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Artificial Intelligence (AI) adoption roadmap for SMEs: From Readiness assessment to strategic alignment and AI-Task suitability evaluation

Supervisor:

Prof. Roberto Pinto

Co-Supervisor:

Prof. Fabiana Pirola

Submitted by:

Saqib Naheed

1090379

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List of Abbreviations

Advanced Planning and Scheduling (**APS**)

Artificial intelligence (**AI**)

Best–Worst Method (**BWM**)

Central Research question (**CRQ**)

Core investigative research questions (**CIRQs**)

Design Science Research Methodology (**DSRM**)

Digital transformation (**DT**)

Generative AI (**GenAI**)

Partial Least Squares Structural Equation Modelling (**PLS-SEM**)

Phase-specific empirical research questions (**PERQs**)

Preferred Reporting Items for Systematic Reviews (**PRISMA**)

Sales and Operations planning (**S&OP**)

Small to medium enterprises (**SMEs**)

Systematic literature review (**SLR**)

Task–Technology Fit (**TTF**)

Technique for Order Preference by Similarity to Ideal Solution (**TOPSIS**)

Technology-Organisation-Environment (**TOE**)

Technology-Organisation-Environment-Human (**TOEH**)

Make-to-Order (**MTO**)

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Abstract

Small to medium enterprises (SMEs) are considered the backbone of global economy, assuming an even heightened significance in the European market as they constitute almost 99% of all businesses. However, their slow progression in digital transformation has widely been reported, typically characterized by lack of awareness and preparedness along with limited strategic planning capabilities for effective artificial intelligence (AI) adoption. The existing body of literature concerning AI adoption in SMEs remain fragmented, contextually insensitive and largely non-operationalizable.

Consequently, this thesis addresses these limitations by proposing a comprehensive AI adoption roadmap for SMEs. It adopts a Design Science Research (DSR) methodology to address the solution-oriented and context-sensitive goals of the study. It helped integrate conceptual modelling, analysis, and industry validation through continuous collaboration with SMEs (in particular, industrial sponsor of the study). Guided through DSRM, three core investigative research questions (CIRQs) of the study are addressed through three interdependent phases. These phases adopt different research methodologies designed to address their phase-specific research questions.

The first phase suggests a Technology-Organisation-Environment-Human (TOEH)-based readiness assessment model. It is constituted upon the dimensional elements and their micro-level attributes to add the necessary level of granularity for addressing the complexities of AI adoption capabilities. These dimensional elements and micro-level attributes were also assigned relative weights through an expert analysis, that helped develop a practical mechanism for revealing heterogeneous readiness profiles and context-dependent maturity patterns.

The second phase assists in aligning the transformational plans with clearly defined strategic performance enhancement goals. It identifies and prioritises the contextual AI enablers across five performance dimensions within two transformation contexts. This emphasises the relatively varying impact of AI enablers across performance outcomes, questioning of sufficiency of one-size-fits-all approaches and underscoring the need for adaptive and context-aware adoption planning.

The third phase advances the strategic alignment to operational feasibility through a Task-Technology Fit (TTF) based suitability model. It proposed a layered conceptualization of AI's functional role describing how different AI applications generate value for SMEs in the given context. It illustrated how different AI technologies can be utilised as interdependent components within a broader Sales and Operations planning (S&OP) decision-support ecosystem.

Together, these three phases integrate into a layered adoption roadmap. It enables SMEs to progress from diagnostic readiness evaluation to strategic alignment and eventually prescriptive task-level deployment. The proposed framework advances theoretical understanding by integrating TOE and TTF perspectives. It offers a practical tool for SMEs and policymakers to foster systematic, risk-mitigated, and performance-oriented AI transformation.

Chapter 1. Introduction

The European Commission (2015) explicated the positive impact of the intelligent use of modern technologies. It is considered as one of the primary factors for gaining competitive advantage, increasing organisational productivity and enhancing their capability to innovate in today's dynamic market. It is considered the main tool of modern industrial revolutions aimed at revolutionizing businesses by learning from data, identifying patterns and forecasting decisions based on its intelligent analysis and interpretation of data (Skilton, 2019). Therefore, this research ventures into the dynamic realm of AI driven digital transformation of SMEs. Sheff (2023), Ivanov et al. (2021) and several others described the present and futuristic role of AI in enhancing the industrial productivity and overall growth of the firms. It holds the promise of reshaping how organisations plan, decide, and execute operations. Whilst industry experts and academics are contemplating the humongous potential of AI, the transformation or AI adoption journey for SMEs yet remains uneven, fragmented, challenging and fraught with uncertainty. Many reports and studies have reported the inability of most businesses, particularly SMEs, to harness the absolute potential of digital technologies (Peter, 2017; Little, 2019; OECD, 2021). They have identified various factors (like financial limitations, lack of IT resources and expertise, misaligned /unrealistic goals and inadequate strategy and lack of plan of implementation) that can disrupt the transformation process. AI adoption is a multiphase process, consisting of numerous interconnected stages forming a coherent AI adoption roadmap (Hansen et al., 2024). Each of these stages represent a key building block that guides the subsequent stages and contributes to the comprehension of the overall adoption lifecycle. Effectively navigating through these transformation stages demands a deep knowledge base and expertise to strategically understand, plan and operationalize transformation initiatives. However, various studies including Bettoni et al., (2021), Mylrea and Robinson, (2023), Badghish and Soomro, (2024) and Tehrani (2024), point towards the limited understanding of AI adoption process among SME stakeholders. They argue that most SMEs lack a clear grasp of aligning these technologies with their strategic goals, operational needs and organisational capabilities. This limited awareness often leads to misguided adoption decisions. Consequently, this thesis begins by situating AI adoption challenges within both the literature and real-world context of SMEs.

1.1. Background and motivation

1.1.1. Industrial case

The foundation for this research was significantly shaped by close collaboration with Pinetti Srl. (co-sponsor), an SME operating in the luxury home decor sector. It is a rapidly growing, luxury leather product manufacturing company specializing in producing unique and diverse collection of interior accessories. A gradual increase in terms of orders is escalating pressure on the existing supply chain planning process of the company demanding innovation and enhancements to keep up with the progress. Therefore, the company sought to explore the AI integration to remain competitive and ready for the evolving market requirements. It is a family-owned small business that had various exploratory transformation ideas without organised plans or roadmap. The engagement revealed several common SME challenges, such as limited strategic clarity around AI and fragmented technological systems. Although highly interested in AI, the firm lacked the direction on how to initiate and operationalize its transformation. This highlighted the absence of a structured, operationally aligned understanding of AI use. Consequently, it was pertinent to initiate the research from the ground up. It commenced with the understanding of AI technologies; specific transformation needs and intended goals. This foundational awareness help anticipating the potential impact of AI adoption and the challenges that may arise throughout the transformation process. Equally important is the systematic evaluation of the company's internal processes, organisational environment, and existing capabilities before initiating the transformation process. Like most SMEs, it was operating in a constrained environment with limited infrastructure, rigid organisational structure, financial resources and digital skills etc. These limitations pose significant challenges to undertaking resource-intensive or large-scale indiscriminate transformation. This implied that AI transformation efforts must be highly focused, context-aware, and strategically prioritised to efficiently utilise their limited resources to areas that offer the greater potential for impact and align closely with their performance enhancement goals. The partner company's involvement provided practical insights, validation opportunities, and a real-life lens through which to design and refine the multi-stage AI transformation framework. Further, the academic literature and knowledge provided lens to effectively frame the research problem.

1.1.2. Research problem

The European Commission (2015) identified the application of intelligent modern information technologies such as AI, Digital Twins and IoT etc., as a critical determinant of competitive advantage within the European market, particularly for SMEs. A significant influence of the advanced technological tools has been reported in responding to the evolving demands of contemporary markets. These are capable of enhancing organisational productivity, efficiency, and its capacity to innovate. This structured integration of such technologies across business functions to enhance performance and competitiveness is typically described as digital transformation (DT) (Brodny and Tutak, 2022). Beyond internal improvements, it also helps create opportunities for new revenue streams and market expansion through innovative, technology-enabled and enhanced business models. However, evidence from multiple studies and industry reports such as (Peter, 2017; Little, 2019; Ghobakhloo and Ching, 2019; OECD, 2021; McKinsey and Company 2022) indicate that a significant proportion of DT initiatives fail to deliver their intended outcomes. For instance, it was revealed by a senior McKinsey partner that almost 70% of digital transformation projects are unable to meet the intended objectives (Robinson, 2019). Another senior McKinsey partner reported a similar failure rate (about 70%) in 2022. This demonstrates a lack of improvement in transformation outcomes during this period. Moreover, a mere 17% of 600 organisations undergoing digital transformation managed the anticipated cost savings. Along with that only 20% achieved the intended revenue gains (McKinsey and Company, 2022). This persistent high failure rate underscores a critical problem. Though considerable research has been conducted in this area, the challenge of improving the success of DT initiatives continues to persist.

Successful transformation requires deliberate and strategically planned design, and implementation, as it should not be regarded as a discrete initiative but rather as an incremental process. It requires SMEs to develop knowledge of available technologies, adopt supportive frameworks for digital transition, and align with enterprise-specific digital demands (Bley et al., 2016). Apart from understanding the digital settings, it is also pertinent for the firms to assess their organisational context, including their existing infrastructural capabilities, financial resources, the routine operations for innovative practices and other digital growth opportunities for sustainable competitiveness. However, Bouwman et al. (2019) highlighted that a critical challenge in advancing DT within the SME sector lies in their limited awareness and knowledge base regarding digitalization initiatives. They lack a comprehensive understanding of the opportunities and requirements of DT, constraining their ability to devise realistic goals and develop operationalizable implementation strategies (Peter, 2017; Little, 2019; Ghobakhloo and Ching, 2019; OECD, 2021). This inadequacy induces the underutilization of digital technologies' potential along with fragmented or misaligned effort. Consequently, SMEs approach towards DT is reactive rather than strategic, lacking the ability to set coherent goals or to establish a structured roadmap for execution. This has contributed significantly to sluggish growth of DT in SMEs (Hansen et al., 2024), raising an urge for strengthening and enhancing the DT knowledge and strategic planning for unlocking SMEs' digital potential.

Within the broader landscape of advanced digital technologies, AI is widely regarded as a key driver of the fourth and emerging fifth industrial revolutions. It aims to transform industries through the seamless convergence of digital and physical domains (Mithas et al., 2022). Various researchers such as Davenport and Ronanki (2018), Dwivedi et al. (2021), Rai et al. (2021), Johnk et al. (2021) elucidated a series of structured activities of AI adoption journey that guide firms towards effective AI adoption. In parallel, numerous challenges associated with AI adoption in SMEs have also been reported. These largely mirror those faced in broader digital transformation initiatives. These include limited understanding of adoption processes, uncertainty regarding appropriate entry points for implementation, and concerns related to organisational readiness (Tehrani et al., 2024; Nortje and Grobbelaar, 2020). These ill-informed, ill-conceived and non-systematic transformation efforts risk failure, causing organisations to often lose confidence in the value of change. This loss of trust intensifies resistance to future innovation and ultimately slows the overall trajectory of transformation (Nortje and Grobbelaar, 2020; Dwivedi et al., 2021; Johnk et al., 2021; Tehrani et al., 2024).

Drawing on the Resource-Based View (RBV), successful AI adoption depends on the SME's ability to identify, access, and strategically deploy key internal resources such as technology infrastructure, workforce competencies, leadership commitment, and financial capital etc. However, (Nortje and Grobbelaar, 2020; Johnk et al., 2021; Badghish and Sumroo, 2024; Tehrani et al., 2024) have reported that many SMEs struggle to assess whether these critical resources are adequately available and aligned to support AI initiatives. They strive to adopt cutting-edge AI technologies without critically evaluating the contextual fit between AI applications and their specific performance objectives or assessing their organisational capabilities to support this integration. Similarly, from the perspective of the TTF theory, the technology adoption is more likely to have a positive impact when the capabilities of the technology match the requirements of the task. Even then SMEs risk adopting ill-aligned complex AI solutions without evaluating their suitability and contextual fitness for the concerned business functions. Consequently, capability gaps in strategic resource management, awareness, and planning limit the effectiveness of AI adoption, highlighting an urgent need for strategic frameworks that can strengthen SMEs' capacity to leverage AI successfully. Therefore, this research problem concerning the lack of a systematic approach to early-stage AI adoption provides the conceptual and analytical foundation for this thesis. It is fundamentally grounded in the development of a strategic, operationalizable and prescriptive framework enabling SMEs to align technological initiatives with internal capabilities and strategic objectives, thereby supporting sustainable and scalable integration.

1.2. Research purpose and objectives

As described above, the primary purpose of the study is to establish a strategic, diagnostic and prescriptive AI adoption framework for SMEs. It seeks to provide SMEs with practical guidance for making informed, goal-aligned, and sustainable AI adoption decisions. This overreaching purpose of the development of a strategic AI adoption framework consists of two objectives.

The first objective of the work is to support organisational awareness and understanding by assisting them to better understand their existing capabilities, the criticality of the required resources and their contextual importance. The initial phase of the study proposes an AI readiness assessment model that incorporates multifaceted AI readiness dimensions, operationalised at a granular level to enable a detailed and systematic evaluation of an organisation's preparedness for AI adoption. Whereas, the next phase seeks to comprehend the direct impact of AI enablers on different sustainable business performance dimensions aimed at enhancing the organisational understanding for aligned and specific sustainable enhancement goals setting.

The second objective is to support identification and prioritisation of AI-adoption opportunities in SMEs by understanding where and which AI technologies can add more value within complex planning environments. Phase three addresses this objective by suggesting a task suitability framework for AI applications that recommends the most appropriate AI application for each task. These in conjunction serve as an integrated roadmap aligning AI readiness, enabler prioritisation, and AI-task suitability into a coherent decision-making framework.

1.3. Thesis overview

This chapter presents an overview of the research of the research undertaken in this thesis. The work builds upon the gaps identified through an extensive literature review conducted on AI adoption and transformation within SMEs. It revealed that the existing body of literature remains fragmented and predominantly conceptual with most studies focusing on isolated aspects of the adoption process. While these contributions have advanced the understanding in specific areas, they are deficient in collectively producing integrated or operational frameworks that can effectively guide decision-making in real organisational settings. As a result, current scholarship lacks both theoretical coherence and practical guidance particularly for SMEs, which face unique constraints in resources, expertise, and implementation capability.

Responding to these shortcomings, this work intended to develop of a context-sensitive and operationalizable framework for strategic, diagnostic and prescriptive AI adoption tailored to the needs of SMEs. It is specifically designed to bridge the gap between conceptual understanding and practical application by aligning organisational readiness, strategic intent, and technology selection within a unified model. As presented in the figure 1.1, the proposed framework consists of three phases, designed to provide a structured pathway that assists SMEs in fostering organisational awareness and preparedness along with the identification of priority AI adoption solutions.

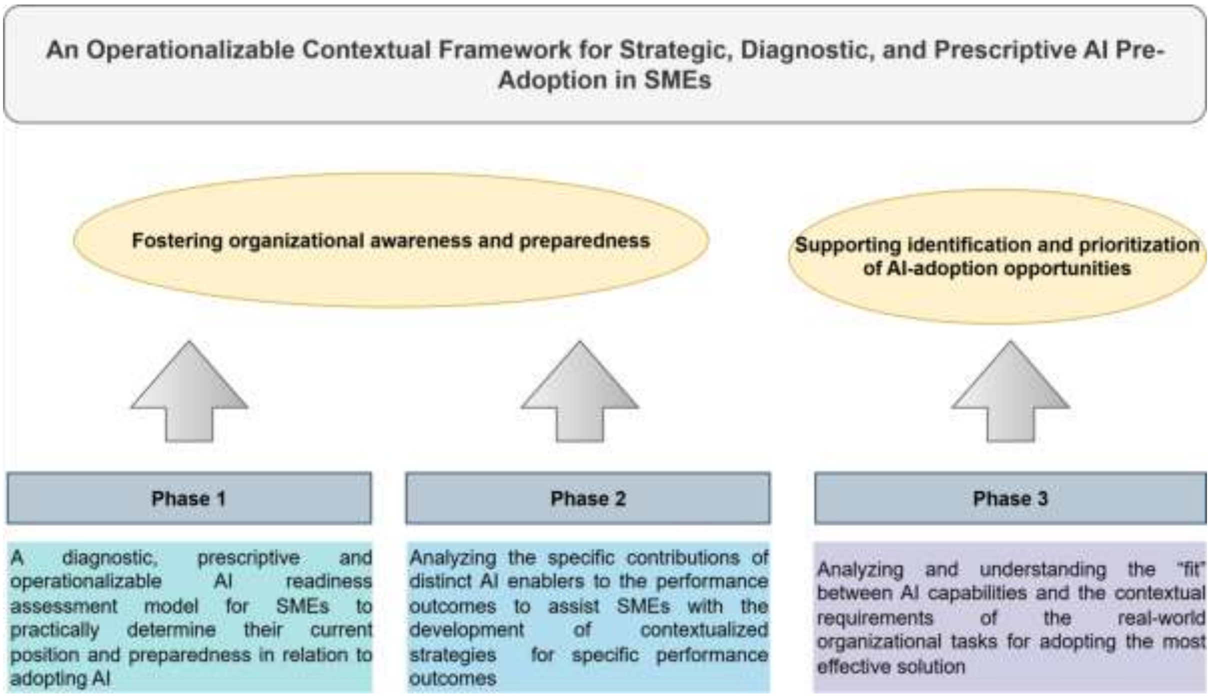


Figure 1.1: Thesis overview

Phase 1: A practical multidimensional AI readiness assessment and guidance model for SMEs

Phase 1 proposes a four-dimensional framework, that is operationalised to a granular level entailing to the micro-level attributes. To establish a strong theoretical foundation, a comprehensive literature review following Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines was carried out. 45 studies finalized after a strict scrutiny were included in the final review. It was undertaken to determine the key constructs of AI readiness, for the development of a comprehensive set of dimensional elements and their micro-level attributes. Extension of the Technology-Organisation-Environment (TOE) framework with a human dimension provided for a more holistic conceptualization. Expert-derived significance weights for these dimensional elements and their attributes were assigned using the Best–Worst Method (BWM). A survey instrument was also designed to capture organisational capabilities. A four-state readiness framework including informal, struggling, approaching and desirable states based on these weighted significance and capability ratings was proposed. It was also validated in real-world settings to determine its applicability. The resultant model provides SMEs with a structured mechanism for AI readiness assessment. It can also assist SMEs with devising prioritised action plans for effective and sustainable adoption.

