. In short, indicators (for eg., TRU1, SSC1,..) are affected by latent variables (TRU, SSC,..) and not the other way around.

Consistently, based on the guidelines from the authors, the analysis is carried out in two key stages. The first stage evaluates the assessment of the reflective measurement model. This stage focuses on determining the reliability and validity of the constructs. Indicator reliability is evaluated based on outer loading values >0.70. Internal consistency reliability is estimated using Cronbach's Alpha (CA) and Composite Reliability (CR), with minimum threshold value of > 0.70. Meanwhile, the model is validated using indicator reliability i.e., Average Variance Extracted (AVE) > 0.50 and discriminant validity is gauged using the Heterotrait-Monotrait ratio (HTMT), for which the minimum acceptable value < 0.85 indicating a suffucient level of discriminant validity. The second stage carries out the evaluation of structural model, which reviews the quality of the relationships along with strength among the constructs in the research model. The explanatory power of the model is assessed through R-squared and the predictive relevance is analyzed using Q-squared. At last, the significance of the hypothesized relationships is proved using a one-tailed bootstrapping procedure with 5,000 subsamples where, the significance is determined based upon a t-statistic greater than 1.645 and p-value under 0.10 (Hair et al., 2019, 2022). A one-tailed test is chosen because the hypotheses were directional and derived from prior literature. A brief summary of this is illustrated in *Table 2*.

Stage	Focus	Criterion / threshold	Interpretation
Reflective measurement model	Indicator reliability	Outer loadings ≥ 0.70	Verifies that each item loads strongly on its intended construct.
	Internal consistency reliability	Cronbach's Alpha (CA) and Composite Reliability (CR) > 0.70	Confirms that the indicators within each construct are consistently measuring the same concept.
	Convergent validity	Average Variance Extracted (AVE) > 0.50	Shows that the construct explains more than half of the variance in its indicators.
	Discriminant (or) Divergent validity	HTMT < 0.85	Indicates that conceptually different constructs are sufficiently distinct from each other.
Structural model	Explanatory power	R^2 *Substantial:* ≥ 0.75 *Moderate:* 0.50 - 0.75 *Weak:* 0.25 - 0.50	Assesses how much variance in endogenous constructs is explained by the model.
	Predictive relevance	Q^2 *High:* > 0.50 *Moderate:* 0.25 - 0.50 *Weak:* 0 - 0.25	Evaluates whether the model has predictive relevance for endogenous constructs.
	Hypothesis testing	Bootstrapping with 5,000 subsamples; significance at $t > 1.645$ and $p < 0.10$	Tests the significance and strength of the hypothesized relationships between constructs.

Table 2: Summary of the two-stage PLS-SEM analysis procedure

5. Empirical Results and Analysis

This chapter presents the empirical results from the two research phases. For the first phase, this includes the themes identified through the document review, followed by interview evidence illustrating how these themes are reflected in the case company, exploring how the executive team views business value from AI and ending with a comparison between the empirical themes and the theoretical constructs used in the quantitative analysis. The second phase presents the results from the PLS-SEM analysis, including the assessment of the measurement and structural models, the evaluation of the conceptual model, and the testing of the hypotheses used to validate the proposed relationships.

5.1 Qualitative results

The themes derived through the inductive thematic analysis of the scoping review are shown in *Table 3*, which illustrates the progression from excerpts identified in the scoping review to first-order codes and then to broader themes. The leftmost column lists the identified needs, potential gaps and potential actions to take, found across the fifty internal and forty external documents as well as supported by many academic papers. The consolidated second-order codes, or broader themes, were developed by the authors of this paper and are found in the rightmost column of *Table 3*. These five resulting themes (Knowledge, Skills & Shared Understanding; Data, Technology & Architecture; Risk, Security & Trust; Leadership, Governance & Operating Model; and Strategy & Value Realization) are not meant to be ranked in any particular order and are not fitted into an existing framework. These themes reflect the recurring empirical categories that appeared most relevant for AI-driven or AI-enabled value realization according to the literature, and therefore most relevant for the case company.

The different broader themes capture smaller, more actionable topics that the literature recommends implementing during an AI transformation, some of which are listed here. For Knowledge, Skills & Shared Understanding, the literature points to upskilling employees and informing them about relevant use cases, creating spaces for knowledge sharing where employees can learn from one another, identifying internal champions and involving them in AI decision-making, and hiring external capabilities when the organization lacks specific expertise. In the case of Data, Technology & Architecture, it is recommended to strengthen data quality and accessibility, improve integration across systems, build scalable technical infrastructure, and ensure that the architecture can support repeated deployment and expansion of AI solutions. Risk, Security & Trust involves establishing clear guidelines for data protection, security, and responsible AI use, while also building confidence in AI outputs through transparency, oversight, and well-defined accountability. For Leadership, Governance & Operating Model, the actions include increasing collaboration within the C-suite, deciding on an appropriate governance model, clarifying who is responsible for implementation efforts, and communicating AI-related decisions throughout the organization. Finally, Strategy & Value Realization, include creating or clarifying an AI strategy, deciding on the company's stance toward AI (whether to defend, extend, or upend existing business models), identifying and prioritizing AI use cases, and determining which capabilities should be bought as off-the-shelf solutions and which should be developed in-house.

Identified Need	**First order code**	**Broad Theme**
Lacking understanding of AI benefits and use		
Unfamiliarity with AI-technology		
Dificulty to find use cases		
Lacking knowledge		
Lacking coordination betweenn CFO, CIO, CDO *(this is part governance, part knowledge-sharing)*	Knowledge sharing & organizational learning	
Capabilities to levarage AI techniques		
Lacking capabilities		
Availability of talent	Skills & capabilities	
Dificulty in use or deployment of AI tools	Adoption & usability	Knowledge, skills & shared understanding
Data scope or quality problems		
Available data		
Unbiased data	Data foundations & quality	
Complexity to integrate into existing infrastructure	Technology & integration	
Access-control to specific data	Access controls	Data, technology & architecture
Security concerns		
Privacy concerns	Security & privacy	
Potential risk or liabilities		
AI TRiSM (Trust and Risk Management)	Risk & compliance (incl. AI TRiSM)	
Sufficient guardrails in place	Responsible AI & guardrails	Risk, security & trust
Insufficient C-suite collaboration		
Lacking coordination between CFO, CIO and CDO	Executive collaboration	
Governance issues or concerns		
Unstructured implementation of AI		
Lacking ownership of implementation	Governance & ownership	
SCP (Service, Control, Policies) organizational maturity		
Alignment between SCP and other enterprise functions	Organizational maturity & alignment	Leadership, governance & operating model
Lacking or unclear strategy		
Undefined AI-ambition		
Decide defend, extend or upend strategy	Vision, ambition & strategy	
Difficulty to find use cases		
Prioritize use cases before scaling		
Determine feasibility before scaling	Use-case & portfolio management	
Miss-aligned spending		
Lack of coordination and dunding for ongoing initiatives		
Lacking money		
Decide build vs buy	Investment & funding	Strategy & value realization

Table 3: Development of analytical themes from the exploratory scoping review

These themes and corresponding actions are the combination of more than ninety articles, guides and frameworks and can thus be used as a list of things to implement and try, based on what the company wishes to imporve on. *Table 3* therefore summarizes the literature-based themes and potential actions, while *Table 4* grounds these themes in the case company through interview quotes from ten employees. The quotes (right column) were selected to show convergence between the document review and the interview data, and were just some of the 230+ quotes developed during the deductive thematic analysis and transcript processing. Together, these tables show how the theoretical topics identified in the literature appear in practice within the organization and strengthen the empirical grounding of the themes.

Theme	**Description**	**Illustrative Interview Excerpt**
Knowledge, Skills & Shared Understanding	Limited AI literacy and uneven understanding across functions	"Of the 25 R&D people maybe 15 understand how these algorithms principally work, maybe five can describe them in detail, and of the remaining 180 maybe 50 use AI in the form of Copilot assistanc. . . the rest doesn't really know what it should be good for." "If you enforce it, there's no benefit. But if I have a problem and I know whom to ask and this other person can help me, that's when I want this exchange because I see the benefits" "I was in this Copilot project with two meetings a week for a year, and it was really difficult with so different levels in that group, so I got tired and didn't want to participate anymore."
Data, Technology & Architecture	Fragmented data and integration challenges	“We generate a lot of data from machines. . . but when it comes to using it, very little of that data is actually analyzed.” “Every information system that we use in R&D is closed for the AI to look at. Every tool is an island.” “When I get requests like automatic AI replies to customers, I'm like: how? We don't even have a system in place.”
Risk, Security & Trust	Concerns around misuse, reliability, and compliance	“We have different security levels. . . up to level three we can use it in ChatGPT, but level four it's not possible. The most confidential data about machines or clients we cannot feed into any AI.” “They have the understanding that not everything an AI produces is true and needs to be checked or double-checked.” “We are very cautious with that because we understand that there are risks associated with letting the AI run too fast without understanding what it's doing.”
Leadership, Governance & Operating Model	Decentralized decision-making and unclear ownership	“I don't see any trace at all in the organizational policy that we are addressing the AI question.” “IT needs to take a stronger ownership. . . right now the whole IT department is drowning in integrations, and no one really has the mandate to decide.” "[Country] decides for one system, one department decides for another, and then we just have various systems. It's very vulnerable and very expensive.”
Strategy & Value Realization	Unclear prioritization and value logic	“It needs to provide something that I didn't do myself. . . like summarizing large texts. That's a good use case.” “It's hundreds and hundreds of hours per month that someone is replying to emails to customers, trying to find information.” “We are probably not losing money, but I don't have any proof or kind of measured impact.”