Phase 2: Identifying high impact AI implementation factors (AI enablers) for sustainable performance improvement in SMEs: A context-specific and goal-aligned prioritisation approach

Phase 2 employed a quantitative design to examine the variable influence of AI enablers across distinct performance enhancement contexts in SMEs. Given the financial and operational constraints typical of SMEs, transformation efforts often lack coherence; therefore, a contextualized understanding of enablers is essential for developing practical roadmaps. A structured survey was used to collect data from 119 Italian SMEs (already using AI or in the adoption phase). The study used a 5-point Likert scale to assess enabler impact on business performance dimensions. Cronbach's alpha was used to confirm the reliability of the data. A hybrid model using Random Forest regression with Partial Least Squares Structural Equation Modelling (PLS-SEM) was used for the analysis. The results challenged the assumption of a uniform impact, and highlighted the varying influence of AI enablers for different performance outcome. These AI enablers based on their relative influence were systematically classified into three categories. It highlighted the need for tailored adoption strategies aligned with SMEs' specific goals and contexts.

Phase 3: Identification of Sales and Operations planning (S&OP) Tasks to Be Supported by Artificial Intelligence and Generative AI (GenAI)

This part of the study aimed to advance a nuanced understanding of where and how AI can generate value within complex planning contexts, with a focus on Sales and Operations Planning (S&OP) as the partner organisation's key area for improvement. To this end, a tailored AI suitability framework was developed to evaluate the alignment between AI capabilities and S&OP task requirements. A hybrid methodological approach was employed to balance literature-based insights with expert-driven validation.

Initially it developed a theoretical foundation by identifying core S&OP functions, relevant AI applications, and key task suitability dimensions through a structured domain-specific literature review. This foundation functioned as the core for evaluating the strengths and limitations of different AI applications within planning processes. Next, an expert elicitation study that involved 15 experts (both academics and practitioners) was conducted to operationalize these conceptual insights. A structured survey was then used to establish ratings for the AI applications against the identified suitability dimensions. It helped record the criticality of task dimensions for effective execution of S&OP tasks. This expert analysis helped produce composite capability and requirement profiles respectively. Finally, these profiles were systematically mapped, to generate AI-for-task fitness rankings, offering practical guidance for the selection of most suitable AI applications for the specific planning tasks. The resulting frameworks can assist firms in making targeted and effective adoption decisions.

1.4. Significance of work

This research contributes to both academic understanding and practical decision-making by developing a structured yet context-sensitive framework to support AI adoption in SMEs. Many SMEs recognise the potential value of AI but often struggle to determine where and how it should be implemented within their organisational environment. The framework proposed in this study addresses this challenge by offering both diagnostic and prescriptive capabilities. It allows organisations to assess their current readiness, identify capability gaps, and prioritise improvement efforts in a way that aligns with their operational context and strategic objectives.

The work is organised around three interrelated phases that explore different but connected aspects of the AI adoption process. In the first phase, the study develops a granular AI readiness conceptual construct and translates it into measurable organisational capabilities. This enables a more detailed and practical assessment of AI readiness within SMEs. The second phase investigates how AI implementation enablers relate to organisational performance outcomes, offering insight into how readiness capabilities may influence the effectiveness of AI adoption in real organisational settings. The third phase focuses on the operational application of AI within planning activities. Here, the research draws on TTF theory and applies it within the S&OP context to evaluate the suitability of AI support across different planning tasks.

Methodologically, the research adopts a Design Science Research Methodology (DSRM) approach, enabling the development and evaluation of an artefact grounded in both theoretical foundations and real-world organisational settings. This approach allows the research to move beyond purely theoretical discussion and demonstrate how the framework can be used as a decision-support tool in practice. In practical terms, the study provides SMEs with a structured roadmap for approaching AI adoption. Rather than treating AI implementation as a purely technological decision, the framework encourages organisations to consider readiness capabilities, organisational context, and task-level requirements together. By linking these perspectives, the research helps bridge the gap that often exists between the ambition to adopt advanced digital technologies and the organisational realities that shape whether such initiatives can succeed.

1.5. Thesis structure

This work is organised into eight chapters, each logically building on the previous to ensure the contextual flow. Chapter 1 introduces the work by describing the background and motivation, outlining the research problem, laying out research objectives and discussing the significance of the work. Next, literature review chapter presents a critical review of existing literature relevant to AI adoption and highlights critical gaps in contexts of SMEs. It synthesizes the key themes from the AI adoption in SMEs literature, establishing the foundation for the research and guiding the development of the proposed study framework. It is followed by research methodology chapter that outlines the research philosophy and approach adopted by the study. It also provides the rationale for the mixed-methods design and rigor in the research process. Chapter 4-6 discuss the three phases of the study in detail. Each presenting the research design, findings, and interpretation of results focused on a distinct phase of the investigation. Collectively, these chapters trace the progression from diagnostic analysis to the articulation of strategic intent and informed technology selection. Chapter 7 synthesizes the insights from the three phases to form a unified adoption roadmap for AI implementation for SMEs. It also presents the contributions of the work to research and industry practices. Lastly, the thesis concludes by presenting a final reflection along with delineating limitations of the work and possible future research directions. The reference to the studies that have been cited by the work are presented in chapter 9 followed by the appendices.

Chapter 2. Literature review

This chapter reviews the existing literature on AI adoption in SMEs to develop a systematic understanding of the research area. It synthesizes the insights extracted through the systematic review to provide a brief overview of existing domain knowledge along with highlighting the underdeveloped and fragmented areas that require further investigation. Thus, assisting with systematic identification of critical gaps and inconsistencies in current scholarly work. These results served as the foundation for shaping the research agenda and justifying the need for a more integrated and context-specific investigation.

2.1. Introduction

AI is considered as one of the primary factors for gaining competitive advantage, increasing organisational productivity and enhancing their capability to innovate in today's dynamic market. Sheff (2023) described the present and futuristic role of AI in enhancing the industrial productivity and overall growth of the firms. However, despite the advantages on offer, several reports and studies have reported the inability of most businesses, particularly SMEs, to harness the absolute potential of digital technologies (Peter, 2017; Little, 2019; OECD, 2021). They have identified various factors (like financial limitations, lack of IT resources and expertise, misaligned /unrealistic goals and inadequate strategy and lack of plan of implementation) that can disrupt the transformation process. AI adoption is a multiphase process, consisting of various interconnected stages forming a coherent AI adoption roadmap (Hansen et al., 2024). Each of these stages represent a key building block that guides the subsequent stages and contributes to the comprehension of the overall adoption lifecycle. Contrary to that, studies have also highlighted SME's lack of understanding regarding the AI adoption process. For instance, Bettoni et al., (2021) emphasised the need for enhancing SMEs knowledge for better aligning the AI solutions with firm's strategic goals, operational needs, and organisational capabilities. It is crucial as firm's limited awareness can lead to unrealistic or misaligned adoption decisions. On the other hand, transformation decisions driven by a structured assessment of business needs along with the contextual understanding of AI's potential can yield better outcomes.

In the progressively evolving industrial landscape, AI is considered a potent tool for gaining competitive edge and ensuring sustainable business performance. It holds the promise of reshaping how organisations plan, decide, and execute operations (Skilton, 2019). Whilst industry experts and academics such as Ivanov et al. (2021), Sheff (2023) and several others are contemplating the humongous potential of AI, the transformation or AI adoption journey for SMEs yet remains uneven, challenging and fraught with uncertainty. Effectively navigating the transformation demands a deep knowledge base and expertise to strategically understand, plan and operationalize transformation initiatives. Whilst a growing body of research has emerged on AI adoption within the context of SMEs, much of this literature addresses the AI adoption process in a fragmented manner. These studies focus on isolated areas such as adoption benefits and challenges, motivating factors, organisational readiness evaluation, challenges, or performance outcomes etc. A limited number of studies adopt a holistic perspective. In addition, the scholarly discourse surrounding adoption of AI further complicates the interpretation of findings by using diverse and inconsistent terminologies. For instance, Radhakrishnan & Chattopadhyay (2020), Hangl et al. (2023) and Alruwaili et al. (2025) referred to factors influencing AI adoption as drivers of AI implementation, motivational factors and determinants of AI adoption respectively. This conceptual uncertainty slows down the development of a coherent and clear AI adoption pathway for SMEs. Thus, it is essential to identify and critically address these existing gaps in the literature. Doing so reveals the fundamental constraints limiting effective transformation and supports the design of more structured frameworks to guide SMEs for effective AI adoption.

2.2.Methodology

As explained in the previous section, the primary aim of the study was to provide a structured synthesis of existing knowledge identify the research gaps and rationalize the future discourse for progression of strategic AI adoption. To ensure the rigor, verifiability, and reliability of findings, a systematic literature review (SLR) methodology guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was employed (Garcia-Penalvo, 2022). It provides a transparent, traceable and replicable framework for identifying, evaluating, and synthesizing relevant academic knowledge. PRISMA offers a well-established structure for reporting systematic reviews, ensuring clarity within the review process (Page et al., 2021).

The review process commenced with the careful formulation of a search strategy capable of capturing the diverse terminologies and conceptualizations related to AI, its adoption strategy and the SME context. To this end, a comprehensive set of keywords and synonyms presented in table 2.1 below was developed, drawing on researcher's prior domain knowledge and a preliminary scoping of the literature. These keywords were organised into three primary conceptual clusters, that are combined using Boolean operators (AND, OR) to construct search strings. The general logic of the search string was maintained across the database for consistency; however, Few database-specific syntax adjustments were made without altering the conceptual logic of the search.

Three prominent academic databases (including Scopus, Web of Science and IEEE Xplore) were used to ensure multidisciplinary coverage across management and technology literature. Examples of search strings for the three databases are presented in table 2.2 below. Supplementary search techniques like backward and forward citation tracking were also leveraged to enhance comprehensiveness, reduce publication bias and systematically refine the search process.

Table 2.1: Key concepts, their synonyms and keywords

Key concept	Synonyms and Keywords
Artificial Intelligence (AI)	"artificial intelligence" OR "AI" OR "machine learning" OR "ML" OR "intelligent systems" OR "AI-based systems"
	AND
Strategic Adoption	"strategic adoption" OR " strategy" OR " adoption" OR " roadmap" OR "transformation" OR " planning"
	AND
Small and Medium Enterprises (SMEs)	"Small and medium enterprises" OR "SMEs" OR "small businesses" OR "medium-sized firms" OR "small firms" OR "micro enterprises"

Table 2.2: Search string examples for the three databases

Database	Query
Scopus	TITLE-ABS-KEY (("artificial intelligence" OR "machine learning" OR "intelligent systems" OR "AI-based systems") AND (strateg* OR adopt* OR roadmap OR transform* OR planning) AND ("small and medium enterprises" OR SMEs OR "small businesses" OR "small firms" OR "micro enterprises"))
IEEE Xplore	(("Document Title": "artificial intelligence" OR "AI" OR "intelligent systems" OR "machine learning" OR "AI-based systems") AND ("Abstract": "adoption" OR "strategy" OR "transformation" OR "roadmap" OR "plan") AND ("Abstract": "SMEs" OR "small businesses" OR "small firms" OR "micro enterprises"))
Web of Science	TS=(("artificial intelligence" OR "AI" OR "machine learning" OR "ML" OR "intelligent systems" OR "AI-based systems") AND ("strategic adoption" OR "strategy" OR "adoption" OR "roadmap" OR "transformation" OR "planning")

	AND ("small and medium enterprises" OR "SMEs" OR "small businesses" OR "medium-sized firms" OR "small firms" OR "micro enterprises"))

Identification, screening, eligibility, and inclusion are the key stages for screening and selection within PRISMA flow diagram. To this end, a comprehensive set of inclusion and exclusion criteria consisting of several criteria items (presented in tables 2.3a and 2.3b) was established. The searches were conducted between October 2023 and April 2024. The scope of the search was restricted to peer-reviewed publications written in English and published between 2010 and 2024. This time frame was selected to capture the evolving discourse and reflect the diffusion of AI technologies in business environments within SMEs. The initial search produced a large number of studies, which were then filtered out according to the pre-defined exclusion criteria in table 2.3b. The filtration was based on a rigorous selection process, beginning with the removal of duplicates. The screening was conducted by the researcher following the criteria defined in tables 2.3a and 2.3b to refine the corpus of literature by assessing their alignment with the research objectives and the scope of work.

Table 2.3a: Inclusion criteria for the literature review

Inclusion criteria item	Criteria
Language	Should be in English
Time period	2010-2024
Document type	Peer reviewed journal and conference papers

Table 2.3b: Exclusion criteria for the literature review

Exclusion criteria item	Criteria
Relevancy	Studies were excluded if AI adoption was not considered in organisational settings or within SMEs context. However limited theoretical exceptions were permitted in cases where literature was limited
Context	Work should be in organisational context and non-commercial
Quality	Studies lacking methodological and theoretical clarity, or empirical support were excluded

Studies explicitly focusing on AI adoption within SMEs were included. The focus was to include the work concerning the adoption process from a strategic perspective, rather than solely emphasizing technical, algorithmic, or implementation-specific concerns. Studies offering insights into distinct areas and stages of AI adoption, such as factors, barriers, enablers, readiness, implementation, or evaluation of the AI adoption process were included. The research contributing to the conceptualization of AI adoption as a lifecycle was prioritised. Conceptual papers and empirical studies meeting established criteria were all considered eligible. Exclusions were largely made due to large enterprises focus and non-availability of full text etc. The selection process is illustrated through the figure 2.1 below (PRISMA flow diagram), which shows the identified studies count, screened studies, and the finalized studies that were included in the review. A final corpus of 66 studies was formulated for in-depth analysis and synthesis. Once the relevant studies were finalized, the next phase involved data extraction and analysis. Bibliographical metadata including publication year, publishing source, focus area, and research methodology of the included studies was recorded.

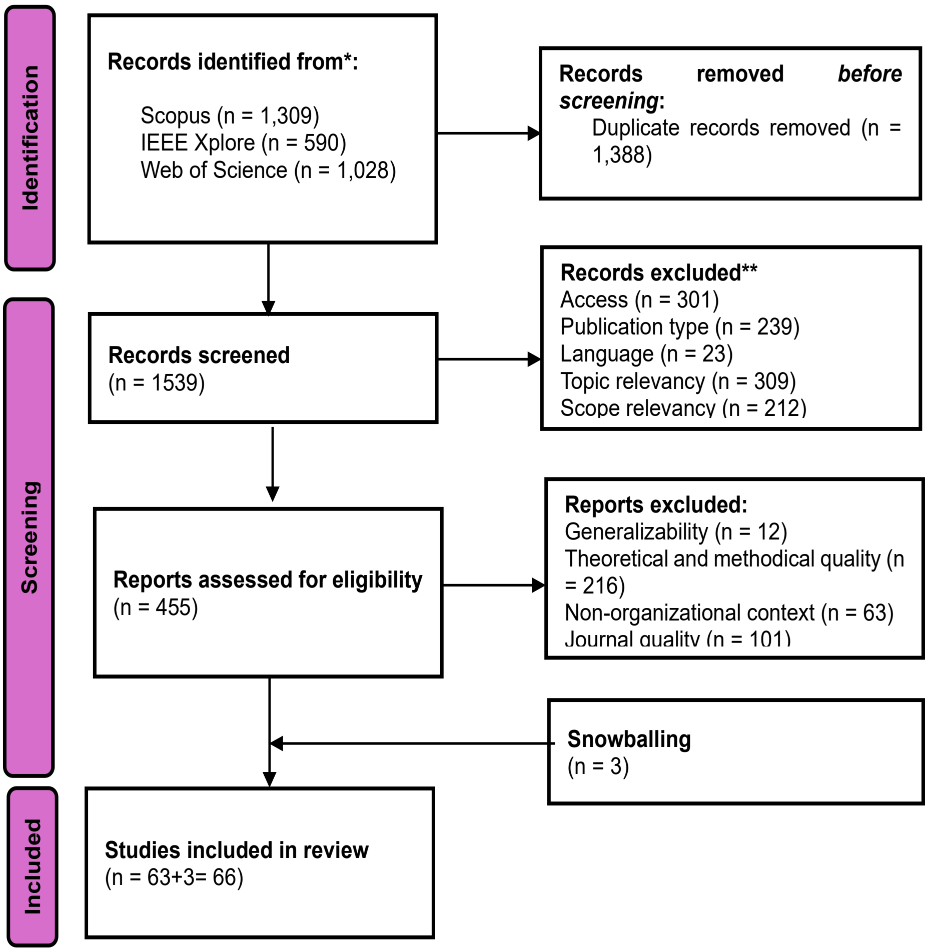


Figure 2.1: PRISMA Flowchart

Verhoef et al. (2021) described AI adoption is as a multi-layered phenomenon involving antecedent conditions, organisational capabilities, implementation strategy and mechanisms and outcome evaluation etc. However, the literature on AI adoption in SMEs remains conceptually fragmented and lacks a shared theoretical structure (Frank et al., 2019). Terms such as AI readiness (Horvat and Heimberger, 2022), AI maturity (Gartner, 2019), and AI preparedness (Al-Murshidi et al., 2024) are often used interchangeably, even though they refer to different phenomena. At the same time, this study seeks to develop and operationalize a structured AI adoption roadmap, which requires moving beyond descriptive evidence toward abstract and measurable constructs. In this context, thematic analysis enables the systematic identification of latent conceptual patterns across diverse studies (Braun and Clarke, 2019). While the systematic literature review establishes a transparent and replicable evidence base, thematic analysis serves as the interpretive synthesis mechanism that transforms dispersed findings into theoretically distinct constructs forming the foundation of the proposed framework (Thomas and Harden, 2008). The process started with the familiarization with the corpus of studies. Full texts were repeatedly read to extract key findings, concepts, and contextual details. The nuanced meanings and contextual variations across studies were coded inductively. The initial extracted contextual variations were iteratively refined using explicit abstraction rules presented in the table 2.4 that ensured conceptual coherence and theoretical separation across levels of analysis. These were clustered into broader categories based on theoretical relevance, conceptual and role similarity and shared analytical level. It not only helped develop a coherent understanding of multiple stages of strategic AI adoption within SMEs but identify areas of conceptual limitations and establish prevailing theoretical paradigms.

Table 2.4: Merging, Splitting and Removal rules for thematic analysis

Rule type	Rule	Example
Merging rules	Conceptual overlap	“AI capability”, “AI readiness”, “AI preparedness” and “AI maturity” etc.
	Role similarity	“determinants or driving factors” and “challenging factors or barriers”
	Shared analytical level	“organisational ”, ”technological”, “environmental”
Splitting rules	Varying conceptual foundation or role	“readiness assessment framework” vs ”adoption framework ”
	Varying measurement logic	“operational efficiency” vs ”task suitability”
Removal rules	Scope of work	Addressing the organisational context
	Limited conceptual variance	“determinants” or “prerequisites” etc.

2.3.Results

This section organises the key findings of the systematic review in alignment with the primary objective of this research study. It presents a bibliometric analysis of the reviewed literature by identifying thematic patterns, dominant research streams, and key gaps relevant to AI adoption in SMEs.

2.3.1. Publication trend

As described in the previous section, the publication trends analysed by this study were restricted between 2010 and 2024. The analysis highlighted an erratically increasing scholarly attention toward AI adoption within SMEs (as shown in figure 2.2). This aligns with earlier concerns about technology infrastructure immaturity and limited awareness of AI's practical implications in smaller business settings. However, the recent abrupt surge from 2023 to 2024 in the growing knowledge may help to educate the stakeholders to make learned decisions but also underscores the need for deeper and more focused exploration in this important area of research.

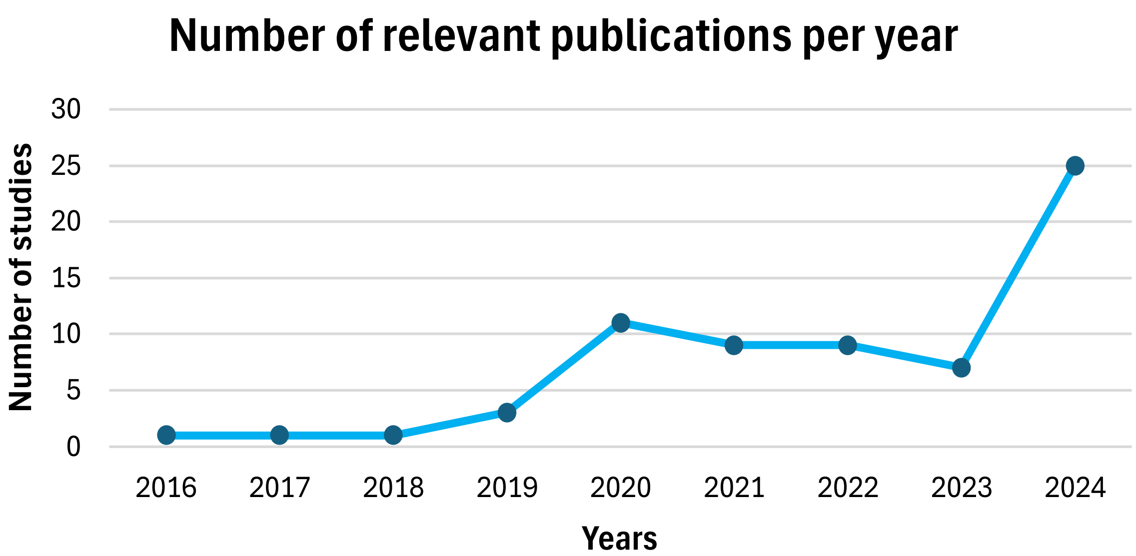


Figure 2.2: Number of relevant publications per year

2.3.2. Theoretical lens adopted in the corpus of studies

Theoretical frameworks function as conceptual lenses that guide the interpretation and systematic delineation of the insights related to the research domain. These provide a foundation in understanding complex phenomena, building the research context and framing the research questions (Luft et al., 2022). The figure 2.3 presents a thematic synthesis of the theoretical frameworks adopted by the studies included in the review. It depicts clear dominance of TOE, across the reviewed studies highlights its broad applicability, widespread acceptance and relevance in the context of AI adoption in SMEs. It is employed across a diverse range of studies, it served as a foundational lens in research examining critical drivers, opportunities, and challenges related to AI adoption (Rawashdeh et al., 2023; Omowole et al., 2024). Furthermore, it is also employed in identifying the key impact enablers of the adoption process (Stenberg and Nilsson, 2020; Almashawreh et al., 2024). In addition, it is also applied for exploring the link between AI and sustainable performance (Badghish and Soomro, 2024) and also leveraged to assess AI readiness, a systematic approach to identify the preconditions necessary for effective AI adoption within SME (Bettoni et al., 2021; Felemban et al., 2024). This suggests an integrative meta-structure of TOE framework that comprehensively expresses the systemic interplay between the important contingencies for SMEs with resource constraints and contextual dependencies.

On the other hand, other frameworks address isolated dimensions offering valuable insights into specific aspects of AI adoption. For instance, dynamic capabilities' framework is used as a structured lens to understand how internal and external capabilities collectively influence the achievement of long-term sustainable outcomes (Li and Jin, 2024; Rashid et al., 2024). Similarly, Unified theory of acceptance and use of technology (UTAT) is specifically employed by studies to evaluate AI readiness (Chatterjee et al., 2020) and determine factors influencing the adoption of AI in SMEs process (Nascimento and Meirelles, 2022; Lada et al., 2023). RBV lens is used by studies to identify drivers and barriers related to AI adoption (Kar et al., 2021) and in context of AI and sustainable performance (Khaw et al., 2022). Likewise, Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI), both are used by the studies examining the AI adoption enablers (Alsheibani, 2020; Bettoni et al., 2021; Hardinata et al., 2024). Whilst certain frameworks, such as Human-centred design (HCD) theory, are intentionally context-specific and tailored to address particular dimensions of the adoption process, their narrow scope limits their applicability as comprehensive models. Whereas the limited use of frameworks like RBV, UTAT and TAM etc., suggests their rigidity or under exploration. These frameworks either lack the flexibility to be effectively applied across the diverse and interdependent aspects of AI adoption or their potential relevance in this context remains underexplored.

Therefore, the study adopts TOE framework as a unifying analytical structure enabling the consolidation of fragmented AI readiness constructs into coherent clusters. It ensures that the investigation remains grounded in a well-established theory of technology adoption while allowing for the inclusion of AI-specific nuances.

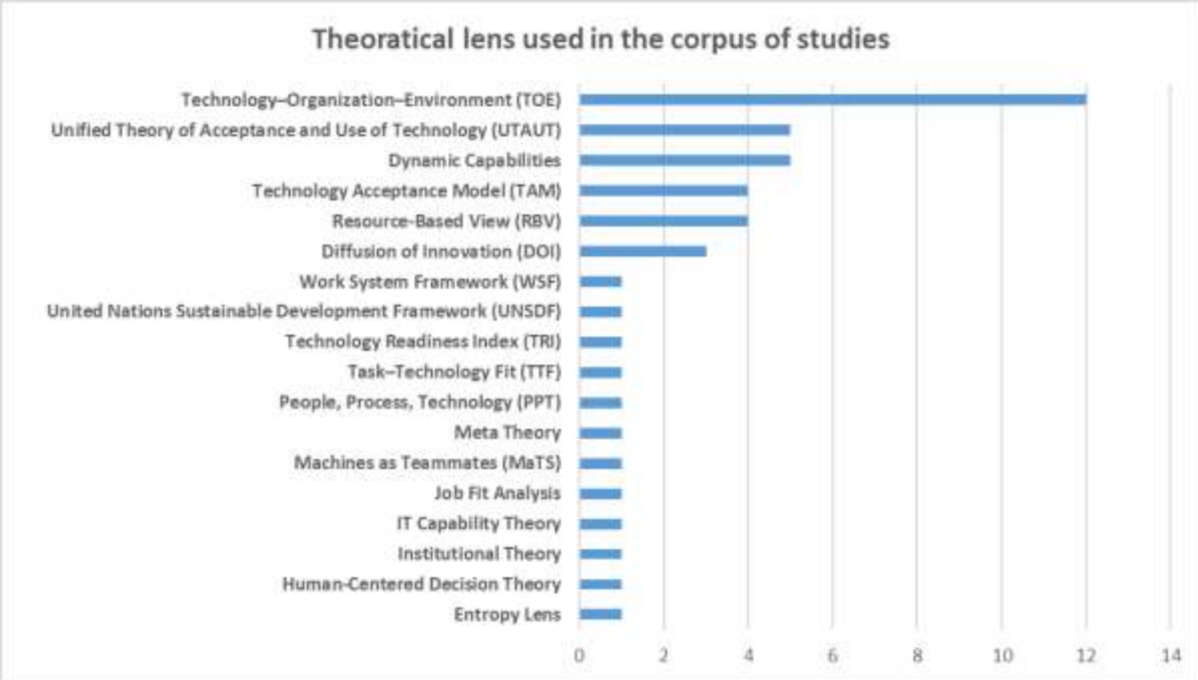


Figure 2.3: Theoretical lens adopted in the corpus of studies

2.3.3. Main focus areas/ Key themes of the studies in the corpus

As presented in table 2.5, five higher-order themes emerged from the initial codes. These themes were derived through a structured thematic synthesis process, following established approaches to qualitative coding and theme development (Thomas and Harden, 2008; Braun and Clarke, 2019). It details the primary codes underpinning these themes, clarifies the distinctions among these themes, and describes how the derived constructs map onto different phases of the study, thereby ensuring analytical traceability. To enhance transparency, the transition from initial codes to abstract themes and subsequently to analytical constructs was guided by explicit aggregation and refinement rules. Specifically, conceptually overlapping codes (such as data availability, accessibility, and quality) reflected a common underlying phenomenon were merged. Whereas the codes representing analytically distinct levels were retained as separate constructs to preserve theoretical clarity. Moreover, codes lacking sufficient representation in the literature were excluded.

While these appear as fragmented research streams, they collectively represent different analytical perspectives on the same phenomenon. Studies on enablers and challenges primarily address contextual determinants of adoption, whereas AI readiness frameworks focus on internal capability preconditions. Research linking AI adoption to business performance provides the outcome-oriented rationale for adoption decisions. AI suitability frameworks operate at the task level, determining where AI application is technically and operationally viable, while adoption process frameworks describe the pathways through which implementation unfolds. Rather than isolated themes, these domains reflect complementary layers of decision logic in organisational AI adoption. These were systematically integrated based on their complementary analytical roles, forming a multi-level structure that connects context, capability, impact, task feasibility, and implementation strategy into a coherent framework.

Their integration enables a multi-level framework that connects context, capability, impact, task feasibility, and implementation strategy into a coherent roadmap. Figure 2.4 below shows the main themes (focus areas of the studies) in the corpus related to AI adoption. Major section of the reviewed studies in the corpus (50%) concerns identifying the opportunities, enablers, and challenges associated with AI adoption in SMEs. Identification of technical, organisational , and contextual challenges and obstacles that hinder AI implementation are extremely relevant and important in resource constrained environments of SMEs to facilitate AI integration. Therefore, there lies field's keen interest in exploring strategic openings and risks offered by AI adoption. Notably, AI readiness also emerges as an extensively explored theme across literature (21%) that aims to assess the preparedness of organisations to embrace AI technologies. This suggests that SMEs are now aware of the opportunities and challenges associated with AI adoption and have shifted their focus to evaluating their readiness for adopting AI technologies. The remaining literature, consisting of relatively smaller sections, explores more focused and emerging areas such as AI suitability, AI adoption framework and the potential for specific performance enhancements enabled by AI adoption. This distribution suggests a growing but still limited emphasis on holistic strategic frameworks, highlighting the key areas that warrant further academic attention. In addition, each derived construct was evaluated based on the criteria of theoretical distinctiveness and empirical measurability, as recommended in prior research (MacKenzie et al., 2011; DeVellis, 2016). The former helps maintain minimal conceptual overlap among constructs, while the latter facilitates their translation into observable indicators suitable for expert elicitation and survey-based assessment. This approach supports the development of a final construct set that is both theoretically robust and practically operationalizable.

Table 2.5 functions as a traceability matrix by explicitly linking (a) initial codes identified through the literature review, (b) abstract themes and corresponding framework constructs, and (c) their application in subsequent empirical phases.

Table 2.5: Main focus areas (key themes) of the studies and traceability

Initial codes	Abstract Theme	Theoretical distinction	Construct mapping	Key references
Organisational culture, Data requirements, Determinant factors, Top management support, Drivers of AI adoption etc.	**Enablers and challenges**	What implementation factors facilitate or hinder effective integration of AI adoption?	Identified the main AI enablers that were used in the **phase 2** to compile the list of AI enablers for analysing their influence on performance dimensions	(Horvat and Heimberger, 2022; Shang et al., 2023; Felemban et al., 2024; Tehrani, 2024; Rane et al., 2024; Yen et al., 2024)
Data quality, Integration capability, Internal and external readiness factors, trust framework and maturity model, Data infrastructure readiness, Tech. readiness and organisational AI journey, Availability of AI tools and Sociotechnical AI readiness etc.	**AI readiness framework**	How to assess an organisation's capability and preparedness to adopt, implement, and derive value from AI technologies?	Reviews existing AI readiness construct that was used as the foundational knowledge in **phase 1** for the development of TOEH-based AI readiness constructs.	(Johnk et al., 2020; Mylrea and Robinson, 2023; Uren and Edwards, 2023; Felemban et al., 2024; Tehrani, 2024; Yen et al., 2024;)
AI-driven decision support, AI adoption and sustainable performance, AI-driven business model innovations, Process optimization and AI, Human-centred AI for sustainable industrial growth and operational efficiency improvement	**AI adoption and business performance**	What are the opportunities offered by AI to significantly enhance business performance (such as enhancing operational efficiency, foster innovation, and promote informed decision-making)?	Identified the studies linking AI adoption with business performance outcomes across multiple dimensions that were linked in **Phase 2** for analysing the influence of AI enablers across these dimensions**.**	(Khan et al., 2023; Panigrahi et al., 2023; Badghish and Soomro, 2024; Martini et al., 2024; Rashid et al., 2024; Shaik et al., 2024)
Human-AI role clarity, Human-AI teaming, Collaboration between humans and AI and decision autonomy in AI-human teams etc.	**AI suitability framework**	What business processes or tasks are most appropriate for AI implementation based on different factors?	Identified the set of key factors for task-technology fitness assessment that were used as the foundational knowledge in **phase 3** ensuring systematic evaluation of task-technology fit.	(Shrestha et al., 2019; Seeber et al., 2020; Mohseni et al., 2021; Gartner, 2023; Mandvikar and Achanta, 2023)
AI roadmap for implementation, AI-driven digital transformation and AI governance and monitoring etc.	**AI adoption frameworks**	What is the systematic process of integrating AI technologies over time, encompassing various stages from awareness to initial planning, management implementation and monitoring?	Informed the overall integration architecture, strengths and limitations of existing frameworks.	(Bettoni et al., 2021; Rizwan, 2024; Taherizadeh and Rizwan, 2024)