Table 4: Overview of qualitative themes and illustrative interview excerpts

The semi-structured interviews followed the interview guides presented in Appendix C and Appendix D, which were developed on the basis of *Table 3*. Since the interview questions were derived from the themes identified in the scoping review, the purpose of the interviews was not to introduce new conceptual areas, but rather to examine whether these themes were also reflected in the case company's organizational context. To avoid leading the respondents, the questions were formulated in an open-ended manner and posed in a neutral way, allowing the interviewees to describe their experiences, perceptions, and practices in their own terms.

The interviewees were selected through a snowball sampling approach and may therefore be seen as core actors in relation to AI implementation and use within the case company. This does introduce a certain risk of bias, as these respondents are more likely than the average employee to be involved in or positively disposed toward AI-related initiatives. At the same time, this also makes them highly relevant informants, since they are among the employees most directly engaged with the company's AI transformation. In this sense, the interviews provide an important empirical lens into how AI is currently being pursued in practice and how the organization is approaching this transformation from within.

One of the more notable observations from the interviews was that several respondents did not perceive their AI initiatives as being clearly aligned with the current strategy of the case company. This suggests that strategic alignment may represent a more critical challenge than initially assumed, and it highlights the importance of ensuring that employees across divisions have a shared understanding of the direction of AI development, both in their day-to-day work and in the products they develop. Consequently, this theme emerged as an important area for the case company to address further before continuing its AI journey.

The development of measurement items for the questionnaire used in the second phase of the thesis presented certain challenges, as these items required prior empirical validation in peer-reviewed literature to ensure construct reliability and validity in SEM analysis. Developing entirely new items from scratch would have been methodologically risky, involving extensive scale purification, reliability testing, and validation against established criteria. These steps were deemed as too demanding in a time-constrained master's thesis. Instead, it is prioritized to adapt constructs and items that had already been validated in prior research, allowing to build directly on established theoretical foundations while maintaining alignment with the empirically derived themes from Phase 1. *Table 5* therefore presents the connection between the empirically derived themes and the corresponding theoretically validated constructs used in the quantitative phase. This table serves two purposes: first, it clarifies the theoretically correct naming of the themes; second, it shows how the inductive findings from the qualitative phase were translated into theoretically validated and established constructs that could be measured in the survey.

5.1.1 Executive Interview Findings

The second part of the first research question (RQ1b) was addressed through a self-completion questionnaire distributed via email (Bell et al., 2022). The targeted respondents were the executive team, and while the number of respondents was limited, with four out of seven executive team members providing input, the collected responses offer insight into how business value from AI is currently perceived at the executive level. The asynchronous and transparent nature of the data collection allowed respondents to view prior submissions and add perspectives if they considered relevant aspects to be missing. As such, the responses are treated as indicative of prevailing executive perspectives rather than as an exhaustive or representative assessment of executive consensus.

The executive interviews suggest that the company is in a mixed but clearly advancing stage of AI maturity. Respondents described AI adoption as uneven across the organization: in some areas, especially close to the core business and in everyday productivity tools, AI is already being used in a more practical and embedded way, while other parts of the company are still learning how to apply it effectively. Overall, the company appears to have moved beyond pure experimentation, but the interviews also show that AI is not yet broadly coordinated as an organization-wide capability. The inconsistency in responses indicates that the executive team might not yet share a unified view of the company's current position in its AI journey. While there is a widespread perception that the organization is working extensively with AI, certain aspects appear not to have been thoroughly discussed at the top management level. For the management team to effectively set the strategic direction for AI adoption, it is therefore crucial that they first align internally, a prerequisite underscored by the literature's emphasis on both top management support and AI strategy alignment as key enablers of organizational readiness.

Across the interviews, AI is consistently framed as a strategic enabler rather than a separate strategy of its own. Executives see AI as something that supports long-term goals by improving efficiency, decision-making, innovation, customer value, and competitiveness. When asked about business value, they pointed

Identified Themes	**Connected Theory**	**Supporting Sources**
Knowledge, Skills & Shared Understanding	Staff Skills & Competency	Liu et al. (2025) Markus et al. (2025) Mathias Kalema & Mokgadi (2017) Snyder-Halpern (2002) Hughes et al. (2026) Gupta & George (2016) Garmaki et al. (2023) Frikha (2025) Jewapatarakul & Ueasangkomsate (2024) Ayoub & Sopuru (2026)
Data, Technology & Architecture	IT Infrastructure	Lewis & Byrd (2003) Mathias Kalema & Mokgadi (2017) Hughes et al. (2026) Fosso Wamba et al. (2024) Islami et al. (2025) Dong et al. (2024)
Risk, Security & Trust	Trust in Organizational AI	McGrath et al. (2025) Hughes et al. (2026) Weisz et al. (2024) R. Sharma et al. (2024)
Risk, Security & Trust	Perceived Risk	Featherman & Pavlou (2003) McGrath et al. (2025) Dang & Erorita (2025) Kim et al. (2008) Olaniyi (2025) Zuo et al. (2025) R. Sharma et al. (2024)
Leadership, Governance & Operating Model	Top Management Support	Dong et al. (2024) Mathias Kalema & Mokgadi (2017) Jöhnk et al. (2021) Mustafa et al. (2026)
Strategy & Value Realization	AI Strategy Alignment	Snyder-Halpern (2002) Mathias Kalema & Mokgadi (2017) Maroufkhani et al. (2019) Ångström et al. (2023) Mariani & Mancini (2025) Frikha (2025)
AI Capability	Organizational AI Readiness	Snyder-Halpern (2002) Mathias Kalema & Mokgadi (2017) Maroufkhani et al. (2019)

Table 5: Identified themes to theoretically proven constructs

to both short-term and longer-term effects, though most agreed that the strongest impact is not always immediately visible in financial metrics. Instead, AI is expected to create value first through better quality, faster processes, lower cognitive load, stronger employee support, and improved ways of working, with financial gains such as EBIT impact, cost reduction, scalability, and margin improvement emerging more clearly over time. *Table 6* was created to visualize the different dimentions of business value mentioned in the executive interviews. This perspective aligns well with the literature, which emphasizes that AI-driven results often take time to materialize in measurable outcomes (Lamarre et al., 2024; Perifanis & Kitsios, 2023). The decision to position AI as a strategic enabler integrated into existing strategies, rather than developing a standalone AI strategy, is also consistent with established recommendations (Kitsios & Kamariotou, 2021). Strategic alignment therefore appears appropriate for a company at this stage of maturity; however, the earlier interviews suggest that this alignment may not yet be effectively communicated or understood across all employee levels.

		Value Dimensions	
		Tangible	Intangible
Outcomes	Operational	• Faster processes and reduced cycle time • Efficiency gains in operations and R&D • Scalability of processes	• Better decision-making • Reduced cognitive load • Higher quality and consistency • Improved ways of working
	Financial	• EBIT impact • Cost reduction • Productivity-driven margin improvement • Long-term financial performance	• Innovation capability • Strategic flexibility • Employer attractiveness • Ability to scale future revenue and business models

Table 6: Matrix of results for business value

In terms of how initiatives are handled, the interviews indicate that AI is usually evaluated through the same general logic as other strategic or digital investments. Business impact, feasibility, scalability, risk, and long-term customer value were repeatedly mentioned as key criteria, and several respondents emphasized that AI initiatives are often embedded in product development or process improvement rather than treated as standalone projects. Governance and funding also appear to follow existing structures rather than AI-specific ones, and most respondents said there are currently no dedicated AI KPIs. Success is therefore still measured mainly through broader operational or commercial outcomes, while some interviewees suggested that future evaluation will need to become more structured, especially around data quality, competence building, portfolio management, and clearer value tracking from idea to realized benefit. Treating AI initiatives the same as regular product development and process improvement projects makes sense given that AI remains relatively new for the case company. These findings present a pragmatic and realistic depiction of current AI management practices, which aligns well with empirical patterns in industry and key insights from the literature (Lamarre et al., 2024). On one hand, this approach facilitates easier incorporation of AI into existing systems and workflows. On the other hand, the absence of AI-specific KPIs carries the risk of inadequate outcome tracking, potentially leading to the digital magic phenomenon where investments yield disappointing returns due to unclear measurement of costs versus benefits (Lamarre et al., 2024). Implementing structured tracking of both spending and generated value, whether through tangible financial metrics or intangible precursors like data quality and competence development, would enable better long-term decision-making and mitigate risks of over- or under-investment in the AI transformation (Schrage et al., 2024). This need is underscored by evidence that up to 85% of AI projects fail to scale due to poor KPI alignment (McKinsey & Company, 2025), highlighting the urgency of developing tailored evaluation mechanisms as the case company progresses (Enholm et al., 2022).

To answer RQ1, it is seen that the case company already has several AI initiatives in place, but the work is still fragmented across divisions and functions. The main capability gaps concern coordination, shared direction, governance, and a clearer way of evaluating business value from AI. At the same time, the findings also show that the company has important enablers in place, including practical experimentation, executive awareness of AI's strategic role, and a growing willingness to use AI in daily work. Overall, the qualitative results suggest that the company is moving beyond early experimentation, but it still lacks the structure needed to turn isolated initiatives into consistent business value.

5.2 Quantitative Results

The measurement model was tested first to assess the reliability and validity of the constructs. Meanwhile, the structural model was examined to test hypothesized relationships in the current study. This was possible using SmartPLS 4.1.1.8 for analyzing the data, following the guidelines by Hair et al. (2019) and Ringle et al. (2024). This study employed reflective measurement specifications, aligning with the hierarchical nature of the research constructs.

Table 7 represents the demographic characteristics of all the 82 respondents who participated in the current study. According to the gender, the majority of the respondents were male, amounting 54 (65.85%), while the 24 (29.27%) accounted for female respondents and 4 (4.88%) respondents chose prefer not to say. Moving on to the age, the highest number of respondents were from 46-55 age range, totaling 27 (32.93%). Simultaeneously, the age group with the least amount of respondents is observed to be 18-25 age group, aggregated to 3 (3.66%) respondents. Relating to the divisions within the case company, division 3 has had the highest amount of respondents for this study, accounting to 42 (51.22%) of the total survey. In contrast, the smallest amount of respondents were recorded from division 2 with 3 (3.66%) respondents.

Classification	Description	Frequency	Percentage
Gender	Male	54	65.85%
	Female	24	29.27%
	Prefer not to say	4	4.88%
Age	18–25 years	3	3.66%
	26–35 years	12	14.63%
	36–45 years	24	29.27%
	46–55 years	27	32.93%
	≥ 55 years	16	19.51%
Division	Division 0	19	23.17%
	Division 1	6	7.32%
	Division 2	3	3.66%
	Division 3	42	51.22%
	Division 4	12	14.63%

Table 7: Characteristics of Respondents

Table 8 illustrates that all the constructs hold mean values around or slightly above the midpoint on a seven-point Likert scale. This generally indicates a moderate to moderately positive response among the participants. The respondents consider Staff Skills and Competency relatively positive with a mean value of 3.81 (SD=1.24). On the other hand, IT Infrastructure has a mean of 3.92 (SD=1.12) and Top Management Support (M=3.83, SD=1.16) are also seen to be perceived as somewhat positive, this indicates that both technological and leadership support for AI initiatives are favourable in general but are not evaluated uniformly in the data. Subsequently, the respondents are inclined towards positive attitudes towards trust in organizational AI systems, as the data on this construct shows a significantly higher mean of 4.79 (SD=1.05). Whereas, Perceived Risk further reflects a reasonable level of concern towards potential risks of AI systems, with mean projected to 3.94 (SD=0.92). Organizational AI Readiness with mean 4 (SD=1.06) and AI Strategy Alignment has a mean 3.84 (SD=1.01) hint that for the case company in this study is viewed as slighlty aligned as well as somewhat more than neutral with regards to AI readiness for AI adoption. Overall, there are no signs of severe floor or ceiling effects for the entirety of the constructs used in this study since they have standard deviations ranging from 0.9 to 1.2, along with the minima and maxima are discovered to be varying from 1.00 to 6.00 show that the variability is adequate along with the evidence of use of most response categories on the seven-point scale.

Variables	**Mean**	**SD**	**Min**	**Max**
Staff Skills and Competency	3.81	1.24	1.00	6.00
IT Infrastructure	3.92	1.12	1.00	6.75
Trust in AI	4.79	1.05	1.75	7.00
Perceived Risk	3.94	0.92	1.75	6.50
Top Management Support	3.83	1.16	1.00	6.25
AI Strategy Alignment	3.84	1.01	1.25	6.00
Organizational AI Readiness	4.00	1.06	1.00	6.00

Source: Primary processed data (2026)

Table 8: Descriptive Statistics

5.2.1 Measurement Model Assessment

The reliability of constructs is proven using Composite Reliability (CR) and Cronbach's Alpha (CA). Following the guidance from Hair et al. (2019, 2022), convergent validity is tested first as presented in *Table* 9 through outer loadings, with values ≥ 0.70 reflecting sufficient validity. Building on this, It can be observed that most items have met this threshold, however those of loading values below 0.40 were removed, as instructed by Fornell and Larcker (1981). Only PR3 was below this threshold (0.342) but due to the overall low convergent reliability of PR, PR2 (0.515) got dropped as well to strengthen the model. PR4 (0.639) was decided to be kept, due to it being close to ≥ 0.70, and PR1 (0.887) compensating for the imbalance. The dropped PR indicators are justified by AVE values above 0.50 (Fornell & Larcker, 1981) and acceptable internal consistency with CR value surpassing 0.70 (Hair et al., 2010). Furthermore, since CA value do not meet the threshold of ≥ 0.70, it is still suggested by many SEM studies to prioritize CR values over CA during a decision making process in removal of a construct as CA is seen more conservative (Hair et al., 2010). TRU2 (0.698) is kept due to being close to the 0.70 benchmark and OAIR3 (0.588) is kept due to the other OAIR indicators being strong and the outcome was not affected by removing it. The remaining constructs in the study satisfied the standards for internal consistency reliability and convergent validity, according to the guidelines by Hair et al. (2010).

Construct	Items	Outer Loading	AVE	CA	CR
Staff Skills and Competency	SSC1	0.857	0.652	0.820	0.882
	SSC2	0.847			
	SSC3	0.706			
	SSC4	0.811			
IT Infrastructure	ITI1	0.812	0.619	0.794	0.866
	ITI2	0.759			
	ITI3	0.832			
	ITI4	0.740			
Trust in AI	TRU1	0.880	0.638	0.810	0.875
	TRU2	0.698			
	TRU3	0.832			
	TRU4	0.775			
Perceived Risk	PR1	0.887	0.597	0.349	0.743
	PR2	*Dropped*			
	PR3	*Dropped*			
	PR4	0.639			
Top Management Support	TMS1	0.753	0.722	0.870	0.912
	TMS2	0.858			
	TMS3	0.891			
	TMS4	0.888			
AI Strategy Alignment	AISA1	0.805	0.641	0.814	0.877
	AISA2	0.846			
	AISA3	0.826			
	AISA4	0.721			
Organizational AI Readiness	OAIR1	0.829	0.564	0.734	0.835
	OAIR2	0.703			
	OAIR3	0.588			
	OAIR4	0.854			

Source: Primary processed data (2026)

Table 9: Measurement model assesment for the first-order reflective constructs

Table 10 displays the HTMT test which is one of the discriminant validity tests used in this study. This test is used to determine whether each construct in the model adequately differs from the others and the analysis show that all the values are below the required threshold of 0.85, as emphasized by Hair et al. (2019, 2022).

Variables	**SSC**	**ITI**	**TRU**	**PR**	**TMS**	**AISA**	**OAIR**
SSC							
ITI	0.561						
TRU	0.292	0.443					
PR	0.106	0.241	0.519				
TMS	0.575	0.515	0.358	0.155			
AISA	0.749	0.625	0.519	0.252	0.725		
OAIR	0.547	0.693	0.615	0.160	0.632	0.845	

Source: Primary processed data (2026)

Table 10: Heterotrait-monotrait ratio (HTMT)

5.2.2 Structural Model Results

The coefficient of determination (R^2) is assessed utilizing the classification provided by Hair et al. (2019). Following this, the R^2 value of 0.75 and above is deemed as substantial, $0.50 \leq R^2 \leq 0.75$ as moderate, and $0.25 \leq R^2 \leq 0.50$ as weak. According to the results shown in *Table 11*, the variable organizational AI readiness has a R^2 value about 0.586, which represents that the predictors in this study i.e., SSC, ITI, TRU, TMS, and AISA together explain about 58.6% of the variance in organizational AI readiness, which Hair et al. (2019) categorizes this as of moderate variance. In simpler words, almost 60% of the explanation as to why organizations differ in AI readiness could be explained by the factors in the current model. The remaining 40% however comes from other reasons that are not in included in this model. In the meantime, trust in AI holds R^2 value of 0.111, this signifies that the indicator perceived risk is able to interpret only about 11% of the variation in the trust in AI, which is classified accordingly as very weak.

Proceeding to the predictive relevance of the model (Q^2) is determined using the indications listed by Hair et al. (2019), where $0 < Q^2 < 0.25$ is considered weak, $0.25 < Q^2 < 0.50$ moderate, and $Q^2 > 0.50$ signals high predictive relevance. Based on the results presented in the *Table 11*, the values for Q^2 for organizational AI readiness and trust in AI are 0.427 and 0.039 respectively. Organizational AI readiness has Q^2 value well above 0 but still under 0.5, signifying that model has a moderate predictive relevance for organizational AI readiness. Contrary to this, the trust in AI has Q^2 value about 0.039, which is over 0 but still hovers under 0.25, showing that the model has low predictive relevance for trust in AI.