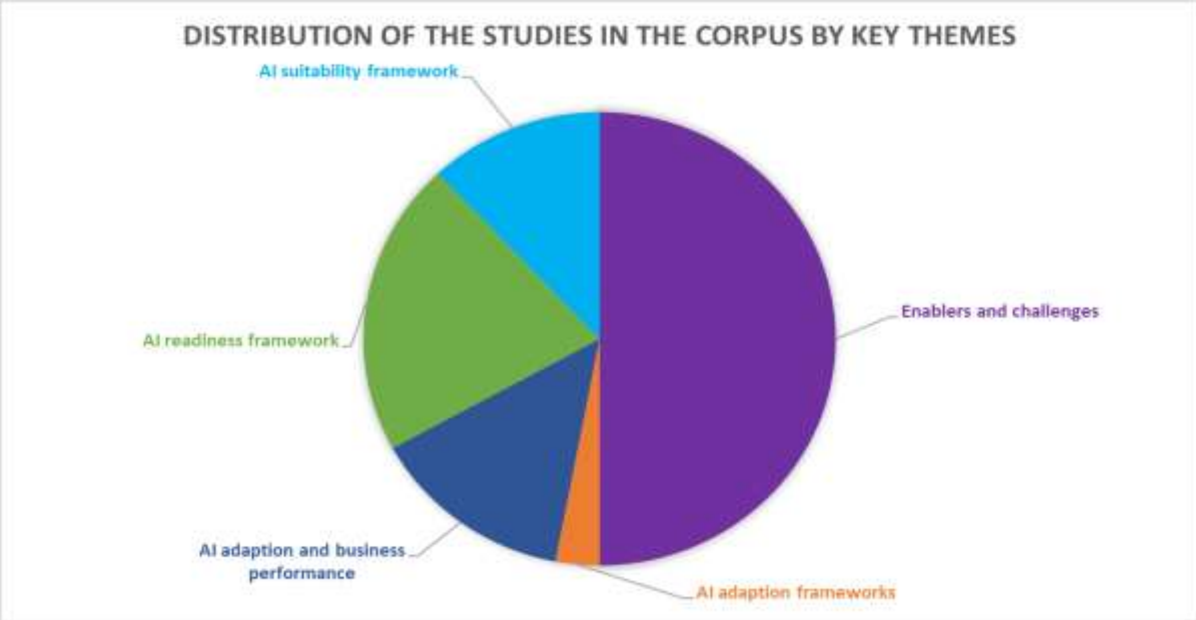


Figure 2.4: Identified themes from literature

Further, the theme-based study distribution across years (as shown in figure 2.5) reflects a notable surge in AI adoption literature focused within the SME context from 2020. This initial rise can be partially attributed to the COVID-19 pandemic as it exposed the vulnerabilities of traditional business models and highlighted the need for technological transformation. It compelled businesses to explore advanced technologies like AI for maintaining operational continuity in the rapidly changing market. However, the number of studies focusing on the targeted area (like AI suitability and Sustainable impact of AI) peaked and was doubled in 2024. This sharp rise reflects the evolving practical relevance and maturing academic interest in adoption of AI. The increased availability of democratized AI tools and increasing interest in Industry 4.0 have also made AI adoption more feasible for the smaller firms.

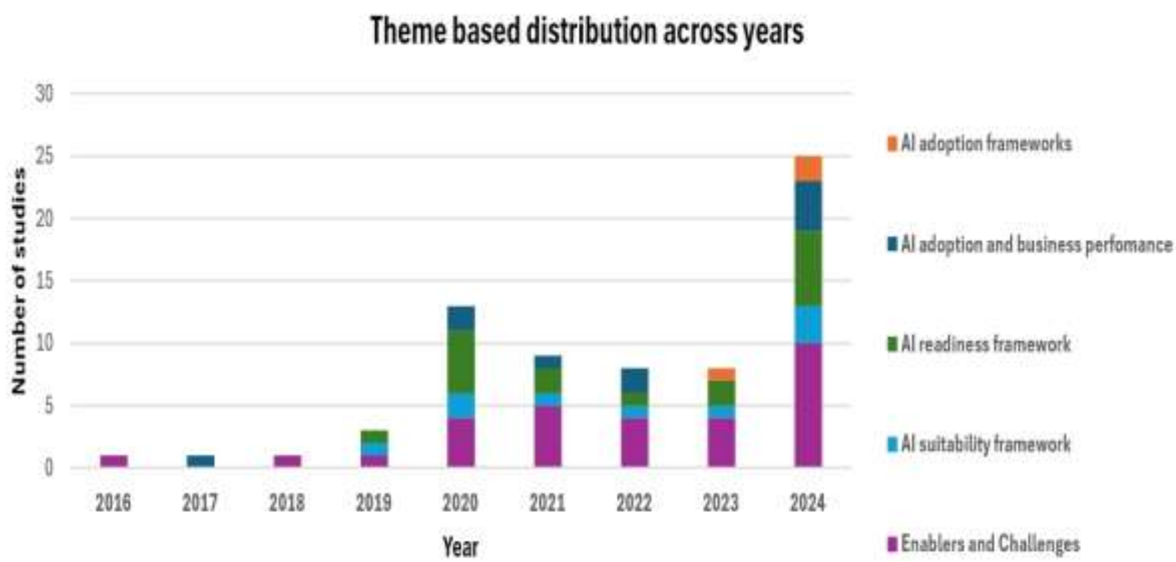


Figure 2.5: Theme based distribution of studies across years

- **Theme 1: Enablers and challenges**

Whilst large enterprises often possess the resources, infrastructure, and expertise required for effective AI integration, SMEs may face additional challenges due to their limited resources, fierce market competition and lack of expertise or digital transformation knowledge (Rupeika-Apoga and Petrovska, 2022). To overcome the challenges and effectively integrate AI adoption, certain enabler can play a part in improving implementation outcomes. Therefore, it is pertinent to develop an integrative understanding of these enablers and challenges that can influence AI adoption journey. This can not only help to effectively strategize resource allocation and design targeted support mechanisms but effectively mitigate the adoption challenges (Rane et al., 2024). Consequently, this study has utilised TOE framework lens to systematically synthesize these enablers and challenges enabling a coherent and contextually relevant understanding of the mapping between enabling factors and adoption hurdles. It is adopted due to its comprehensive and integrative nature, making it particularly suitable for the complex, multi-faceted nature of AI adoption. Tables 2.6a and 2.6b present an overview of these identified challenges and enablers.

Table 2.6a: Challenges with adoption of AI in SMEs

Category	Challenges	References
Technological	Solution complexity (integration & use)	(McKinsey, 2018; Gartner, 2019; Swoboda et al., 2019; Blut and Wang, 2020; Nortje and Grobbelaar, 2020; Stenberg and Nilsson, 2020; Szedlak et al., 2020; Bettoni et al., 2021; Iftikhar and Nordbjerg, 2021; Ulrich and Frank, 2021; Holmstrom, 2022; Mylrea and Robinson, 2023; Felemban et al., 2024; Rane et al., 2024; Tehrani, 2024)
	Immature or inadequate infrastructure	
	Lack of data and/or data quality	
	Lack of standards	
	Security concerns	
Organisational	Lack of clarity of vision	(McKinsey, 2018; Gartner, 2019; Blut and Wang, 2020; Najdawi, 2020; Nortje and Grobbelaar, 2020; Porcher, 2020; Szedlak et al., 2020; Bettoni et al., 2021; Iftikhar and Nordbjerg, 2021; Bhalerao et al., 2022; Holmstrom, 2022; Vidu et al., 2022; Uren and Edwards, 2023; Rane et al., 2024; Tehrani, 2024; Yen et al., 2024)
	Lack of AI know-how	
	Workflow integration challenges	
	Lack of organisational infrastructure	
	Limited funding or financial resources	
	High cost and Uncertainty with ROI	
	Lack of knowledge about the role of AI	
	Resistance to change	
	Lack of digital skills	
	Employees' negative perception about AI	
Environmental	Regulatory and compliance hurdles	(McKinsey, 2018; Gartner, 2019; Nortje and Grobbelaar, 2020; Szedlak et al., 2020; Ulrich and Frank, 2021; Bhalerao et al., 2022; Horvat and Heimberger, 2022; Vidu et al., 2022; Hanenko, 2023; Uren and Edwards,
	Governance issues or concerns	
	Risks and biasness	
	Market maturity	
	Collaborators' willingness and maturity	

	Suppliers’ willingness and maturity	2023; Villegas-Ch and García-Ortiz, 2023; Felemban et al., 2024)

Table 2.7b: AI implementation factors or Enablers

Category	AI enabler	References
Technological	Mature tech. infrastructure	(Nortje and Grobbelaar, 2020; Stenberg and Nilsson, 2020; Holmstrom, 2022; Horvat and Heimberger, 2022; Kinkel et al., 2022; Shang et al., 2023; Tehrani et al., 2024)
	Data Access and Quality	
	Security capabilities	
	Clear IT management strategy	
Organisational	Leadership support and commitment	(Clohessy and Acton, 2019; Dasgupta and Gupta, 2019; Mahroof, 2019; Blut and Wang, 2020; Kellogg et al., 2020; Pfeffer, 2020; Srisathan et al., 2020; Stenberg and Nilsson, 2020; Flavian et al., 2022; Tehrani et al., 2024)
	Operational integration	
	Sustained financial capability	
	Clear AI adoption & change-management strategy	
	Cooperation and interaction	
	Digital skills and expertise	
	Employee’s awareness and experience with AI	
Environmental	Awareness of competitors threats	(Gorla et al., 2017; Aboelmaged and Hashem, 2019; El-Kassar and Singh, 2019; Liao and Tsai, 2019; Machado and Martínez, 2019; Huang and Rust, 2021; Jun et al., 2021; Murray et al., 2021; Holmstrom, 2022; Fast et al., 2023; Kokshagina et al., 2023; Minkkinen et al., 2023)
	Ethics and Regulations	
	Government Support	
	Awareness of Customers and Market Tech. requirements	
	Supplier and Collaborators’ coordination	

From a technological perspective, one of the foremost challenges lies in the complexity of AI solutions, which often makes their integration into existing systems intricate and resource intensive (Stenberg and Nilsson, 2020; Felemban et al., 2024). This is further intensified by immature or inadequate infrastructure, where firms lack the computing, interoperation or integration capabilities to effectively deploy AI (Nortje and Grobbelaar, 2020; Taherizadeh and Rizwan, 2024). Correspondingly, mature and scalable technology infrastructure necessary to host AI solutions acts as an enabler for effective AI adoption (Holmstrom, 2022; Kinkel et al., 2022; Felemban et al., 2024). Additionally, the lack of access to Similarly, availability of relevant and superior quality data is the primary driver of AI solutions (Johnk et al., 2020; Holmstrom, 2022; Horvat and Heimberger, 2022; Kinkel et al., 2022; Tehrani, 2024), however, data access and its quality are also one of the most cited obstacles within AI adoption literature (Johnk et al., 2020; Tehrani, 2024). Persistent security concerns remain a significant impediment to AI adoption, particularly among the firms where sensitivity of data is crucial (Mylrea and Robinson, 2023). Nonetheless, a clear technology information management strategy can provide assurance against these risks related to privacy, trust, and compliance (Horvat and Heimberger, 2022; Mylrea and Robinson, 2023; Shang et al., 2023; Tehrani, 2024).

With regard to organisational enablers, leadership support and commitment is a requisite in translating strategic AI adoption vision into implementation (Clohessy and Acton, 2019; Flavian et al., 2022; Tehrani et al., 2024). However, lack of clarity of leadership vision regarding AI's strategic implementation is yet one of the recurring themes in the literature that impacts the alignment between technology adoption and business objectives (Uren and Edwards, 2023; Felemban et al., 2024). This synthesized with limited AI-specific know-how and digital skill gaps, leads to adoption, implementation and maintenance planning issues (Porcher, 2020; Yen et al., 2024). Additionally, the immature or inadequate organisational infrastructure including no-availability of governance structures and dedicated technical experts may pose significant constraints on the effective execution of AI initiatives (Nortje and Grobbelaar, 2020; Tehrani, 2024). High upfront costs, uncertainty regarding Return of Investment (ROI), long-term investment commitment are the prominently featuring financial dimension factors (Blut and Wang, 2020). Equally critical are socio-cognitive barriers such as employee mistrust, resistance to change and negative perceptions about AI can impede acceptance and adoption (Holmstrom, 2022; Tehrani, 2024). However, these challenges are not insurmountable. A sustained financial capability mitigating funding constraints and ROI uncertainty coupled with a clear change-management strategy can create coherence across units, reducing resistance and ambiguity (Bettoni et al., 2021; Bhalerao et al., 2022; Uren and Edwards, 2023; Yen et al., 2024). Lastly, workflow integration remains a critical challenge, as embedding AI solution into existing organisational processes may require significant enhancement or modification (Yen et al., 2024).

The environmental dimension includes external constraints that are least controllable by the firm. Regulations and compliance issues relating to ethical and data governance requirements are increasingly shaping AI adoption. However, these can also act as enablers when organisations embed strong ethical principles and regulatory alignment into their strategy (Nortje and Grobbelaar, 2020; Ulrich and Frank, 2021; Vidu et al., 2022; Uren and Edwards, 2023; Villegas-Ch and Garcia-Ortiz, 2023). Risks of bias are also increasingly becoming a reputational and legal threat (Felemban et al., 2024). Customers and market immaturity may also influence AI adoption initiatives as sense of reduced incentives against the investment may deter organisational urge of AI adoption (Uren and Edwards, 2023). Therefore, awareness of customers and market technological requirements is crucial for the alignment between organisational AI initiatives and ecosystem needs (Uren and Edwards, 2023; Felemban et al., 2024). The willingness and readiness of collaborators and suppliers is another critical variable that can influence AI adoption initiatives as it operates in an ecosystem-wide integration rather than in isolation (Nortje and Grobbelaar, 2020; Horvat and Heimberger, 2022). Finally, government support can significantly reduce adoption challenges, particularly in SME contexts where resources are scarce (Tehrani, 2024).

This mapping illustrates that each challenge has a corresponding enabler that mitigates its impact or drive effectiveness. For instance, resistance to change is countered by leadership commitment and change-management strategies and data scarcity is offset by access to quality data. This alignment confirms that AI adoption is more about systematically embedding enablers to transform adoption vulnerabilities into manageable risks. Further it emphasises the multidimensional nature of AI adoption that demands significant attention towards the organisational and environmental challenges along with addressing the technological deficits. This necessitates the importance of challenges planning against financial, structural, cultural and eco systemic frictions.

- **Theme 2: AI readiness framework**

AI incorporates a variety of intelligent business applications stretching across multiple operational domains. Successful integration of these AI technologies demands a comprehensive assessment of an organisation's capabilities (Simon et al., 2024). However, AI adoption process in SMEs can be more complex and uncertain, due to additional technological, organisational and environmental challenges (Rawashdeh et al., 2023; Uren and Edwards, 2023; Tehrani et al., 2024). Further, the rapid technological advancements intensify these complexities as these require continuous redesign and enhancement of the business model. These enhancements can incur substantial financial costs and escalated uncertainty for top management along with other strategic challenges (Tehrani et al., 2024). To address this complicated scenario, it is crucial for SMEs to predetermine their readiness for AI adoption. Readiness refers to a preliminary phase of AI adoption that determines if organisation's capabilities fulfil the requirements of intended technological change (Simon et al., 2024). It conceptually differs from 'maturity' as Schumacher (2016) describes readiness as an initial evaluation to confirm the commencement of the transformation process whereas maturity concerns the developmental state of an organisation during or after the implementation stage (Demir, 2023).

The utilised body of work on AI readiness presented in table 2.7 reveals rich but fragmented areas, where major contributions focus on conceptual categorizations of AI readiness dimensions rather than development of operationalizable and practically applicable tools. Recent contributions by Felemban et al. (2024), Tehrani (2024) and Yen et al. (2024) extend the discourse by explicitly identifying the key readiness dimensions or factors. These models are largely descriptive in orientation and only few (e.g., Tehrani (2024)) validated their frameworks through empirical testing. They lack diagnostic rigor, as the dimensions are not operationalised into measurable or actionable indicators. This is important in context of SMEs, as they lack technical expertise and AI adoption know-how due to financial constraints and limited resources (Rawashdeh et al., 2023; Uren and Edwards, 2023).

Mylrea and Robinson (2023) and Uren and Edwards (2023) enrich the theoretical discussion by introducing security, privacy, and cross-functional considerations adopting entropy-based trust framework and Technology Readiness Level (TRL) inspired adoption journey respectively. However, both the studies lack empirical validation and demonstrate limited generalizability restricting their operationalizability in a real-world setting.

Earlier frameworks, such as Najdawi (2020), Nortje and Grobbelaar (2020), Porcher (2020), Stenberg and Nilsson (2020), Johnk et al. (2020), Holmstrom (2022) and Horvat and Heimberger (2022), also offered socio technical or TOE-based categorizations of readiness. While these studies contribute valuable taxonomies (ranging from four to seven readiness areas), they also remained at the conceptual stage. Their limited empirical validation, reliance on descriptive categories, and failure to capture interdependencies between factors reduce their practical value. For instance, the seven-dimension framework by Nortje and Grobbelaar (2020), while comprehensive, remains largely conceptual and difficult to operationalize. Johnk et al. (2020) take a step forward by proposing more actionable indicators across five readiness categories; although not fully validated, their work begins to bridge the gap between theory and practice.

Overall, the literature approaches AI readiness from multiple perspectives, such as trust, sociotechnical systems, and maturity, and identifies a range of influencing factors. However, two key limitations persist. First, most frameworks remain conceptual, with limited translation into measurable and actionable constructs. Secondly, there is a lack of empirical validation and standardized assessment methods, which constrains their real-world applicability. Together, these gaps point to the need for more granular, operational, and context-sensitive approaches that can translate AI readiness into measurable indicators and structured evaluation methods.