Variables	**R-square**	**R-square Adjusted**	**Q^2**
Organizational AI Readiness	0.586	0.558	0.427
Trust in AI	0.111	0.100	0.039

Source: Primary processed data (2026)

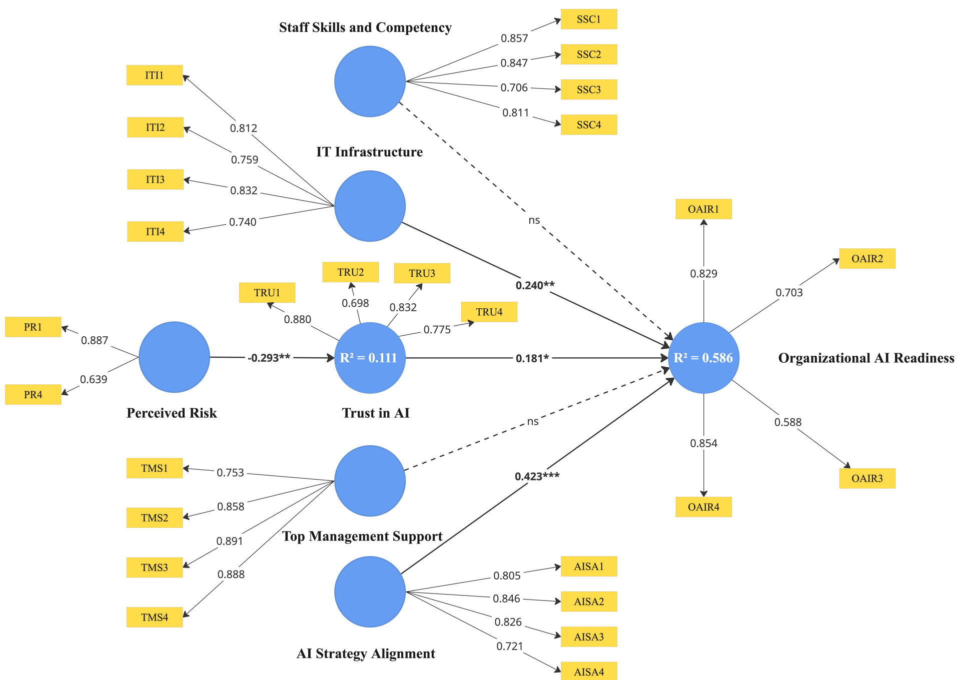
Table 11: Structural Model Explanatory and Predictive Power

5.2.3 Common Method Bias Testing using Random Dependent Variable

In order to mitigate the response bias, the survey was designed to keep the responses anonymous and respondents were assured of the anonymity and confidentiality. This was adapted to mitigate socially desired responses. To check the common method bias statistically, a test was conducted using the methods recommended by Kock (2015) and Kock and Lynn (2012) in SmartPLS. This is assessed using the full colinearity VIF procedure implemented by creating a random dependent variable and regressing all the latent variables on it as seen in *Appendix E*. Building on this, as per Kock (2015), values greater than 3.3 indicated as potential pathological colinearity and common method bias. Consequently, it can be observed that all the values are under this threshold (refer *Appendix E*), reflecting that the model in this study is less likely to constitute a risk to the validity of the estimated realtionships.

5.3 Hypothesis testing

The testing of hypothesis is carried out to review the influence of one variable onto the other in structural model using bootstrapping. An overview of the same is demostrated in *Figure 5* and the detailed data is illustrated in *Table 12*.



Source: Primary processed data (2026)

Figure 5: Results of structural model testing

Note: (***p < 0.001, **p < 0.01, *p < 0.05, ns=not supported). Dotted line indicates a non-significant relationship statistically, and continous line represents a significant relationship empirically.

Hypothesis	Path	Coefficient (β)	T-statistic	P-value	Supported
H1	SSC → OAIR	-0.023	0.247	0.805	No
H2	ITI → OAIR	0.240**	2.456	0.014	Yes
H3	TRU → OAIR	0.181*	1.718	0.043	Yes
H4	PR → TRU	-0.293**	2.920	0.004	Yes
H5	TMS → OAIR	0.108	1.043	0.297	No
H6	AISA → OAIR	0.423***	3.524	0.000	Yes

Source: Primary processed data (2026)

Table 12: Hypothesis Testing

Note: the minus sign (-) indicates the negative direction of the relationship between two variables.

5.3.1 Staff Skills and Competency - A bottleneck

Staff Skills and Competency (SSC) does not have a significant influence on Organizational AI Readiness in the structural model shown in *Figure 5*. The data in the model (β = -0.023, t = 0.247, p = 0.805) further supports the statement. Thus, H1 is not supported. The magnitude remains small and the path coefficient being negative (direction is positive in hypothesis), resulting in statistically treating the value as zero. Contrary to the expectations, this result conflicts with prior literature since they see how staff skills is a central driver of AI readiness and value realization. Studies like Ayoub and Sopuru (2026), Gupta and George (2016), Hughes et al. (2026), and van de Wetering (2026) consistently interpret that internal capability building and upskilling are among the crucial indicators of predicting whether AI initiatives scale beyond initial pilots. Numerous explanations can help make sense to this inverse result, one of primary ones is, in the case company, AI literacy and digital skills are possibly relatively high already among the employees, so in a way increased in skills do not change their perception of readiness as much as structural factors like infrastructure and strategy alignment. Another possibility could be in the way the survey was designed for the SSC construct, capturing mainly individual competencies and training, while on the other hand the OAIR captures overall organizational capabilties in a broader aspect such as culture, and processes, which could arguably depend more on structural factors rather than on individual skill levels (Jöhnk et al., 2021; Scaccia et al., 2015). Finally, the minimum sample size required for this study to capture SSC may not have been sufficient. Nonetheless, for practice, this does not mean that staff skills and training are unimportant, it implies instead that in the case company, staff skills alone are not sufficient to measure OAIR.

5.3.2 Role of IT Infrastructure

Hypothesis H2 (ITI → OAIR) is supported (β = 0.240, t = 2.456, p = 0.014), demonstrating a statistically significant positive relationship between ITI and OAIR in the case company. The path reflects a medium effect size along with both t-value and p-value displaying high significance, which aligns well with previous literature. The results correspond with the expectations that a robust IT infrastructure act as a foundational enabler for AI transformation (Fosso Wamba et al., 2024), and thus a key component for determining an organization's AI readiness (Gupta & George, 2016). In the context of AI, IT infrastruture address barriers like data silos, workflow integration and scaling initiatives beyond pilots (Lamarre et al., 2024). For the case company, these findings suggest that siloed infrastructure across global sites constrains AI readiness, whereas investments in unified data lakes, API standards, and hybrid cloud environments would reinforce the technical foundation required for future AI initiatives (Lamarre et al., 2024). The result also aligns with TOE framework literature, which consistently positions technological infrastructure as a foundational determinant of AI readiness by enabling data integration and scalable deployment across organizational boundaries (Drazin et al., 1991; Mathias Kalema & Mokgadi, 2017). Since IT infrastructure is observed as the second most influential factor affecting OAIR in this model, standardizing the infrastructure across divisions could further accelerate value creation by enabling more effective data sharing and coordination.

5.3.3 Impact of Trust in AI

Hypothesis H3 (TRU → OAIR) is supported (β = 0.181, t = 1.718, p = 0.043), confirming a statistically significant positive relationship between Trust in Organizational AI and Organizational AI Readiness within the case company. The t-value of 1.718 exceeds the threshold ($t > 1.645$, $p < 0.05$,) (Hair et al., 2019), establishing significance despite being the model's weakest among the significant paths. Somewhat surprisingly, this relationship proved weaker than anticipated, contrasting sharply with R. Sharma et al. (2024)'s $\beta = 0.731$ for similar trust-AI adoption dynamics. While both studies confirm that users engage more readily with AI perceived as competent, moral, and beneficial, which aligns with trust-based acceptance theory ((Dang & Erorita, 2025)), the substantial difference likely stems from methodological factors. Potential explanations include sample size limitations (fewer respondents), indicator heterogeneity in the TRU construct, or contextual divergence: R. Sharma et al. (2024) examined consumer-facing AI within healthcare, whereas this study captures enterprise AI readiness in a high-tech manufacturing context.

The results might also be attributed to the specifics of the case company, where respondents may undervalue generative and agentic AI's corporate potential relative to product innovation applications, diluting trust's organizational impact. Survey feedback (from the open-ended questions in the questionnarie) revealed respondent uncertainty to answer some of the trust questions, expressing a desire for "I don't know" options unavailable in PLS-SEM designs. This may potentially introduce measurement noise across the wide-ranging TRU indicators. The company's decentralized structure likely amplifies competing enablers like strategy alignment (AISA → OAIR: β = 0.423), positioning trust as a supplementary rather than primary driver of readiness. Despite this borderline significance, the finding remains theoretically and practically meaningful. Trust operates as a necessary precondition, incrementally building readiness atop stronger structural factors (Hair et al., 2021). For the case company, practical implications emphasize low-cost trust interventions: transparent AI governance, pilot success showcases, and executive messaging framing generative AI as complementary to R&D expertise.

5.3.4 Influence of Perceived Risk on Trust in AI

Hypothesis H4 (PR → TRU) is supported (β = -0.293, t = 2.920, p = 0.004), revealing a statistically significant negative relationship between Perceived Risk and Trust in Organizational AI within the case company. The negative path coefficient indicates that as perceived risk increases, trust in AI decreases. This finding aligns with established risk-trust theory (Dang & Erorita, 2025; R. Sharma et al., 2024). *Table 12* shows that PR's impact on TRU (β = -0.293) represents the second strongest path coefficient in the model (behind only AISA → OAIR, 0.423), consistent with expectations from Dang and Erorita (2025), who found that perceived risk (with trust as a mediator) substantially reduced purchase intentions for AI autonomous vehicles. Although this study examines organizational AI rather than consumer products, the same risk-trust dynamic applies, particularly for a high-tech manufacturer where AI errors could carry million-dollar consequences. This strong negative effect confirms theoretical expectations that heightened risk perceptions erode trust in AI systems, something Kim et al. (2008) identified as a core barrier to effective adoption. Trust-based decision-making models further explain why technically capable AI initiatives often fail without deliberate trust-building measures (Dang & Erorita, 2025).

A distinctive aspect of the PR construct is that two indicators (PR2 and PR3) were dropped due to low relevance, leaving PR measured by fewer items and thus capturing a more focused version of perceived risk. The retained indicators, PR1 (potential errors from AI decision outputs) and PR4 (risks from system misuse), both contribute to perceived risk but differ slightly: PR1 addresses AI-generated errors, while PR4 concerns human-input errors or misuse. Notably, removing PR2 and PR3 improved the path coefficient, composite reliability, and AVE to acceptable levels by eliminating measurement noise from these weaker indicators. In PLS-SEM, it is common practice to exclude underperforming items to enhance indicator reliability and reduce noise in latent variable scores, even though it may narrow the construct's conceptual scope (Hair et al., 2019). Consequently, the observed negative relationship between perceived risk and trust should be interpreted as robust for the final PR operationalization used in this paper, with appropriate caution regarding generalization beyond the retained indicators.

5.3.5 Top Management Support challenges

The results of this study demonstrate that Top Management Support does not indicate a statistically significant direct influence on Organizational AI Readiness (β = 0.108, t = 1.043, p = 0.297), thus H5 is not supported. Even though the path coefficient is positive as predicted from previous scholar work, the effect is still insignificant since it is too small and ambiguous to support the hypothesis that higher support from top management leads to overall organizational AI readiness. This came out as a surprise since in the literature, Jöhnk et al. (2021) identifies top management support as one of the 18 AI readiness factors while also stating that a dynamic leadership is a need for both kickstarting AI initiatives and signalling encouragement for bottom-up explanatory projects. Consequently, Mustafa et al. (2026) describes in order to build change readiness and align structural factors for programs which involve transformations (like AI), it is crucial that top management is actively involved in supporting and boosting the organization. Building on this, Lamarre et al. (2024) and Matt et al. (2015) contribute in the context of digital transformation studies, consistently highlight that leadership committment is important along with clear vision and resource allocation as some of the requirements for persistent change. So, one reasonable interpretation of the why the contrary result is, in the context of case company, the effect of TMS on AI readiness is mostly indirect. This is further supported statistically in the *Appendix F* representing that the indirect effect of TMS on OAIR with AI strategy alignment (AISA) acting as a mediator is significant. However, this claim could not be validated in literature while also bearing in mind the timeframe limitations of this study. Another possible reason is that employees within the organization may not experience leadership support firsthand due to the decentralized nature of the case company, so the sole scores of TMS are multifarious to cause a strong and clear relationship with OAIR (Nyberg & Vasileva, 2024). At last, the cross-sectional design may not successfully capture the importance of leadership in a long term for sustaining AI initiatives, rather only a snapshot in time (Mustafa et al., 2026).

Although H5 is not supported statistically, the findings from the prior literature reveal that Top Management Support is still considered in practice, particularly for instructing clear vision on new technologies like AI, and also guaranteeing persistent funding for infrastructure and capability building (Jöhnk et al., 2021). For the case company, this indicates that the executive team should focus on concrete actions that are visible for employees like coherent AI strategy and consistent improvements in infrastructure so that the team is involved in day-to-day work rather than just remaining as a general message from C-suite (Jöhnk et al., 2021).

5.3.6 AI Strategy Alignment as a key driver

Hypothesis H6 (AISA $\rightarrow$ OAIR) is supported (β = 0.423, t = 3.524, p < 0.01), suggesting that strategic alignment is an important driver of readiness in the case company. There is no strict benchmark for the β-value to indicate the strength of the relationship, but generally 0.423 is considered medium-high when meassuring path coefficience. Paired with the t-value and p-value however, it indicates a large positive association (Hair et al., 2019), confirming the hypothesis. This indicates that a better defined strategy for use of AI within a company, improves the company's readiness to implement AI, something that correlates with the theory by, for example, Mathias Kalema and Mokgadi (2017) and Snyder-Halpern (2002). This also aligns well with Ångström et al. (2023) and Gartner (2025) that explains that when AI initiatives are explicitly linked to organizational priorities, resource allocation becomes more coherent, governance structures gain legitimacy, and cross-functional coordination improves. In other words, the strategic alignment is creating the structural conditions for readiness. For the case company, a cross-functional AI strategy for the entire organization would thus increase the AI readiness. This provide the nesecary foundation for scaling technology in the future. According to the literature on business value, the improvement in OAIR will increase business value both long- and short-term (Åström, 2020; Enholm et al., 2022; Frikha, 2025). This spread between short-term and long-term aligns with the business outcomes the executive team wished to gain from AI, see *Table 6*. Taking these factors together, as well as the strength of this path coefficient, it underscores that refining the organizations AI strategy should be prioritized in the near future. At the very least, the case company need to designate accountable owners at the business unit level, and create feedback loops linking pilot outcomes to strategic objectives. Without such alignment, even well-executed technical deployments risk remaining isolated projects rather than scalable capabilities.

5.4 Linking hypotheses to RQ2

The results from the PLS-SEM analysis (Figure 5, Table 12) directly address RQ2: *What technological and organizational capabilities are required for effective AI value realization, and what key capability gaps constrain that realization in the case company?*, by quantifying the relationship between the identified capability needs found in RQ1 and the endogeneous variable OAIR. The predictive power (Table 11) show R^2 = 0.586, which indicate a moderate explanatory power, and Q^2 = 0.427, which indicate a moderate prediction of OAIR in the model (Figure 5). These values indicate that the constructs will predict organizational AI readiness with moderate certainty, meaning that it can be used to identify strengths and weaknesses within a company. The model confirms that all hypothesized antecedents contribute to OAIR perceptions, with strategy alignment (AISA) emerging as the dominant driver (H6 supported, β=0.423, p<0.001), followed by infrastructure (H2, β=0.240) and trust (H3, β=0.181). The risk-trust mediation (H4, β=-0.293) further validates theoretical expectations found in literature. The literature (for example Ångström et al. (2023), Dang and Erorita (2025), Dong et al. (2024), Fosso Wamba et al. (2024), Hughes et al. (2026), Liu et al. (2025), and Snyder-Halpern (2002)) suggest that all constructs are needed to meassure OAIR successfully, which leads to the understanding that the non-significant paths, H1 (SSC $\rightarrow$ OAIR, β=-0.023, ns) and H5 (TMS $\rightarrow$ OAIR, β=0.108, ns), are bottlenecks at the case company. This signals potential gaps: while baseline competencies may exist per qualitative themes (Dong et al., 2024; Liu et al., 2025), they do not strongly differentiate readiness perceptions, possibly due to case company-specific circumstances or measurement sensitivity (caveat N=82). Connecting to RQ1, the executives showed strategy misalignment, which might explain the behaviour of TMS in the statistical SEM model.

The implications these results have on RQ2 are thus that the low β values can be seen as the constraining gaps within the case company, since all six required capabilities were validated conceptually in RQ1 and structurally in the SEM. The path strength can therefore be seen as priorities for the case company, indicating that improving SSC and TMS should be prioritized. This aligns with RQ1 findings (e.g., uneven competencies, exec misalignment) and suggests the case company must prioritize upskilling (SSC) and C-suite commitment (TMS) to unlock fuller OAIR. Connecting these findings to Mikalef and Gupta (2021) who used tangibles, human skills and intangibles as a meassurement for capability, we see that effective AI value realization requires balanced development across technological (ITI), human (SSC/TRU), and leadership/strategic (TMS/AISA) dimensions, with current constraints centered on skills upskilling and executive commitment.

To answer RQ2 in simple terms, the quantitative analysis shows that Organizational AI Readiness is mainly driven by AI Strategy Alignment and IT Infrastructure in the case company. Trust in Organizational AI also has a positive effect, while Perceived Risk reduces Trust in Organizational AI, which confirms that risk matters indirectly for readiness as well. Staff skills and top management support were not significant in the final model, which suggests that individual competence and leadership support alone are not enough to explain readiness in this context. Taken together, the results indicate that the company's ability to realize AI value depends more on alignment, infrastructure, and trust than on isolated capability building.

6. Discussion

The study provides evidence on how Organizational AI Readiness is shaped in the case company. The structural model describes a reasonable share of variance in OAIR (R^2=0.586) showcasing that the chosen readiness capbilities provide a meaningful interepretation of how the ability of the case company to adopt, govern, and scale AI is formed. The same model also shows (Q^2=0.427) predictive relevance for OAIR. This indicates that framework has an acceptable level of explanatory and predictive assessment in this organizational context and is significant at the 5% level ($p < 0.05$). The findings reveal that AI readiness in the case company is not decided primarily by the presence of isolated pilots or AI tools, but rather by allowing AI initiatives to be coordinated, governed, and trusted. This explanation supports the theory of dynamic capabilities and resource-based view, where resources that are linked to AI only turn out useful when they are ingrained in firm specific routines, strategic alignment, infrastructure, and processes of learning (Enholm et al., 2022; Mikalef & Gupta, 2021; Teece, 2007). In the same line of logic, the findings from qualitative and quantitative together demonstrate that case company has moved past the stage of early AI awareness, however it has yet to fully develop AI as an integrated enterprise-wide capability.