Table 2.8 :Included studies addressing theme 2

Reference	Focus of research	Theoretical framework used	Outcomes and limitations
Tehrani (2024)	Exploring organisational readiness to adopt AI	Work system framework	• Conceptualization of AI readiness (AIR) for businesses • Empirically investigated • Descriptive rather than operationalizable
Yen et al. (2024)	Framework for assessing the readiness of AI in SMEs in Malaysia.	TOE (capability-based extensions)	• Identifies key readiness dimensions • Lacks empirical validation • Descriptive rather than operationalizable
Felemban et al. (2024)	Exploring the readiness of organisations to adopt artificial intelligence	Sociotechnical systems	• Identifies key readiness factors • Guidance framework rather than a practical assessment model • Descriptive rather than operationalizable
Mylrea and Robinson (2023)	AI trust framework and maturity model applying an entropy lens to improve security, privacy, and ethical AI	Entropy lens	• Development of an AI trust framework and maturity model with key dimensions • Requires technical expertise • Limited empirical validation • Limited to ethical consideration
Uren and Edwards (2023)	Technology readiness and the organisational journey towards AI adoption	People, Processes, Technology lens	• TRL-based AI adoption stages • Emphasis on cross-functional alignment • Generalizability concerns • No quantitative validation
Holmstrom (2022)	An AI readiness framework	Dynamic capabilities theory	• 4-dimension AI readiness framework • Sociotechnical analysis enablement • Not empirically validated • Conceptual, not practical for Implementation
Horvat and Heimberger (2022)	An Integrated Socio technical AI readiness Framework	Sociotechnical systems	• A socio technical AI readiness framework • Single-case validation • Not practical for Implementation
Kinkel et al. (2022)	A conceptualization of the prerequisites for the adoption of AI technologies	TOE	• Conceptual rather than operationalizable • Only indirect effects modelled
Najdawi (2020)	Assessing AI readiness across organisations	Maturity model approach	• Four-dimensional readiness model • Abstract overview • No quantitative validation
Stenberg and Nilsson (2020)	Factors influential in readiness for AI adoption	TOE	• Identified key TOE-based readiness factors • Not practical for Implementation

Johnk et al. (2020)	Organisational AI readiness factors	Dynamic capabilities and organisational learning	• Identification of five readiness categories • Development of actionable indicator • No quantitative validation • Not practical for Implementation
Porcher (2020)	AI capabilities and readiness	n/a	• AI Capabilities and a readiness model • No quantitative validation • Not practical for Implementation
Nortje and Grobbelaar (2020)	A framework for the implementation of AI in business enterprises	Sociotechnical systems	• Seven-dimensional AI readiness framework • Not validated • Descriptive and lack practicality

Dimensionally, prior studies have proposed between seven and ten capability dimensions for readiness assessment. For instance, certain models like Johnk et al. (2020) and Porcher (2020) encompass work base system framework (WSF) based dimensions, Stenberg and Nilsson (2020) and Kumar and Kalse, (2021) utilised the TOE framework, whereas Johnk et al. (2020) and Holmstrom (2022) viewed these influencing factors through dynamic capability lens. Despite the variations in the terminologies and theoretical framing, these exhibit a substantial convergence grounding as their underlying elements or subcomponents describe the similar readiness conditions. The related work summarized in table 2.7 demonstrates a fragmented yet evolving understanding of AI readiness, with substantial variation in context, scope, and application. The readiness factors synthesized from these studies are organised into the TOE cluster to maintain conceptual consistency and overall coherence. This allows a structured way to bring together the AI adoption construct under a shared theoretical lens, helping to reduce fragmentation and ensuring logical alignment.

- **Technological**

Multiple studies highlight technological AI readiness factors, in particular data availability and quality, and system interoperability, as critical enablers. Swoboda et al. (2019), Porcher (2020) and Horvat and Heimberger (2022) reported that SMEs often lack scalable computational resources and unified data architectures necessary for AI deployment. Similarly, Nazaritehrani (2024) argued that technical capability gaps also encompass issues related to security, privacy, and system integration. From the DOI perspective, these limitations act as restraints in the innovation decision process. These increase uncertainty and reduce the perceived relative advantage of AI adoption.

- **Organisational**

Organisational internal capabilities, governance, and process alignment have been frequently cited as determinants of effective AI adoption. Kumar and Kalse (2021), Horvat and Heimberger (2022) and Felemban et al. (2024) point to structural rigidities, static decision-making and misaligned workflows as key restraint. Studies such as Najdawi (2020) and Holmstrom (2022) note that readiness is highly dependent on strategic clarity and the ability to integrate AI capabilities into existing operational processes. According to TOE framework (Tornatzky & Fleischer, 1990), even robust technical solutions may fail of they are not corresponding to organisational processes and structures. Johnk et al. (2020), Uren and Edwards (2023) and Yen et al. (2024) concern workforce competencies, user acceptance, and their trust in AI systems. They emphasise that a lack of AI-specific skills, insufficient change management, and limited awareness of AI capabilities impede readiness. These findings situated within the theoretical perspectives of Human-Computer Interaction (HCI) asserts that without targeted training and participatory processes, intended outcomes may not be achieved.

- **Environmental**

Studies such as Lee et al. (2018), Liao and Tsai (2019) and Najdawi (2020) elucidated the context specific nature of AI readiness. They have identified various external elements such as cultural attitudes, regulatory pressures, and sector norms that can impact both the readiness of firms along with administration of AI initiatives (Liao and Tsai, 2019; Najdawi, 2020; Zhang et al., 2020; Huang and Rust, 2021). STS perspective emphasises that sustained adoption relies upon the alignment of technological factors and organisational capabilities with the environmental constraints and stakeholder expectations. Among these external expectations, customer demand plays a decisive role in compelling firms to explore and integrate innovative technologies to fulfil personalization needs and deliver enhanced experiences for gaining market advantage (Tisdale, 2015; Garcia-Machado and Martínez-Avila, 2019).

○ Theme 3: AI adoption and business performance

AI is considered a strategic facilitator by SMEs due to its transformative potential that can help enhance organisational performance, efficiency, and resilience. Studies adopt various theoretical frameworks to discuss the opportunities it offers in enhancing operational efficiency, foster innovation, and promote informed decision-making. These frameworks include TAM, TOE framework, DOI theory and UTAUT etc.

For example, Na et al. (2022) developed a TAM-based model to assess AI acceptance in construction firms and understanding how users can be encouraged to accept and utilise new technologies; Emon et al. (2023) applied DOI for analysing the rate and pattern of diffusion of innovations to predict AI adoption intentions among professionals. Ali et al. (2024) utilised UTAUT for the evaluation of user intentions and behaviours toward information systems. Amini and Jahanbakhsh (2023) implemented a cloud-based supply chain management system through the lens of technological, organisational , and environmental factors. Collectively, these frameworks highlight the multidimensional construct of AI adoption across multiple application contexts. Whilst TAM and UTAUT primarily focus on technology diffusion among individuals, DOI and TOE are more oriented toward organisational -level innovation adoption. The TOE framework is particularly relevant, given the objective of the proposed study that seeks to analyse the multidimensional factors facilitating AI implementation in SMEs. Stenberg and Nilsson (2020) elucidated that TOE provides a comprehensive perspective for investigating technology implementation in organisations by examining technological, organisational , and environmental characteristics. The framework has been widely applied across diverse contexts such as Salah and Ayyash (2024) investigated SME e-commerce adoption and its impact on marketing performance using TOE, whereas Abaddi (2024) explored factors influencing AI adoption in Jordanian MSMEs.

Table 2.8 presents the studies linking AI adoption with business performance outcomes. These studies have discussed these outcomes across diverse performance dimensions. Such as Badghish and Soomro (2024) studies the impact of AI adoption in driving economic and operational sustainability. Shaik et al. (2024) discussed the potential of AI in enforcing business growth, compliance and promoting innovation. Rashid et al. (2024) studied AI as a catalyst for promoting green supply chain practices whereas Abrokwah-Larbi and Awuku-Larbi (2024) examined the role of AI in sales growth, market efficiency, and customer satisfaction. Martini et al. (2024) also discussed the role of ethical, human-centred AI in driving sustainable industrial innovation. Khan et al. (2023) described that AI along with complementary technologies can help enhance SME operational efficiency, transparency, and competitive edge. Vrontis et al. (2022) stress on its capabilities in promoting value creation, innovation, and stakeholder benefits. Chaudhuri et al. (2022) linked it to innovation, governance, and economic performance enhancements. Lastly, Goralski and Tan (2020) conceptualizes AI as a catalyst for strengthening governance and ethical safeguards.

Table 2.9: Included studies addressing theme 3

Included studies	Key Outcomes	Performance dimensions
Badghish and Soomro (2024)	TOE factors drive AI adoption, leading to improved sustainable performance.	Profitability and process efficiency
Shaik et al. (2024)	AI-driven strategic business model innovations in SMEs	Business growth, Innovation, environmental compliance
Rashid et al. (2024)	AI and BDA enhance sustainability through green supply chain practices.	Supply chain efficiency, cost reduction and environmental policy adherence
Abrokwah-Larbi and Awuku-Larbi (2024)	AI in marketing enhances SME performance through improved targeting and customer engagement.	Sales growth, market efficiency and customer satisfaction
Martini et al. (2024)	Emphasises ethical, human-centred AI for sustainable industrial growth.	Ethical and human centric design for Innovation
Panigrahi et al. (2023)	Supply chain sustainability through efficiency and information sharing.	Operational efficiency, cost reduction and responsiveness
Khan et al. (2023)	Combined technologies enhance SME efficiency, transparency, and sustainability.	Operational efficiency, competitive edge and transparency.
Vrontis et al. (2022)	Digital adoption boosts sustainability and value creation, influenced by entrepreneurial orientation.	value creation, Innovation and stakeholder benefits
Chaudhuri et al. (2022)	AI supports SME innovation and sustainability but needs strategic direction.	Innovation, competitive advantage and strategic alignment
Goralski and Tan (2020)	AI can accelerate SDGs but requires governance and ethical frameworks.	Goal alignment, societal impact and sustainable tech solutions

- **Theme 4: AI suitability frameworks**

AI suitability refers to the degree to which a given task's characteristics fits or align with the technical capabilities, data requirements, and operational constraints of AI systems. While existing literature has discussed this from a task-based perspective across various contexts (see Table 2.9), the problem remains insufficiently addressed in complex, real-world environments. These works tend to remain largely conceptual. These outline what should be considered, such as data characteristics, task complexity, or level of automation without offering a structured or systematic approach to assess how these factors interact in practice. Frameworks proposed by Gartner (2023) and Mandvikar & Achanta (2023) outlined dimensions for assessing task suitability for generative AI (GenAI). Seeber et al. (2020) proposed a seven-dimensional human-AI teaming framework to determine task delegation.

Whereas Brynjolfsson et al. (2017) identified six technical and data-related criteria for evaluating tasks suited to machine learning (ML).

Table 2.10: Included studies addressing theme 4

Framework	Scope	Factors/dimensions
GenAI Use Case Scoring **(Gartner, 2023)**	GenAI task evaluation	1. Complexity 2. Creativity
IPA 2.0 Framework (Mandvikar and **Achanta, 2023)**	GenAI in automation	1. Nature of data 2. Reasoning (language understanding, creativity, or contextual awareness) 3. Error tolerance 4. Personalization 5. Volume and repetition 6. Integration feasibility
Multidisciplinary Perspectives on Human-Centred AI: A Review for Research and Practice **(Mohseni et al., 2021)**	Human-AI task suitability and interaction through the lens of Human-Centred AI	1. Task Complexity 2. User Expertise 3. Interpretability 4. Trust and Transparency 5. Risk Sensitivity 6. Human-AI Role Allocation 7. Feedback and Learning
Task Delegation to AI **(Seeber et al., 2020)**	Human-AI teaming	1. Task Complexity 2. Task Interdependence 3. Communication Requirements 4. Adaptability 5. Trust 6. Transparency 7. Accountability
Organisational Decision-Making Structures in the Age of Artificial Intelligence **(Shrestha et al., 2019)**	Focuses on collaboration between humans and AI, proposing when AI should augment or replace humans in business tasks.	1. Specificity 2. Interpretability 3. Size of the alternative set 4. Decision-making speed 5. Replicability
Ask Not What AI Can Do, But What AI Should Do: Towards a Framework of Task Delegability **(Lubars and Tan, 2019)**	Develops a human-centred framework on task delegability to AI, considering human perceptions and preferences.	1. Motivation 2. Task Complexity 3. Risk 4. Trust
What Can Machines Learn and What Does It Mean for Occupations? **(Brynjolfsson et al., 2017)**	Analyses which tasks are suitable for ML based on technical and data criteria.	1. Task Complexity 2. Data Availability 3. Repetitiveness 4. Cognitive and Social Skills Requirement 5. Human-Machine Interaction 6. Learning and Adaptability
A Future That Works: Automation, Employment, and Productivity **(McKinsey Global Institute, 2017)**	Analyses potential of automation across industries and tasks based on different factors such as technical feasibility.	1. Technical feasibility 2. Development and deployment cost 3. Labor market dynamics 4. Benefits beyond labor substitution 5. Regulatory and social acceptance 6. Task characteristics

Only Humans Need Apply: Winners and Losers in the Age of Smart Machines **(Davenport and Kirby, 2016)**	Categorize roles to guide task assignment to AI.	1. Structured and repetitive tasks 2. Quality data 3. Predictable outcomes 4. Low social complexity 5. High task execution frequency 6. Error tolerance 7. Economic viability 8. Human-Machine collaboration

The coalescence of the studies provided in table 2.9 enlist a set of key factors or dimensions that serve as benchmarks for AI-task suitability evaluation. These provide a structured lens for assessing the alignment between task characteristics and AI capabilities. This ensures that contextually fit AI solutions are deployed to deliver optimal value and performance.

- **Task complexity**

  Task complexity represents the degree of procedural intricacy along with computational and cognitive efforts demanded to successfully complete the task concerned. High complexity tasks may often involve interconnected processes, real-time decision-making, and deep contextual awareness. These may demand advanced problem-solving capabilities, data consolidation, and seamlessly synchronized activities or systems (Brynjolfsson et al., 2017; Davenport and Ronanki 2018; Shrestha et al., 2019). For instance, Brynjolfsson et al. (2017) described that ML is highly effective for moderate to high complexity tasks, however, its suitability reduces significantly as complexity increases. Whereas Reinforcement learning (RL) and simulation models are effective for complex tasks involving multiple variables, constraints, and interdependent decisions (Sutton and Barto, 2018; Fujimoto et al., 2017). Similarly, GenAI is considered ideal for moderately complex tasks (Gartner, 2023).

- **Task objectivity**

  It measures the degree to which a task's objectives and decision-making logic can be precisely defined and objectively evaluated. The tasks that exhibit well-defined rules, clearly defined outcomes and are standardized are generally more responsive to AI adoption (Shrestha et al., 2019). Conversely, ambiguous tasks with context-dependent reasoning or subjective outcomes require subtle interpretation, flexibility, and adaptability that are beyond AI capabilities (Brynjolfsson et al. 2017; Shrestha et al., 2019). Therefore, it serves as a crucial factor in determining AI suitability for various operational and strategic functions. ML, simulation models and RL perform well when inputs and outputs are highly objective and can be quantified; whereas they struggle with vaguely defined and non-measurable outcomes (Xu et al., 2014; Arulkumaran et al., 2017; Kunze et al., 2022). However, GenAI AI is capable of generating subjective outputs (OpenAI, 2023).

- **Data Availability and Quality**

  AI systems are heavily dependent on the availability of high-quality data in large volumes to produce precise and reliable results (Russell and Norvig, 2020). The quality and richness of data play a vital role in determining the effectiveness of AI models, in particular prediction, decision-making and classification models. Insufficient, incomplete, noisy and non-symmetric data records can greatly impact a model's performance, which can result in reduced accuracy and consistency of results (Brynjolfsson et al. 2017; Russell and Norvig, 2020). Data-rich environments enhance the performance of all AI models including ML, RL, simulation models and GenAI (Kritzinger et al., 2018; Scott, et al., 2021; Fu et al., 2022; OpenAI, 2023), however RL can also perform well with limited data in simulated environment (Fu et al., 2022).

- **Repetitiveness and Predictability**

Consistent tasks with repetitive occurrences are amenable to superior AI performance as these present a reliable and consistent environment for the model to learn, optimize, and implement with high efficiency. However, AI may struggle with the tasks with high unpredictability, context-dependence or novelty due to less exposure to similar scenarios within training data (Brynjolfsson et al., 2017; McKinsey Global Institute, 2017). For instance, Liu et al., (2023) elucidated the high suitability of ML for highly repetitive tasks; Tsao et al. (2020) explained the capability of simulation models for modelling repeatable scenarios and Brown et al., (2020) highlighted that GenAI is adept at generating consistent and repetitive output. Whereas RL thrives in both repetitive and dynamic environments (Padakandla, 2021).

- **Adaptability**

Tasks performed in dynamic and rapidly changing environments demand high level adaptivity and learning capabilities. Variable inputs, behaviours, and conditions cannot be comprehensively handled by static models and the accuracy may suffer. Such dynamic environments with frequent changes require constant retraining, learning, and adaptation to address the dynamic nature of the problem (Brynjolfsson et al. 2017; Shrestha et al., 2019; Seeber et al., 2020). For instance, Simulation models do not learn or adapt themselves, but multiple iteration runs allow planners to adjust (Fernandes et al., 2022). ML algorithms are capable of adapting over time through retraining, but certain models may struggle to autonomously adapt in real-time (Brynjolfsson et al., 2017). GenAI Improves the output through prompt engineering (Mandvikar and Achanta., 2023). Whereas dynamic learning and adaptability are core strengths of RL models (Sutton and Barto, 2018).