The robust finding is the positive significant effect of AI Strategy Alignment on OAIR (β = 0.423, t = 3.524, $p < 0.01$). This confirms that the readiness is primarily moulded by the fact if AI initiatives are aligned well with business priorities, supported by clear decision rights, and shared across functions. This statement is consistent with the results obtained in qualitative stage, where challenges such as ownership unclear, fragmented initiatives, and the existence of weak value logic constantly showed up as recurring problems. In the meantime, AI strategy alignment operates mainly as a cooperating capability, meaning that it helps the case company transition from fragmented pilots to meaningful AI transformation.

On the same page, IT Infrastructure also displayed a significant positive effect on OAIR (β = 0.240, t = 2.456, p = 0.014). This underlines that AI readiness depends primarily on infrastructure that can support AI integration, accesible data, interoperable systems, and scalable platforms. In parallel, the findings from qualitative findings reinforce this result, as the participants depicted limited data accessibility, described isolated digital environments and, put emphasis on fragmented systems that exist within the organization as barriers to AI use. Hence, the case company presents itself the risk of holding the AI initiatives as local pilots unless the technical foundation that underlies this is improved.

Trust in Organizational AI had a moderately feeble but still significant positive effect on OAIR (β = 0.181, t = 1.718, p = 0.043). This signifies that the willingness of the employees to depend on AI contributes to readiness, mainly when AI systems are perceived as safe, reliable, and usable enough. Meanwhile, Perceived Risk had a significant negative effect on Trust in AI (β = -0.293, t = 2.920, p = 0.004) as expected from the prior literature. This strenghthens the concerns about confidentiality, security, misuse, and inaccurate outputs substantially reduce staff's trust in AI. Nevertheless, the low explanatory power fot Trust i.e, R^2=0.111, points out that perceived risk may only explain only the parts of trust formation, while other factors like prior experience, transparency, commmunication, system reliability, and transparency might also play a major role.

In a wider contrast, the Staff Skills and Competency clearly reported a non significant direct effect on OAIR (β = -0.023, t = 0.247, p = 0.805). This result is not indicative of being irrelevant. Rather, it signifies that competence based on individual AI does not lead to readiness untill it is endorsed by infrastructure, strategy, governance, and relevant use cases. Likewise, Top Management Support did not have a significant direct impact on OAIR (β = 0.108, t = 1.043, p = 0.297). This showcases that leadership support in general may be too brief in order for it to have an affect on readiness directly in the case company, unless it is made clearly visible through concrete funding, communication, strategic alignment, prioritization, and ownership.

Combining them all together, the overall findings show that OAIR in the case company is mainly outlined by AI Strategy Alignment, IT Infrastructure, and Trust in Organizational AI, while increase in Perceived Risk weakens the readiness indirectly by reducing Trust in Organizational AI. Furthermore, results clarify that even though leadership support and staff skills are important theoretically, they are not sufficient on their own. In total, the case company has been positioned beyond early AI awareness stage however yet to acheive a mature stage of AI value realization. It has interests of executives, experimentation ability, and somewhat relevant use cases, but still it lack all the mechanisms required to scale AI consistently. Relative to RQ2, the current study thus displays that effective AI value realization thus demands a nuanced development of capabilities involving technology and organization with the current dominant priorities being strategic alignment, infrastructure, and mechanisms involved in trust-building.

6.1 Theoretical Contribution

In this study, we attempt to understand what capabilities are needed to succeed during an AI transformation by developing and validating a measurement model of Organizational AI Readiness in a case company. By integrating qualitative exploration with quantitative PLS-SEM analysis, the study identifies context-specific capability gaps and empirically tests how core readiness constructs relate to a firm's ability to scale AI and realize business value. This dual focus positions Organizational AI Readiness as a measurable, actionable construct rather than a vague goal.

This study, albeit limited to the context of the case company, provides multiple contributions to research on Organizational AI Readiness and value creation from AI initiatives. First of all, this study contributes to research within business value creation from AI by clarifying which organizational capabilities and competencies are crucial for transforming generative and agentic AI pilots into scalable results. The results indicate that AI Strategy Alignment, IT Infrastructure, and Trust in Organizational AI exert the strongest influence on Organizational AI Readiness, with AI-aligned strategy showing the most pronounced effect. This indicates that business value from AI is less about finding the perfect use case and more about: 1. whether the AI initiatives are clearly connected to strategic priorities, 2. supported by a robust and reusable infrastructure, and 3. embedded in an environment where employees interpret AI systems as reliable and safe to use. Secondly, the study contributes to the emerging research field of Organizational AI Readiness by systematically connecting inductively derived themes from advisory documents, industry reports, interviews, and an executive questionnaire to theoretically validated readiness constructs. The constructs derived from an extensive literature review are: Staff Skills and Competency, IT Infrastructure, Trust in Organizational AI, Perceived Risk, Top Management Support, and AI Strategy Alignment. This bridging work connects the language of practitioners and advisory frameworks with the cumulative, construct-based tradition in information systems and digital transformation research. It provides a template for future research to translate consultant-like readiness narratives into validated measurement models that can be compared across organizations and over time. Third, by testing the model in case company, the study highlights how readiness capabilities behave in an industry context. The results reinforce the importance of strategic alignment, IT infrastructure, and trust as contributors to organizational AI readiness, while the weaker or non-significant direct effect of staff skills & competency and support from top management suggests that some capabilities may operate more indirectly, for example via AI strategy alignment or trust-building mechanisms. This nuance is important for theory building since it points researchers towards a more complex, potentially mediating relationship between leadership, AI-related capabilities, and readiness, rather than simple direct effects. It also suggests that investments in "more skills" or "more visible support" from top management may be insufficient if these efforts are not translated into concrete mechanisms such as aligned AI strategies, governance structures, and shared infrastructure. Lastly, the study strengthens the conceptual link between AI readiness and AI-enabled business value. Readiness is framed as a necessary precondition for realizing both short-term efficiency gains and long-term strategic and learning effects from AI initiatives (Mikalef & Gupta, 2021). The business value matrix (Figure 6) and executive perspectives show that the case company pursue a combination of financial, operational, and capability-building outcomes, but often find it challenging to connect these outcomes back to specific capability gaps.

6.2 Practical Implications

This study shows that organizations aiming to go from scattered AI pilots to scalable value realization need to treat AI readiness as something manageable, measurable and constantly evolving, not as a vague readiness concept. The results especially point toward three areas where practical implications have the largest impact: strategic direction or alignment, infrastructure conditions and trust in AI in the organization.

First, the top management team at the case company should explicitly formulate how AI is connected to their business goals and anchor this direction in the entire organization. For a decentralized structure, this means that local initiatives need to be governed through joint principles for prioritization, financing and monitoring, rather than through ad-hoc projects. Practically, the result that AI Strategy Alignment has a strong connection with Organizational AI Readiness implies that the company should spend time translating their AI vision into concrete goals, decision rights, ownership and portfolio management of AI initiatives. Second, the study shows that IT Infrastructure acts as an enabler for scaling AI use beyond pilot projects. Practically, this implies that investments in shared data and platform solutions, standardized integration patterns and common tools for generative and agentic AI often have a larger impact than investing in more isolated use cases. In a decentralized environment, it therefore becomes important to define a "base level" of common infrastructure that each division can build from, while retaining some local flexibility. Third, the model underlines that Trust in Organizational AI and management of Perceived Risk are essential for employees to actually use the solutions. For practitioners, this implies that governance is more than just compliance, but also includes clear guidelines, transparency surrounding data and decisions, and support for employees who experience uncertainty surrounding AI. Actions like training or upskilling, setting ethical boundaries, establishing testing environments and a clear division of responsibilities can decrease Perceived Risk and thereby strengthen both Trust in Organizational AI and actual use. Lastly, the conceptual model for Organizational AI Readiness gives a concrete structure for diagnosing capability gaps and prioritizing efforts. By following up on key areas (seen in *Figure 4*) over time, the company can tie their AI initiatives to business value instead of only focusing on a few projects or technical implementations. The study therefore indicates that a systematic approach to AI readiness can act as a practical management tool that helps organizations direct their AI investments towards areas where the likelihood of measurable results is the greatest.

6.3 Limitations and Future research

Limitations

Based on the qualitative and quantitative analysis performed in this study, several methodological and empirical limitations are acknowledged. First, even though PLS-SEM is appropriate for complex models, with comparatively small samples, the use of the current sample size of 82 respondents from an internal organization can still limit the overall statistical power of SEM and may explain why certain theoretically critical paths lacked statistical significance. Additionally, this may also limit the generalizability of the findings to other contexts or industries and the stability of path estimates in a model with multiple latent constructs (Hair et al., 2019). Extending this, the current study overlooked an estimation of minimum sample size using a prospective approach as recommended by Kock and Hadaya (2018) to be conducted before the data collection process for an accurate estimation of the sample size required for the model. The alternative retrospective approach was avoided due to inaccuracies. Second, selected constructs do not directly lead to AI readiness; instead, they operationalize AI adoption as the endogenous variable. In this research, this can only be connected loosely as organizational AI readiness is conceptualized as a precursor to AI adoption. However, while some studies explicitly follow a sequential logic by assessing readiness first and then testing adoption, other models assess adoption directly without testing readiness at all, which creates ambiguity about whether readiness is, in fact, a necessary intermediate stage before AI adoption. Third, the cross-sectional design adopted in the study also signifies that data captures one specific moment in time i.e., a single snapshot of the company rather than tracking changes over the long term. Fourth, the reliance on self-reported survey responses captures the potential risk of response bias in the prior literature despite using CMB testing with a random dependent variable (or full collinearity VIF approach in SmartPLS) since they only test whether the method itself artificially inflated the shared variance to an extreme degree. As a result, the scope of this study cannot account for every delicate psychological bias of an individual respondent, such as social desirability, mood, or selective memory. Fifth, in the context of measurement model adjustments, two indicators which underperformed for perceived risk were decided to be dropped to ascertain model reliability, while this enhanced the model's overall statistical clarity, it missed out on capturing a fully accurate conceptual scope of risks that could have been measured. Finally, the survey was designed without providing an "I don't know" option; this was because the data collection behavior of SEM analysis restricted it to a standardized Likert scale for consistency across all the data from respondents, resulting in minor measurement noise.

Future Research

Future research could build on these findings by testing the OAIR model in larger, diverse samples across different industries or multiple firms, allowing for multi-group analysis of centralized versus decentralized structures, and cross-sector/industry comparisons. Consistent tracking of an organization's progress over the long term could completely change the results and could contribute more to this study, since AI is such a rapidly changing technology. This means that a longitudinal study would better capture how different factors impact ongoing training programs and may reveal hidden readiness constructs that might prove effective. This is also described in the work of Rindfleisch et al. (2008), as longitudinal designs that follow an organization over time are valuable for scrutinizing how changes in infrastructure, staff skills, trust, and strategy alignment shape shifts in measurable business value and AI readiness, thereby aiding in addressing the causal constraints of cross-sectional data. While two indicators of perceived risk (PR2 & PR3) do not remain relevant for this study, future research should employ more tightly aligned perceived risk items. Regarding survey data, in order to reduce the bias for future studies, objective indicators such as performance metrics, AI usage logs across different domains/firms can be combined with perception-based survey measures as recommended by Podsakoff et al. (2003). In parallel, future research could provide a deeper exploration of indirect factors, such as Top Management Support having no direct significant relationship with OAIR in this study, but instead having an indirect effect on OAIR through AI Strategy Alignment. Future studies should incorporate the literature support for the mediating effect of AISA. Moreover, extending this model with some critical additional constructs like external environmental pressures, and data governance would possibly reveal a more comprehensive view of AI transformation and refine the measurements of Trust in Organizational AI contexts and Perceived Risk. Finally, another natural extension of the entire study is to measure and report AI adoption as an endogenous variable, as readiness is often prescribed as a precursor to it. Jöhnk et al. (2021) highlights this in their study that organizational AI readiness is not just a precursor but rather a fundamental and integral element throughout the entire AI adoption process. This could potentially extend the knowledge for an organization internally in an accurate manner now that readiness is assessed for this study. Refer to *Figure 6* for an overview of this suggestion.

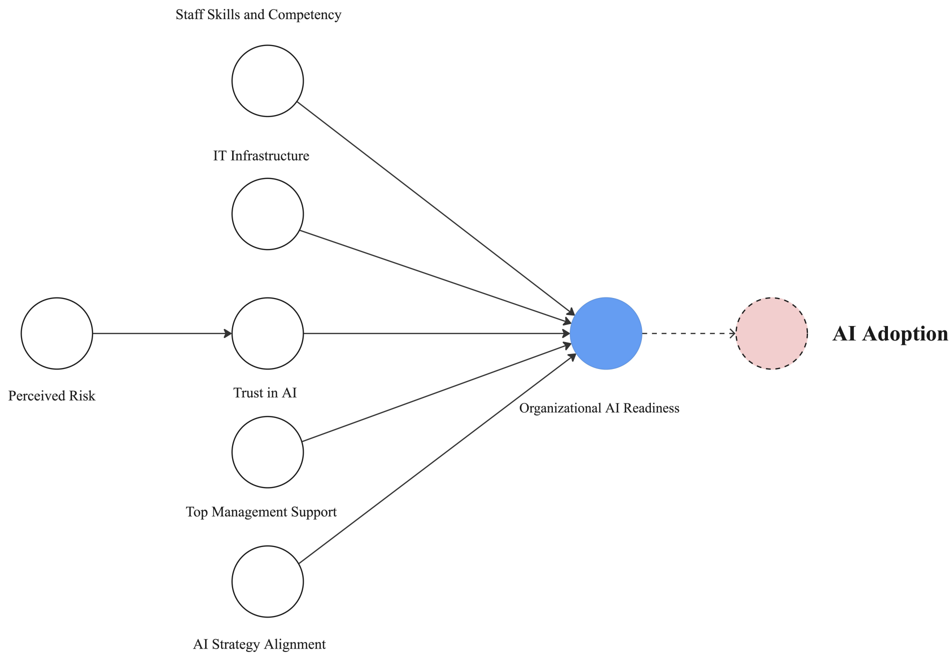


Figure 6: Extended future research to AI adoption

7. Conclusion

This study contributes to the growing research on Organizational AI Readiness by consolidating capabilities identified in advisory and academic sources and applying them in a case company. For research question one, the qualitative phase of the thesis shows that the company already has several AI initiatives, but they remain fragmented across divisions. The main gaps concern coordination, shared direction, governance, and how AI-related business value is evaluated. At the same time, the company has important enablers in place, including practical experimentation, executive awareness of AI's strategic role, and increasing willingness to use AI in daily work. Overall, the company is moving beyond early experimentation, but it still lacks the structure needed to turn isolated initiatives into consistent business value. To answer the second research question, a conseptual model was developed and tested to meassure the AI readiness within the case company. The quantitative analysis shows that Organizational AI Readiness is mainly driven by AI Strategy Alignment and IT Infrastructure. Trust in Organizational AI also has a positive effect, while Perceived Risk reduces Trust in Organizational AI. Staff Skills and Competency and Top Management Support were not significant in the final model, which suggests that individual competence and leadership support alone do not explain readiness in this context. Taken together, the results indicate that the company's ability to realize AI value depends more on strategic alignment, infrastructure, and trust than on isolated capability building.

Practically, these results indicate that leaders in the case company must prioritize strengthening strategic alignment related to AI and IT infrastructure, as well as establish an organizational environment in which employees trust AI-enabled systems and feel supported in developing the skills needed to use them effectively and responsibly. Beyond the immediate case, the findings also offer broader implications for how Organizational AI Readiness can be conceptualized and assessed in similar contexts. The study therefore provides an empirically grounded basis for future AI transformation work.

Appendix A Constructs, items and sources

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Construct	Item	Statement	Source
Staff Skills and Competency	SSC1	People in this organization have sufficient skills to identify suitable opportunities to apply AI in their work.	Liu et al. (2025) Markus et al. (2025) Mathias Kalema & Mokgadi (2017)
	SSC2	Employees here understand the basic concepts, strengths, and limitations of the AI technologies used in this organization.	Liu et al. (2025)
	SSC3	We have enough staff who can technically implement, configure, or integrate AI solutions when needed.	Liu et al. (2025) Markus et al. (2025) Mathias Kalema & Mokgadi (2017)
	SSC4	Employees receive adequate training and development to keep their AI-related skills up to date.	Liu et al. (2025) Markus et al. (2025) Snyder-Halpern (2002)
IT Infrastructure	ITI1	Our existing IT systems can reliably handle the data volumes required for AI solutions.	Lewis & Byrd (2003) Mathias Kalema & Mokgadi (2017)
	ITI2	Data needed for AI use cases is accessible across systems in a consistent and usable format.	Lewis & Byrd (2003)
	ITI3	The organization has computing resources (for example, cloud or servers) that can scale to support AI workloads.	Lewis & Byrd (2003) Mathias Kalema & Mokgadi (2017)
	ITI4	AI solutions can be integrated with our existing applications and workflows without major technical issues.	Lewis & Byrd (2003) Dong et al. (2024)
Trust in Organizational AI	TRU1	I trust the AI systems used in this organization to produce reliable results for my work.	McGrath et al. (2025)
	TRU2	I believe the AI systems used here are applied in a way that is fair to employees and other stakeholders.	McGrath et al. (2025)

Construct	Item	Statement	Source
Trust in Organizational AI	TRU3	I am confident that decisions supported by AI in this organization are made with appropriate human oversight.	McGrath et al. (2025)
	TRU4	I feel comfortable relying on AI-generated recommendations when performing my job in this organization.	McGrath et al. (2025)
Perceived Risk	PR1	Using AI in this organization could lead to serious errors in important decisions.	Featherman & Pavlou (2003)
	PR2	AI systems used here might compromise the privacy or confidentiality of sensitive information.	Featherman & Pavlou (2003)
	PR3	AI adoption in this organization creates a significant risk of job loss or role reduction for employees.	Featherman & Pavlou (2003)
	PR4	I am concerned that AI systems in this organization may be misused or behave in unintended ways.	Featherman & Pavlou (2003) McGrath et al. (2025)
Top Management Support	TMS1	Top management actively communicates a clear vision for how AI should be used in this organization.	Dong et al. (2024)
	TMS2	Top management allocates sufficient budget and other resources to AI initiatives.	Dong et al. (2024) Mathias Kalema & Mokgadi (2017)
	TMS3	Top management personally champions AI projects (for example, by sponsoring pilots or attending key reviews).	Dong et al. (2024)
	TMS4	Top management holds leaders accountable for delivering business value from AI initiatives.	Dong et al. (2024) Snyder-Halpern (2002)
AI Strategy Alignment	AISA1	AI initiatives in this organization are clearly linked to our overall strategic priorities.	Snyder-Halpern (2002) Mathias Kalema & Mokgadi (2017) Maroufkhani et al. (2019)