- **Human-Machine Interaction Needs**

Certain tasks require close collaboration between human users and technology systems. It assesses the required level of interaction and collaboration between human and the systems for the execution of a task. HMI basically refer to the evaluation of a task for complete automation, partial assistance, or collaborative assistance (Brynjolfsson et al., 2017; Mohseni et al., 2021; Meng et al., 2022). For instance, Brynjolfsson et al. (2017) and Cruz and Igarashi, (2020) reported limited interpretability capabilities of ML and RL models, particularly with tasks requiring higher interaction. Whilst simulation models typically offer human interpretability and engagement through specialized interfaces, GenAI offers prompt based control (Bommasani, 2021).

- **Creativity**

Certain tasks involve creative processes like content generation, ideation, and original or novel solutions. Creativity as a key dimension of AI task suitability refers to assessing if the task requires imaginative or divergent thinking, conceptual blending, or ideation that goes beyond rule-based or historical pattern replication (Gartner, 2023; Mandvikar and Achanta, 2023). For instance, ML and simulation models are not inherently creative (Calder, et al., 2018; Brown et al., 2020) whereas creativity is yet an emergent phenomenon for RL models (Colin, 2020). On the other hand, creativity is the strongest suit of Gen AI (OpenAI, 2023).

- **Decision Impact and Risk**

This dimension refers to the degree to which a task can allow inaccuracies, uncertainties, or deviations from ideal outcomes without leading to significant negative consequences (Davenport and Ronanki, 2018). High stakes domains like healthcare, finance and legal systems etc., precision, robustness, and transparency are of utmost importance. Therefore, this dimension basically assesses how precise and reliable output should be and how tolerant the task environment is to errors made by AI systems (Davenport and Kirby, 2016; Lubars and Tan, 2019; Mohseni et al., 2021). For instance, Ribero, et al. (2016) and OpenAI, (2023) respectively described that ML and GenAI may only be suited for low to moderate risk tasks. Whereas RL can be suitable for trial-and-error in high-risk tasks environments (Dong et al., 2020) and simulation models are ideal for high-risk testing decision domains in virtual settings (Barat et al., 2022).

- **Theme 5: AI adoption frameworks**

As described above, AI adoption in SMEs has gained growing scholarly attention, however, there remains a notable scarcity of holistic and empirically grounded frameworks for effective AI adoption. Only a handful of studies (presented in table 2.10) like Bettoni et al. (2021), Hussain and Rizwan (2024) and Taherizadeh and Rizwan (2024) have proposed AI adoption frameworks. Taherizadeh and Rizwan (2024) suggested a grounded theory-based, five-dimensional sequential roadmap for AI adoption in SME. It primarily highlights experiential dimensions without clearly defining structured pathways for adoption. The model does not address the industry-specific challenges and lacks metrics for operationalisation of the roadmap stages. Similarly, Hussain and Rizwan (2024) presented a prescriptive framework for strategic AI adoption. However, it lacks generalizability across sectors and contexts. Further, it focuses on theoretical recommendations rather than operationalizability. Bettoni et al. (2021) also conceptualised a diagnostic and descriptive AI adoption model, offering limited operational guidance for actionable implementation.

Table 2.11: Included studies addressing theme 5

Studies	Study outcome	Limitations
Strategic AI adoption in SMEs: A Prescriptive Framework **(Hussain and Rizwan, 2024)**	• A structured, phased framework aimed at guiding SMEs through AI adoption • Awareness for leadership • Adoption of General-Purpose GenAI Tools • Adoption of Off-the-Shelf Task-Specific Tools • In-House Development of GenAI Tools • In-House Development of Discriminative AI Models	• Lack of empirical validation • Unaddressed implementation challenges • Theoretical focus
An emergent grounded theory of AI-driven digital transformation: Canadian SMEs' perspectives **(Taherizadeh and Rizwan, 2024)**	• A five dimensional sequential and stage-like progression roadmap for AI adoption in SMEs • Evaluating transformation Context • Auditing Organisational Readiness • Piloting AI Integration • Scaling Implementation • Leading the Transformation	• Limited generalizability • Absence of Metrics for operationalisation of the roadmap stages • Lacks longitudinal validation
An AI adoption model for SMEs: a conceptual framework **(Bettoni et al., 2021)**	• A conceptual AI adoption model helping firms to pinpoint their current stage and areas for improvement	• Abstract level theoretical understanding • Conceptual model without validation

2.4. Discussion on identified gaps

The themes identified by this work reveal varying gaps. For example, whilst enablers and challenges of AI adoption are widely acknowledged in the literature, they are typically presented in broad, generalized terms. Their significance across the transformation contexts or industries have not been examined to determine if these hold the same weight. Similarly, the body of research on readiness offers valuable conceptual foundations but lacks operationalizability. Studies concerning AI adoption and business performance assess its outcomes in an aggregated manner. Only a limited number of studies have examined the influence of AI adoption across specific performance dimensions. On the other hand, existing AI suitability frameworks primarily focus on exploring human-technology delegation dynamics rather than offering a holistic structure to examine the capabilities of AI technologies against specific task requirements. Finally, AI adoption models tailored specifically to SMEs are scarce. Even these frameworks address AI adoption at a high level, overlooking the distinct constraints. However, this work does not treat these gaps in isolation, rather it emphasises how many these transcend and intersect across multiple thematic areas. By integrating these insights, the work offers a more cohesive critique to position itself for proposing a unified model that addresses the interconnected deficiencies.

2.4.1. Contextual insensitivity

AI adoption represents a multifaceted process shaped by a diverse range of enabling and constraining factors. The influence and relative importance of these factors are highly context-dependent, varying across organisational size, region, industries, areas of implementation and levels of technological maturity. Existing research has offered valuable insights into the technological, organisational , and environmental determinants that facilitate or hinder adoption. However, their context-specific dynamics, relative influence and interrelationships remain insufficiently examined. This limitation is particularly acute for SMEs. While reshaping the adoption pathways, their immature technological infrastructure, limited financial resources, and market saturation amplify the gravity of challenges. A nuanced understanding requires identifying these factors along with analysing how they interact, reinforce, or counteract one another across different environments. Such interplay can significantly alter their collective effect. For instance, advanced digital skills of employee may compensate for the limited digital infrastructure and limited skills may condense the benefits of advanced digital infrastructure. Similarly, the impact of technology infrastructure may be greater when the transformational objective focuses on improving operational efficiency, compared to contexts where the primary goal is enhancing decision-making. Examining these within diverse contextual settings can enhance the precision and applicability of AI adoption frameworks.

Further, one-fit-all AI readiness assessment frameworks neglecting contextual specificity can be too general with their assessments lacking actionable guidance for SMEs navigating AI implementation. Moreover, theme three highlights AI's role in delivering a variety of performance outcomes, such economic, operational, governance and social etc. However, the most of these studies examine a generalized effect of AI adoption rather than inquiring the distinct contributions of enabling factors such as infrastructure, leadership, or human capital. The absence of such granularity somewhat conceals an extensive understanding of influence these enablers exert on performance outcomes. This enveloped understanding limits the organisational capability to design targeted and context specific strategies for SMEs. Also, existing models concerning AI-task suitability employ a generic, one-size-fits-all approach, leaving a significantly limited understanding of the nuanced 'fit' between AI's functional capacities and the contextual demands of real-world organisational tasks. This demands an integrated approach that explicitly map AI capabilities across task-specific requirements to ensure informed and contextually grounded adoption decisions.

2.4.2. Lack of operationalizability

The AI readiness literature highlighted the importance of alignment between the multidimensional dimensions for effective AI adoption. However, most of these studies remain focused on developing a descriptive conceptual construct rather than developing operationalizable frameworks. It is crucial to translate these readiness dimensions into measurable, practitioner-oriented indicators, for the development of concrete tools for readiness assessment and guidance framework. This signals the need for a contextually-aware, actionable readiness models that extends this conceptual framing to its practical application. Similarly, a scarcity of holistic adoption models is evident in theme five, that are largely conceptual and theoretical, offering strategic insights but rarely extending into operational guidance. These models enrich academic discourse by establishing AI adoption in broader multidimensional contexts. However, their practical application is severely constrained due to the lack of their empirical validation, operational efficiency, and structured deployment guidelines. Thus, they serve like high-level reference points than actionable tools capable of guiding SMEs along structured adoption pathways

2.4.3. Lack of coherence

The reviewed contributions highlight the need for a coherent framework rather than addressing discrete AI adoption issues in isolation. Non-cohesive frameworks derived from various fragmented studies represent the isolated nature of current scholarship on AI adoption. This fragmentation could be due to the versatility of the field or the varying contexts of AI adoption. It may also arise from diverse assumptions and analytical boundaries across the disciplines.

Collectively, the reviewed contributions highlight critical limitations in current scholarship. What emerges is a clear need for a comprehensive, coherent, context-sensitive and operationalizable adoption framework (presented in figure 2.6) that systematically aligns organisational existing capabilities (where do the organisation stands with regard to AI adoption), organisational motivation (why AI adoption is to be pursued) and the selection and scope of AI capabilities (what to adopt). Such a framework would not only bridge conceptual gaps in the literature but also provide SMEs with structured, context-sensitive pathways for minimizing risks, accelerating value realization, and ensuring that AI adoption remains scalable, sustainable, and strategically aligned with organisational goals.

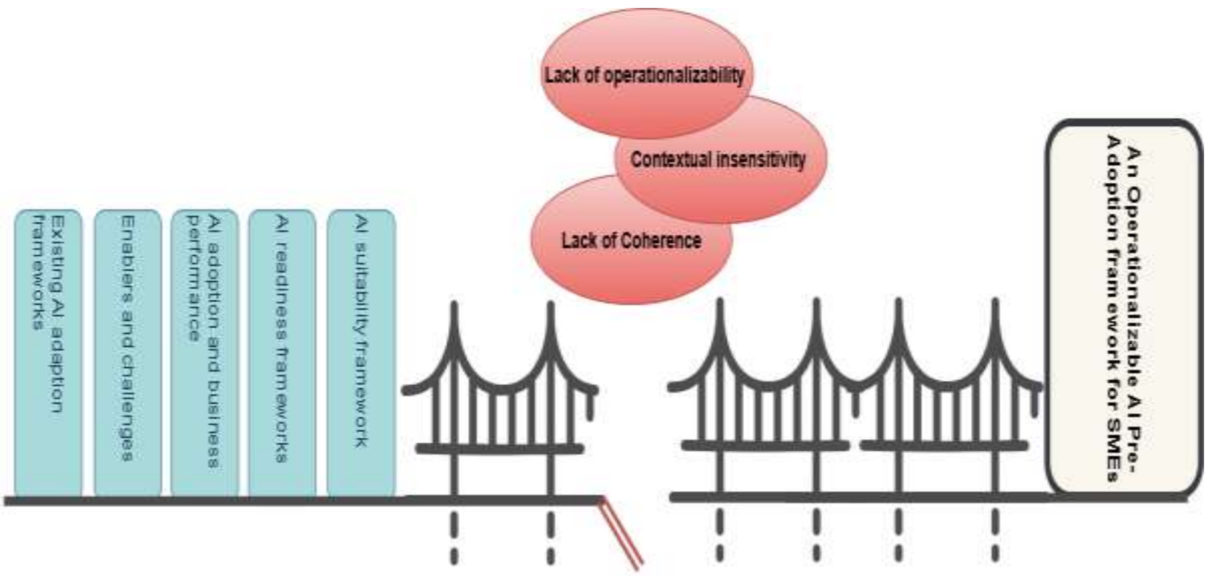


Figure 2.6: Synthesizing the identified gaps and future discourse for progression of strategic AI adoption

2.5.Conclusion

This review underscores the fragmented state of current scholarship on AI adoption. It is recognized that the existing frameworks either concern isolated areas or are largely non-operationalizable. Though each strand of research expands the literature, lack of integration among these stands restricts the systematic theoretical advancement and practical utility. This limitation is particularly critical for SMEs as they face acute resource and capability constraints. The study highlights the key gaps by synthesizing the contributions across five themes within AI adoption literature. It underscores the need for context-sensitive analysis of factors influencing AI adoption, the development of operationalizable readiness assessment models, finer-grained frameworks analysing AI enablers for performance outcomes, detailed task-technology fit approaches, and the design of evidence based, actionable adoption frameworks. A descriptive and conceptual investigation toward integrated, practice-oriented approaches connecting why, what, and how organisations adopt AI can help address these gaps.

Consequently, a comprehensive adoption framework aligning organisational capabilities, motivations, and AI technology selection proposed by this study offers a step in this direction. This proposes a structured guidance to SMEs reducing adoption risks, accelerate value creation along with ensuring scalability and sustainability.

Chapter 3. Research model

The gaps identified in the literature point to the need for a structured, multidimensional inquiry. This chapter therefore outlines the research design and the guiding questions to address the research purpose that is to develop a holistic, context-sensitive and operationalizable AI adoption framework.

3.1. Research questions

The central research question addressing the purpose of the study is:

'How can a strategic, diagnostic and prescriptive AI adoption framework be developed for SME?'

However, based on the insights from the literature review carried out in chapter 2, the overreaching purpose is decomposed into two primary research objectives. These included fostering organisational awareness and preparedness (by assisting SMEs in understanding their existing capabilities and the criticality of the required resources) and supporting the alignment of AI adoption strategy with business goals (by helping them to identify where and which AI technologies can add more value). In alignment with these objectives, a tailored set of core investigative research questions (CIRQs) are formulated as shown in table 3.1. To develop a methodological direction, a three phased study is carried out. These phases intend to guide the design, development, and evaluation of the intended strategic, diagnostic and prescriptive AI adoption framework. The table 3.2 presents the phase-specific empirical research questions (PERQs) associated with each study with an overall aim of facilitating AI adoption in SMEs.

Table 3.1: Research questions

Main Research Question	CIRQs	Research phases
How can a strategic, diagnostic and prescriptive AI adoption framework be developed for SME?	**Objective 1** Fostering organisational awareness and preparedness for effective AI adoption in SMEs **RQ.1.** How can a diagnostic and prescriptive approach be designed to identify critical resource gaps and provide actionable and context-specific guidance for effective AI adoption?	**Phase 1: Diagnostic framework** Development of an AI readiness assessment and guidance tool embedding varying significance of organisational capabilities into the readiness construct
	RQ.2. How can a structured approach be developed to align transformational plans with clearly defined strategic performance enhancement goals?	**Phase 2: Transformation planning and performance goal linkage** Empirical analysis to identify the influence of AI enablers on difference performance dimensions
	Objective 2 Supporting identification and prioritisation of AI-adoption opportunities in SMEs	**Phase 3: Task level AI Adoption decision support** Construction of an AI task-suitability evaluation model to guide SMEs in identifying best

	RQ.3. How can task-level AI adoption opportunities be identified and prioritised to guide effective decision-making in SMEs?	suited implementation solutions in the given context.

Table 3.2: PERQs for the three phases

Phase	PERQs
Phase 1: Diagnostic framework	1.1 What elements constitute a valid and comprehensive construct for measuring AI readiness in SMEs? 1.2 How can these elements be weighted to determine their relative significance? 1.3 How can a diagnostic and prescriptive scheme be developed to calculate organisational readiness in a structured and operationalizable way?
Phase 2: Transformation planning and performance goal linkage	2.1 Which are the key AI enablers that can impact different sustainable performance dimensions in SMEs? 2.2 Do these multifaceted enablers exert uniform impact across different sustainable performance dimensions?
Phase 3: Task level AI adoption decision support	3.1 Which dimensions best characterize the contextual and operational AI-task suitability? 3.2 How do the core AI applications vary in terms of their capabilities across these dimensions? 3.3 How can a framework be constructed to determine AI-task fitness rankings?

The study-map presented in figure 3.1 below depict the contribution of each research question towards theoretical and practical advancement of knowledge for effective and sustainable AI adoption in SMEs. It underscores the alignment between research questions and the overarching goal of enabling effective, context-sensitive, and sustainable AI adoption. Phase 1 seeks to develop a diagnostic model for AI readiness assessment, enabling SMEs to evaluate their current preparedness and contextual conditions for AI adoption. Phase 2 identifies and prioritises AI enablers or implementation variables that contribute to strategic performance outcomes. Insights from these two phases support the first objective outlined in section 1.2 that is enhancing the organisational awareness and understanding for transformation goals setting by assisting them to better realize their existing capabilities, the criticality of the required resources and their contextual importance. Phase 3 constructs a task suitability framework model to guide SMEs in identifying viable implementation opportunities. This phase addresses the second objective that is to support identification and prioritisation of AI-adoption opportunities in SMEs by understanding where and which AI technologies can add more value within complex planning environments. By mapping the contributions of each question, the study emphasises how theoretical constructs are translated into actionable frameworks or decision-support tools that assist SMEs to address the challenges through the adoption journey.