Construct	Item	Statement	Source
AI Strategy Alignment	AISA2	There is a shared understanding across functions of how AI supports our business goals.	Snyder-Halpern (2002) Mathias Kalema & Mokgadi (2017)
	AISA3	AI projects are selected and prioritized based on clear business value criteria.	Snyder-Halpern (2002) Maroufkhani et al. (2019)
	AISA4	Responsibilities and decision rights for AI (between business and IT teams) are clearly defined.	Snyder-Halpern (2002) Maroufkhani et al. (2019)
Organizational AI Readiness	OAIR1	Overall, this organization is ready to adopt AI solutions at scale across multiple functions.	Snyder-Halpern (2002) Mathias Kalema & Mokgadi (2017) Maroufkhani et al. (2019)
	OAIR2	We have the processes and governance needed to manage AI-related risks effectively.	Snyder-Halpern (2002) Maroufkhani et al. (2019)
	OAIR3	The organizational culture here is open to changing ways of working based on AI-enabled insights.	Snyder-Halpern (2002) Mathias Kalema & Mokgadi (2017)
	OAIR4	If we decided to expand AI use in this organization today, we could do so quickly and in a controlled way.	Snyder-Halpern (2002) Maroufkhani et al. (2019)

Appendix B Executive Questions

Questions sent to the executive team by email.

1. How would you describe where [case company] currently is on its AI journey?
2. What role do you see AI playing in the company's overall business strategy?
3. When you think about business value from AI, what does that mean to you?
   (a) Financial metrics?
   (b) Non-financial metrics?
4. Once a potential AI initiative is identified, how is it evaluated and prioritized?
5. What criteria are most important when deciding whether to invest in an AI initiative?
6. Do AI initiatives get evaluated differently from other IT or digital projects? Why or why not?
7. Could you describe the governance structure around AI initiatives?
8. How is funding for AI initiatives structured?
9. What KPIs do you use to measure whether AI is successful?
10. Looking ahead 3–5 years, what changes do you think are needed in how the company evaluates and structures AI initiatives to maximize business value?

Appendix C Interview Guide 1

Questions asked in a semi-structured format during online interviews with three employees from the case company.

1. Can you briefly describe your role and responsibilities at [Case Company]?
2. How, if at all, does your work relate to Artificial Intelligence (AI), data, or automation?
3. What specific AI initiatives have you been involved in, supported, or observed within [Case Company]?
4. What AI-related projects or initiatives are you currently involved in or aware of?
5. How would you describe the purpose and expected outcomes of these initiatives?
6. What current stage of development or maturity are these initiatives in?
7. Can you walk me through how this AI initiative was developed and implemented?
8. What were the key steps or milestones?
9. Who was involved during each phase?
10. What technical skills, tools, or infrastructure were required?
11. What competencies did your team already have, and which had to be learned or developed?
12. What organizational factors enabled or constrained progress?
13. What have been the outcomes of the AI initiative so far?
14. Have you seen measurable improvements, or more qualitative benefits?
15. How would you assess the overall success of the initiative?
16. What have you and your team learned from this initiative?
17. Have these learnings been shared or applied elsewhere within [Case Company]?
18. Are there mechanisms for reusing solutions, models, or knowledge?
19. What do you think [Case Company] needs to strengthen in order to scale AI further?
20. What capabilities are missing today?
21. What would help your team implement AI more effectively?
22. Is there anything we haven't talked about that you think is important?
23. Do you have any questions for us?
24. Would you be open to a follow-up discussion if needed?

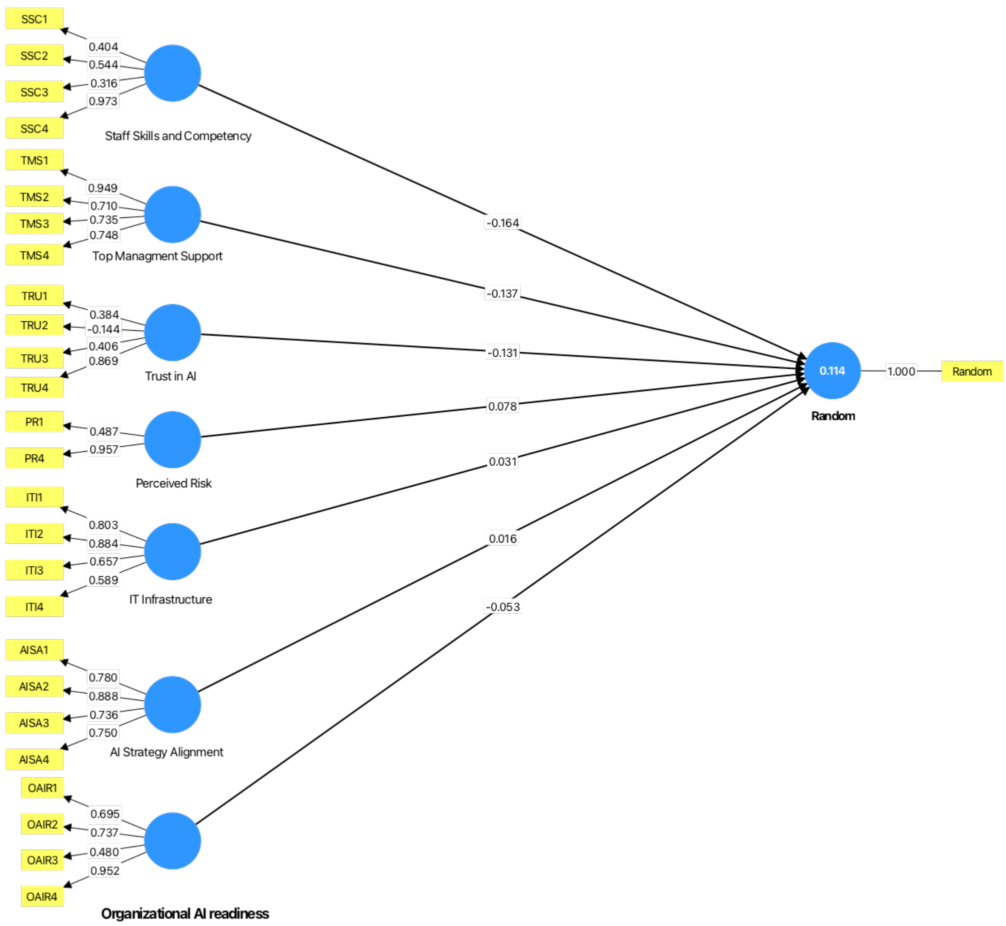
Appendix D Interview Guide 2

Questions asked in a semi-structured format during online interviews with seven employees from the case company.

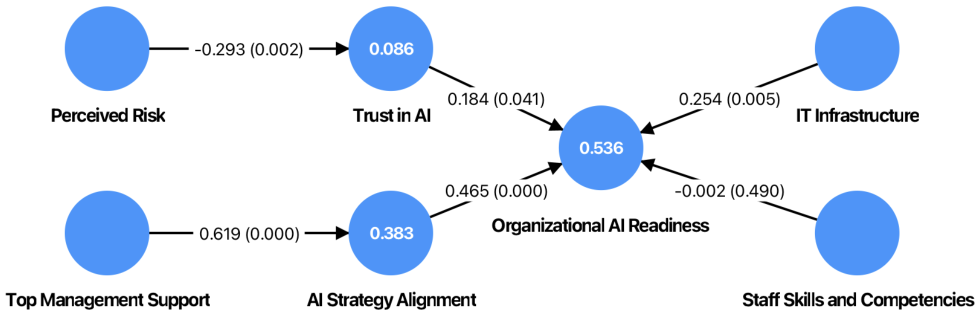
1. What is your role at [Case Company], and in what ways have you worked with or been involved in AI in your daily work so far?
2. How would you describe how AI fits into your organization's overall strategy, and what impact you expect it to create?
3. What roles do leaders and governance structures play in how AI initiatives are guided, prioritized, and followed up today?
4. How well do people across the organization understand AI and know how to use it in their work, in your experience?
5. From your perspective, how well do the current data, technology, and systems support the use of AI?
6. How do people in your organization think about risks connected to AI - such as security, privacy, accuracy, or trust?
7. What is your view on the impact of competitive pressures (from the sector or other organizations), to adopt GenAI and how has this shaped organizational policy?
8. How does the speed of AI innovation in your sector affect your organization's motivation or urgency to adopt AI?
9. Is there anything else about your experience with AI in the organization that you think is important for us to understand?

Appendix E   Common method bias testing with a random dependent variable (using VIF in SmartPLS)

	VIF
AI Strategy Alignment	2.254
IT Infrastructure	1.578
Organizational AI Readiness	1.865
Perceived Risk	1.097
Staff Skills and Competency	1.679
Top Management Support	1.795
Trust in Organizational AI	1.152



Appendix F Analysis of path TMS to AISA



Path	Path Coefficient	T statistics	P values
Top Management Support → AI Strategy Alignment	0.625	8.248	0.000

Mediation Analysis of the path (TMS → OAIR)

Path	Path Coefficient	T statistics	P values
Top Management Support → Organizational AI Readiness	0.288	3.553	0.000

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