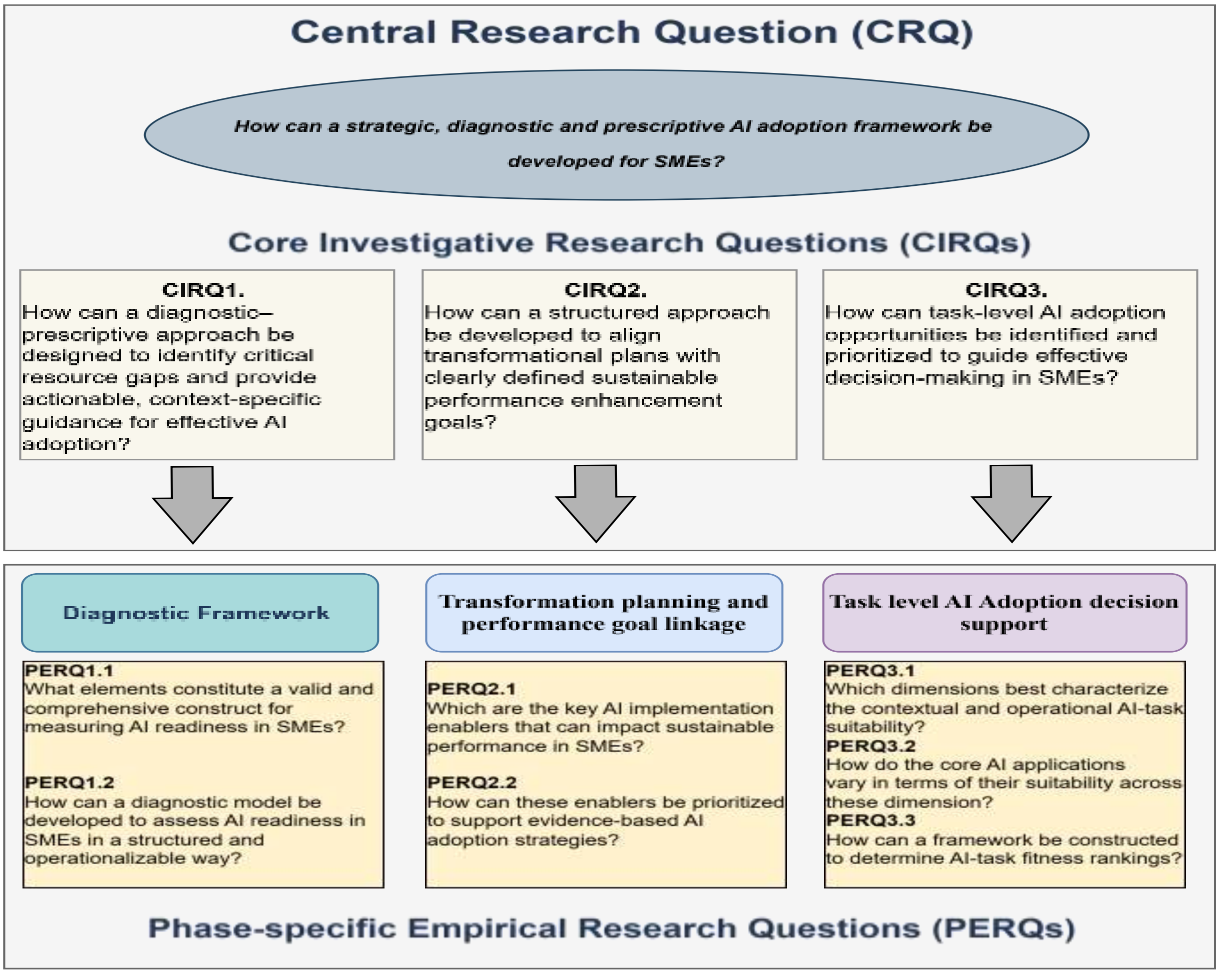


Figure 3.1: Study-map mapping contributions of each research question

3.2.Design Science Research Methodology (DSRM)

The work adopts DSRM proposed by (Peffers et al., 2007) to develop this multi-stage AI adoption framework for SMEs. It is a process-oriented approach focused on building, refining, and validating purposeful artifacts and is widely used for conducting and presenting design science research in information systems (IS). It is comprised of six steps including problem identification and motivation, objectives for solution, design and development, evaluation, and communication (Peffers et al., 2007). It is particularly suited to this inquiry. It emphasises both the construction of innovative solutions and the generation of actionable knowledge through iterative cycles of design, implementation, and assessment to address organisational challenges and support for effective AI adoption. Its structured yet flexible nature allows for methodological pluralism. It refers to accommodating multiple research techniques and paradigms across different stages of the inquiry (Chamberlain et al., 2011). Given the applied, solution-oriented, and context-sensitive goals of this study, DSRM offers a robust foundation for linking theoretical understanding with practical implementation guidance.

Chapter 2 identifies critical gaps within the existing literature on AI adoption in SMEs. It formulates the basis for DSRM artefact by defining the research problem. Based on that, two overarching research objectives, as outlined in the table 3.3, are established. Guided by the design and development stage of DSRM, the study is structured into three sequential and interdependent phases. Each phase incrementally contributes to the development and refinement of the comprehensive and operationalizable AI adoption framework for SMEs. Collectively, these phases form a coherent and cumulative research trajectory. It is aimed at equipping SMEs with practical, evidence-based guidance for making informed, strategically aligned, and sustainable AI adoption decisions. Each of these phases employs a tailored methodological approach that is designed to align with its specific research objectives (explained in the next section).

Table 3.3: Description of DSRM elements of the study

DSRM element	Description
Problem identification and Motivation	SMEs lack awareness and understanding of the structured mechanisms to assess their existing capabilities, understand the criticality of required AI-related resources in their specific context. This limited awareness impedes their ability to make informed and strategically aligned AI adoption decisions.
Objectives for solution	1. Foster organisational learning and preparedness for AI-driven transformation by enabling SMEs to • carry out AI readiness assessment of SMEs at a granular level to identify their resource gaps and their criticality along with guiding them in formulation of future action plans. • comprehend the direct impact of AI enablers on different business performance dimensions aimed at enhancing the organisational understanding for aligned and specific sustainable enhancement goals setting. 2. Supporting identification and prioritisation of AI-adoption opportunities in SMEs • to understand where and which AI technologies can add most value
Design and development	**Phase 1-** Diagnostic Framework Development: Develops an operationalizable AI readiness assessment tool to evaluate organisational preparedness. **Phase 2-** Analytical Model Construction: Employs empirical analysis to identify the influence of AI enablers on difference performance dimensions. **Phase 3-** Application Model Design: Constructs an AI task-suitability evaluation model to guide SMEs in identifying viable implementation opportunities.
Evaluation	Progressive evaluation, whereby different aspects of framework validity are examined at successive stages of development.
Communication	Academic dissemination through publications

The research model reflects a structured, multiphase process with a layered progression of analysis rather than an iterative refinement of a single set of constructs. Each phase addresses a distinct level of the AI adoption decision problem. Phase 1 provides a diagnostic baseline that defines the boundaries of feasible AI adoption. Building on this foundation, Phase 2 introduces a performance-oriented analytical perspective that complements the diagnostic assessment by enabling strategic prioritisation within identified capability constraints. Rather than extending Phase 1 outputs, it offers a distinct but related lens for decision-making. Phase 3 further develops the model by translating these strategic considerations into task-level deployment decisions, supporting the evaluation of AI suitability in specific operational contexts. Taken together, the phases are linked through a progression in decision-making abstraction while remaining methodologically distinct. The final framework thus emerges through analytical deepening across levels, integrating organisational preparedness, performance-driven prioritisation, and context-specific deployment into a coherent and operational AI adoption roadmap for SMEs.

3.3. Research Context and Industrial Collaboration

Consistent with DSR principles, the work was conducted in collaboration with Pinetti to ensure practical grounding and contextualized relevance of the framework. It also served as the primary validation environment complemented with evaluations conducted with other SMEs across different phases of the research process. Extensive customization, high product variability, and the simultaneous use of manual and semi-automated operations are the primary characteristics of Pinetti's production planning process. Its operations demand close coordination among the design, procurement, and production to operate effectively under tight lead times and keep up with fluctuating customer specifications. Its complex and challenging production environment provided a complicated setting to explore effective AI adoption strategies. Data from Pinetti informed multiple stages of the research. For instance, in the initial AI readiness assessment phase, the company set the foundation for the framework by contributing empirical insights to help identify and assign weights to the dimensional elements and their attributes. In the next phase, it supported the examination of AI implementation enablers and their relationships with performance goals by providing the managerial data. Finally, the selection of S&OP as the focal functional area was predetermined by the industrial collaboration context rather than emerging as a diagnostic output of the proposed framework. The company identified production planning and coordination challenges as a priority domain for exploration prior to framework application. Accordingly, the S&OP case is positioned in this thesis as a demonstrative application environment used to evaluate the operational applicability and analytical usefulness of the framework, rather than as evidence of framework-prescribed problem identification.

In such research settings, validation does not primarily seek causal proof of performance improvement, but rather evaluates whether the proposed artefact provides analytically sound, contextually meaningful, and practically usable decision support. Accordingly, validation in this thesis is conceptualised as a multidimensional evaluation process conducted across the three interdependent studies. Rather than relying on a single validation mechanism, the thesis applies progressive evaluation, whereby different aspects of framework validity are examined at successive stages of development. Each empirical phase contributes distinct but complementary evidence regarding the framework's robustness and applicability:

1. Phase 1 evaluates analytical validity through the operationalisation and empirical application of a weighted AI readiness assessment model.
2. Phase 2 examines contextual validity by analysing differentiated relationships between AI implementation enablers and multidimensional performance outcomes.
3. Phase 3 assesses operational feasibility and usability through an in-depth case-based application of the TTF component within an organisational planning context.

Consequently, validation in this thesis should be interpreted as evidence of framework usefulness, coherence, and decision-support capability, rather than confirmation of universal causal performance effects. This evaluation logic aligns with design science research traditions, where artefact quality is demonstrated through structured empirical application across multiple contexts and analytical levels.

This participatory approach reflects the core of the DSR paradigm by integrating design and evaluation within an industrial setting. The firm's feedback supported construct normalization and explication of findings to ensure framework's theoretically soundness and operationalizability . Thus, this partnership not only functioned as a case study but also as an empirical evaluation partner contributing to the development of a contextually grounded framework for AI adoption in SMEs.

3.4. Research philosophy

The work is grounded in a multi-epistemological paradigm to effectively inform and guide the preliminary phase of AI adoption SMEs. This multi-paradigm approach reflects the design-oriented, solution-driven nature of the overall work, where different philosophical tools were employed to address different layers of the AI adoption challenge in SMEs. This multi-paradigm approach reflects the design-oriented, solution-driven nature of the overall work, where different philosophical tools were employed to address different layers of the AI adoption challenge in SMEs.

Phases 1 and 3 used pragmatist reasoning as a guiding paradigm, given their applied nature. These are seeking to support SMEs in navigating through the complexities of AI adoption focused on solving context-specific problems through applied model development. Both phases generate decision-support insights that are practically useful to firms planning AI adoption. The emphasis is on practical application and usefulness rather than theoretical generalization. Whilst phase 1 focuses on generating actionable knowledge to guide SMEs in evaluating their preparedness for AI adoption, phase 3 helps them evaluate the suitability of different AI application for specific business tasks. The inherent flexibility of pragmatist reasoning allowed to adopt a pluralistic approach. This paradigm advocates the adoption of diverse approaches instead of being constrained by a single methodological tradition. The approaches are selected for their appropriateness to the problem under investigation. Such flexibility ensures that the inquiry remains anchored in addressing the core problem and oriented toward meaningful outcomes. This help producing insights that are not only theoretically robust but also practically applicable. For instance, phase 1 integrated literature-driven conceptual development with quantitative surveys that are used both for empirical validation and expert-based evaluation of the developed models. This approach, consistent with the pragmatist paradigm ensures that it generates knowledge that is both theoretically robust and practically actionable for SMEs

On the other hand, phase 2 seeks to objectively measure and rank AI enablers through a structured questionnaire. The use of empirical, quantitative data from experts to derive generalizable insights through statistical analysis aligns with a positivist logic.

Chapter 4. AI Readiness Assessment Model (Phase 1)

As explained above, phase 1 addresses CIRQ1 (PERQS 1.1-1.3) to develop a diagnostic framework intended to foster organisational awareness and preparedness for effective AI adoption in SMEs. One of the main findings of the literature review presented in chapter 2 is the lack of operationalizability of the existing AI readiness assessment models. It is elucidated that these models are primarily concerned with the categorization and description of AI readiness dimensions positioning them as general recommendation frameworks lacking diagnostic capabilities. Further, the literature review also highlighted that the existing body of work concerning AI implementation factors has not yet explored the relative importance, interplay, and context-specific nature of these factors. Therefore, this chapter addresses these needs for a diagnostic, prescriptive and operationalizable AI readiness assessment model. Within the broader context of this research, the aim of this phase is to address the "where do we stand" aspect in the adoption lifecycle (as shown in figure 4.1). It focuses on enabling SMEs to determine their current position and preparedness in relation to adopting AI and highlighting gaps that must be addressed before moving towards implementation phase.

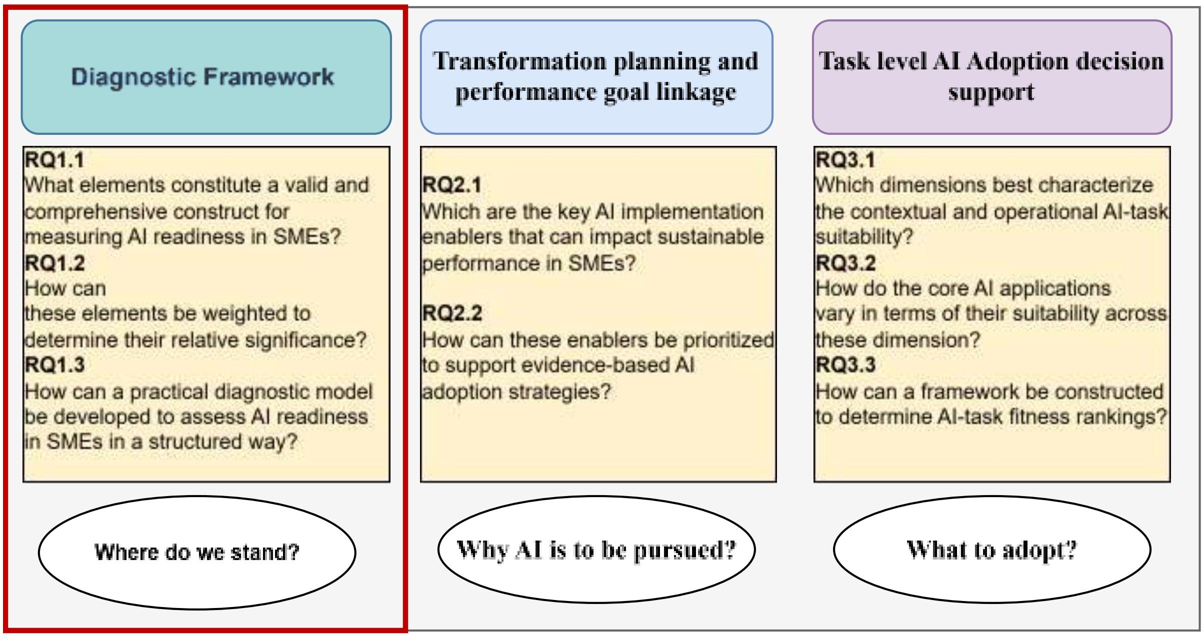


Figure 4.1: 'Where' aspect of AI adoption lifecycle

4.1. Introduction

AI is widely regarded as a transformative technology with the capacity to substantially improve the efficiency and effectiveness of business operations. By reducing production time and costs, AI enables organisations to enhance productivity and streamline processes (Wamba-Taguimdje et al., 2020). The global AI market, which includes hardware, software, and services, is expanding rapidly and is projected to reach approximately 1.8 trillion USD by 2030 (Grand View Research, 2023). Contemporary AI solutions have become increasingly advanced. These often surpass human performance in specific tasks with respect to efficiency and accuracy (Jankuloski et al., 2020). Their application spans across multiple domains including healthcare, finance, education, manufacturing, and marketing. These can help fosters competitive advantage through process optimization, data-driven decision-making, and productivity gains (Borges et al., 2021).

AI represents an opportunity for SMEs to strengthen strategic decision-making and remain competitive in resource-constrained and saturated markets (Borges et al., 2021). However, its adoption remains uneven despite its benefits and the ever-increasing maturity of AI systems. Organisations continue to face significant challenges like limited knowledge, financial challenges, uncertainty in identifying suitable entry points, concerns about organisational preparedness and technological maturity (Goasduff, 2019; Benbya et al., 2020). Prior studies such as (Holmstrom, 2022; Tehrani et al., 2024) highlight that many firms, particularly SMEs, struggle to assess their preparedness. They are unable to determine if they possess the capabilities required for AI adoption or must first develop or upgrade them.

Such an assessment requires a structured evaluation of the key dimensions that shape an organisation's readiness for transformation. While existing AI readiness literature (Najdawi, 2020; Nortje & Grobbelaar, 2020; Holmstrom, 2022; Tehrani et al., 2024) offers a variety of conceptual and diagnostic frameworks across contexts ranging from large enterprises to SMEs and governments, these approaches often fall short in practice. Many remain largely descriptive, providing limited guidance for real-world assessment. They also tend to treat readiness components as static and equally important, overlooking how their relative relevance can vary. Understanding the relative importance of these dimensions is crucial for accurately evaluating capabilities and setting meaningful priorities. Moreover, the lack of practical evaluation methods further limits their usability. Therefore, this study proposes an AI readiness assessment model built on a multidimensional, granular and weighted readiness construct. By defining readiness to the attribute-level, it enables a detailed evaluation of organisation's preparedness for AI adoption. It further proposes an operationalizable readiness calculation scheme, tested in real-word settings, demonstrating its practical applicability and capability to meaningfully assess organisational preparedness.

4.2. Framework development scheme

This framework seeks to design around a set of core dimensions or key areas that are used to evaluate an organisation's preparedness to adopt or implement a particular change, technology, strategy, or process. To establish these dimensions in a comprehensive manner, it is essential to specify the constituent elements of each dimension together with their underlying micro-level attributes. These dimensional elements capture the sub-areas within each dimension, whereas micro-level attributes are the capabilities associated to different dimensional elements. Figure 4.2 illustrates the research plan guiding the model's development, which is structured into two main phases: (1) the preliminary phase and (2) the AI readiness calculation phase.

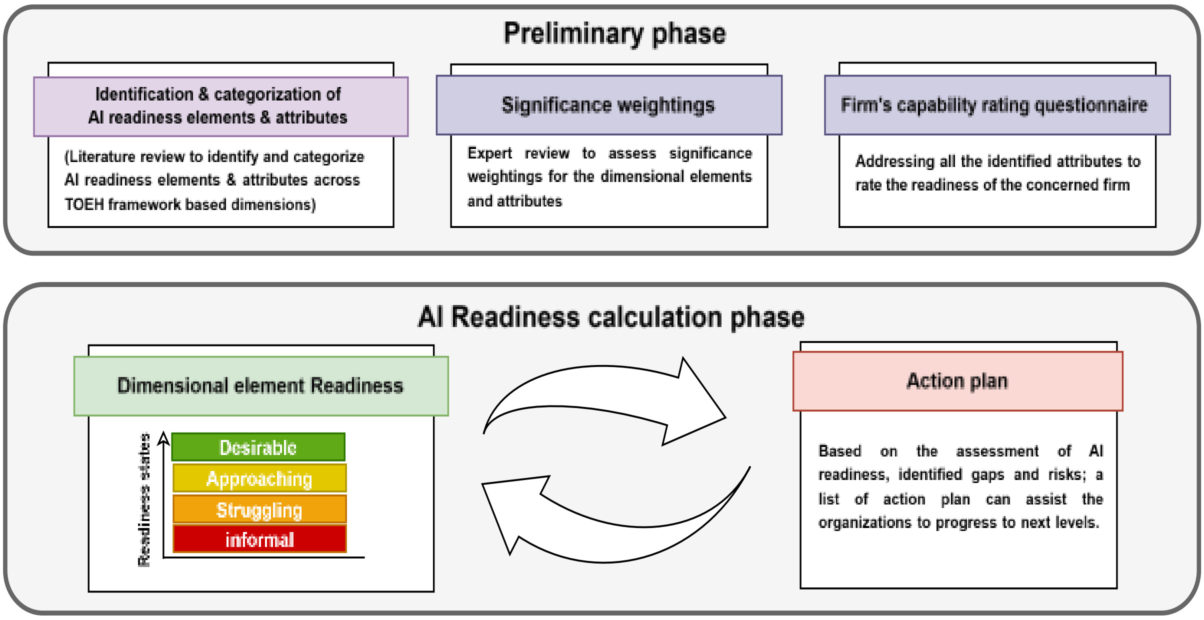


Figure 4.2: Proposed AI readiness assessment model

4.2.1. Elements and Attribute identification

A targeted literature review was conducted to refine and operationalize the AI readiness evidence base provided in Chapter 2. Building on the foundational SLR, this review focused on studies providing detailed insights into AI readiness construct, including the operational attributes relevant to SMEs. The goal was not exhaustive synthesis, but rather to translate broad, theoretically-derived constructs into contextually meaningful and empirically measurable dimensions. Searches were performed in Google Scholar and Scopus due to their extensive coverage and advanced querying features. Search strings combined synonyms for "dimensions," "elements," and "attributes" with keywords such as "AI adoption," "AI readiness," and "AI implementation." From these studies, a comprehensive list of AI readiness dimensions and micro-level attributes was derived (see Section 4.3.1). The findings of this targeted review were systematically organised in alignment with the structure established in foundational SLR, employing the TOE framework to maintain conceptual consistency and theoretical coherence.

AI differ fundamentally from other digital technologies as it does not merely automate predefined workflows but introduces adaptive, and intelligent systems into organisational processes. Unlike transactional IT systems, AI applications do not operate as fully deterministic tools (Amershi et al., 2019). They involve varying degrees of autonomy that require context-dependent human oversight, trust calibration and augmentation (Seeber et al., 2020; Mohseni et al., 2021). Their effectiveness is therefore directly conditioned by employees' analytical skill depth, literacy, awareness, cognitive adaptability, and capacity to collaborate with algorithmic agents (Vuong et al., 2019; Horvat & Heimberger, 2022; Mylrea & Robinson, 2023; Uren & Edwards, 2023). These dynamics extend beyond the structural, financial, or environmental conditions, and expose a limitation within the traditional TOE framework. While it captures technological infrastructure and institutional arrangements, it does not explicitly theorize the embodied human capabilities required to interpret, govern, and integrate intelligent systems into decision-making processes. Contemporary research on human-AI collaboration emphasises that AI introduces sociotechnical coupling, cognitive uncertainty, and hybrid human-machine teaming arrangements (Seeber et al., 2020; Mohseni et al., 2021), where human involvement shifts from continuous control to supervisory, interpretive, and exception-based roles. Accordingly, this study conceptualizes Human readiness as a distinct analytical domain rather than subsuming it within the organisational dimension. It helps operationalizing the micro-foundations through which technological and organisational resources are translated into effective AI utilization.

4.2.2. Significance weighting

As illustrated in Figure 4.2, the process begins with identifying key areas and associated capabilities, followed by evaluating the significance of dimensional elements and their micro-level attributes in the context of AI adoption. This evaluation clarifies how each element and attribute contributes to organisational readiness for AI implementation and enables their systematic prioritisation according to relative importance. The outcomes support the development of a targeted action plan by highlighting areas requiring immediate intervention against those suited for gradual improvement. There ratings are primarily derived based on the significance weightings. To establish these ratings, a rigorous expert evaluation (as detailed in Section 4.3) was conducted. Best-Worst Method (BWM), a multi-criteria decision-making approach proposed by Rezaei (2015), was applied for the analysis. It helped assigning optimal weights to dimensional elements and attributes (as discussed in section 4.3.1). Thereby determining their relative significance. It was selected for its ability to generate quantitative weightings reflecting the relative strength among the factors. This not only establishes the required prioritised rankings but also yields a consistent ratio scale, enabling a more robust interpretation of the interdimensional significance in the AI adoption context.

Eleven experts were initially invited based on demonstrated expertise in AI implementation and SME digital transformation. All of them initially consented to participate; however, three experts could not ensure participation due to personal issues and time constraints. Therefore, the final aggregation of weights was conducted using responses from eight experts. As presented in the Table 4.1, the panel comprised of four university lecturers specializing in digital transformation research, two mid-level professionals, and two consultants from leading IT firms. The representation from academia ensured the integration of theoretical perspectives and current scholarly insights, whereas a balanced composition of the industry experts (two consultants and two team leaders) ensured an integration of strategic, technical, and operational viewpoints. This reduced the risk of single-perspective dominance. Whilst, the consultants contributed with the cross-industry strategic insights and exposure to diverse implementation contexts, the team leaders provided the practical perspectives with day-to-day implementation realities within organisational settings. The convergence of these academic and diverse industrial perspectives supports the robustness of the weighting process. Consequently, the resulting weights are informed by substantial expert knowledge and provide a credible representation of domain-specific priorities.

However, the relatively small size of the expert panel inevitably limits the statistical generalizability of the derived weightings. In addition, the panel lacked the representation from individuals with long-term operational ownership roles within SMEs. This composition partly reflects the structural reality of many SMEs, which typically lack dedicated in-house IT functions and instead depend on external vendors or service partners. Consequently, the derived weights may slightly privilege strategic and organisational readiness dimensions over deeply embedded operational realities. The findings should therefore be interpreted as contextually grounded expert assessments that provide analytically informed and directionally robust judgements with strong indicative value. A large-scale empirical validation can further confirm their robustness across a wider range of SME settings.

Table 4.1: Participant details for evaluating the significance weightings

Code	Sector	Role	Experience (years)	Expertise
1	Academia	Teaching/ Research	12	Human-computer interaction expert

2	Academia	Teaching/ Research	3	Smart applications for the industry
3	Academia	Teaching/ Research	8	Smart applications for the industry
4	Academia	Teaching/ Research	5	Digital supply chain
5	Industry	Consultant	16+	Project management
6	Industry	Team leader	4	Solution implementation expert
7	Industry	Team leader	4	Solution implementation expert
8	Industry	Consultant	7+	Project management

4.2.3. Firm's capability rating questionnaire

Building on the TOEH framework established through systematic literature review a structured survey questionnaire was developed (presented in table 10.1). The questionnaire is comprised of 58 close-ended questions designed to measure AI readiness for SMEs. For a granular, comprehensive, and theoretically grounded assessment, the survey questionnaire is developed using a formative logic. In formative logic, a construct is conceptualised as being formed by a set of distinct and non-interchangeable indicators, each representing a unique aspect that collectively defines the meaning of the construct (Diamantopoulos and Winklhofer, 2001; Coltman et al., 2008). In this approach, AI readiness is conceptualised as a multidimensional construct formed by a set of distinct capability domains. Each construct is operationalised through indicators that represent specific dimensions of organisational readiness, with each item capturing a unique aspect contributing to the overall construct.

Given that each attribute represents a distinct component of AI readiness, the omission of any item would alter the substantive meaning and scope of the overall construct. This is consistent with formative measurement principles, where indicators are defining elements rather than interchangeable manifestations of an underlying latent variable. Accordingly, internal consistency metrics were not considered appropriate, as formative models theoretically do not require inter-item correlation. Grounding each item in peer-reviewed literature and subjecting to expert validation ensured content validity,. This maintains direct traceability between conceptual framework development and empirical operationalisation.

To ensure operationalizability and enhance diagnostic precision, a five-point ordered progression scale depicting the advancement from absence of capability to expert-level maturity was adopted. Unlike, conventional Likert agreement scales, these structured anchors guide respondents to clear and evaluative conditions rather than subjective agreement. This approach is influenced by the maturity model logic that allows the instrument to distinguish between the incremental stages for achieving the optimal level. For example, the item assessing 'Flow, smoothness and reliability of data across operational layers' evaluates data integration capability using clearly defined operational states ranging from 'Significant disruptions' to 'Consistently excellent' rather than asking respondents for their level of agreement. These anchors represent qualitatively different level of performance maturity. Whilst, the former indicates frequent breakdowns and instability in cross-layer information exchange, the later reflects reliable, uninterrupted, and embedded interoperability. The intermediate categories represent progressive reductions in inefficiencies and increasing system robustness. This ordered progression follows the developmental nature of capability accumulation, reducing the perceptual bias and interpretive ambiguity. Although formal pilot testing was not performed, the instrument underwent iterative refinements through repeated internal review and alignment with the underlying conceptual framework for clarity, coherence, and contextual relevance. Procedural safeguards such as consistent organisational -level framing and neutral wording of items were applied to mitigate potential common method bias. Collectively, these measures strengthen the methodological robustness and validity of the instrument.

The questionnaire was administered to relevant organisational personnel. Their responses provided attribute-level ratings within each dimension. These ratings form the basis for evaluating the overall readiness level across the four dimensions.

4.2.4. AI readiness calculation

Building on the derived weightings and the firm's capability scores, a four-tier readiness framework is proposed, as illustrated in Figure 4.2. A comprehensive explanation of these readiness states, together with the underlying calculation procedure, is provided in Section 4.

4.3. Description of the Model

4.3.1. TOEH framework-based AI readiness dimensions

As established in the preceding section, an extensive literature review was conducted to identify the dimensional elements and their corresponding micro-level attributes pertinent to AI readiness. The findings are synthesized in Table 4.2, providing a structured overview of AI readiness dimensions organised within the TOEH framework.

- **Technological Readiness**

The technological context of AI readiness encompasses both internal and external technologies relevant to an organisation. It involves the assessment of technological characteristics such as IT infrastructure, digital competencies, and system interoperability and their influence on adoption outcomes (Lada et al., 2023). Internal technologies reflect the organisation's baseline capabilities for digital transformation, whereas external technologies represent the aspirational technological advancements that firms seek to integrate in order to remain competitive (Horvat and Heimberger, 2022).

From a theoretical standpoint, the TOE framework frames technological readiness as a core AI adoption determinant. It points to the influence, maturity and suitability of technological resources on the viability of new technological initiatives (Star and Bowker, 2006; Nortje and Grobbelaar, 2020; Tehrani et al., 2024). In parallel, the RBV argues that well-managed technological assets can become valuable, rare, inimitable, and non-substitutable (VRIN) resources that contribute to long-term advantage. Thereby serving as enablers of sustainable competitive advantage. However, unlike static resource possession, the dynamic capabilities perspective underlines that firms must continuously reconfigure and adapt their technological assets to match the evolving complexity and requirements of AI systems (Shang et al., 2023). In particular, the maturity of IT infrastructure emerges as a critical determinant of AI readiness, as it ensures the availability of the hardware, software, platforms, and services necessary for advanced analytics and intelligent decision support (Star and Bowker, 2006; Nortje and Grobbelaar, 2020; Tehrani et al., 2024). This maturity extends to essential considerations which shape an organisation's level of technological preparedness. These include storage requirements for handling large volumes of data, communication networks to facilitate rapid data transfer and the degree of centralization or distribution of computational resources etc. (Taherizadeh and Beaudry, 2023).

The reliability of algorithmic outputs heavily relies upon the quality and integrity of data. It also directly affects managerial trust and willingness to rely on AI-supported decisions. Knowledge-based theory views data and information as the central knowledge assets for organisational learning and innovation (Caputo et al., 2019). Kinkel et al. (2022), Holmstrom (2022), Taherizadeh and Beaudry (2023) and Tehrani et al. (2024) also explained that the high-quality, abundant, and standards compliant data is indispensable for training and deploying AI systems. This implies that data readiness represents the foundation of AI adoption. Reliable data transforms AI from a basic automation tool into a system capable of generating actionable intelligence. Thereby distinguishing intelligent systems from non-intelligent ones (Johnk et al., 2020). In addition, the scale and sensitivity of data used in AI applications elevate the importance of cybersecurity and data governance. These elements have evolved to become strategic imperatives for organisational survival in the digital era (Nortje and Grobbelaar, 2020; Tehrani et al., 2024). Firms increasingly adopt cybersecurity measures for functional protection and to comply with regulatory mandates and industry norms. Thereby enhancing legitimacy in the eyes of stakeholders. Organisations risk eroding customer trust and exposing themselves to compliance violations without robust data governance and cybersecurity practices. Such violations or trust erosion can severely undermine AI adoption efforts (Tisdale, 2015; Nortje and Grobbelaar, 2020; Stenberg and Nilsson, 2020).

Overall, technological readiness extends beyond infrastructure and data. It reflects the firm's ability to align, secure, and dynamically advance its technological capabilities. This integrated readiness encompassing infrastructure, data, and cybersecurity etc., enables effective AI implementation and contributes towards sustained performance enhancement.

- **Organisational Readiness**

The organisational context of AI readiness encompasses operational, financial, structural, and strategic elements, as well as the resources required to support AI adoption (Blut and Wang, 2020; Stenberg and Nilsson, 2020). Prior studies have examined a broad set of organisational factors including leadership commitment, organisational structure, internal processes, culture, financial capacity, and resource availability. These collectively provide the internal foundation for leveraging advanced technologies and enabling technological transformation (Gonzalez-Benito, 2006; Eljasik-Swoboda, 2019; Zhang et al., 2020; Tehrani et al., 2024). Given their pivotal role, these factors have been extensively investigated in relation to organisational readiness for digital and AI-driven initiatives (Huang and Rust, 2018; Mahroof, 2019).

The TOE framework considers organisational characteristics such as leadership, culture, processes, and resources as central to technology adoption. The RBV complements this by asserting that both tangible (like financial and technological resources) and intangible (such as leadership vision, culture, and knowledge) organisational resources hold strategic value. When effectively utilised, these can yield sustained competitive advantage. At the same time, the dynamic capabilities perspective extends this argument by emphasizing the organisation's ability to reconfigure, integrate, and adapt its existing assets and processes in response to the evolving demands of AI adoption (Huang and Rust, 2018). Thus, organisational readiness is not merely a reflection of static resource availability. But it indicates its adaptive capacity to mobilize these resources effectively in uncertain and dynamic technological environments.

Among these factors, leadership commitment is repeatedly highlighted as central to AI readiness. Technology-oriented and innovation-driven leadership significantly enhances the likelihood of effective AI adoption by setting direction, endorsing technological change, and ensuring the optimal allocation of resources, and mobilizing resources (Kellogg et al., 2020; Murray et al., 2021). They are better equipped to overcome organisational inertia and effectively embed AI into strategic priorities. Organisational culture also exerts a decisive influence on readiness by shaping organisational attitudes toward technological change. A culture characterized by openness to learning, collaboration, experimentation, and innovation foster employees trust to engage with disruptive technologies (Bhattacherjee and Hikmet, 2008; Dasgupta and Gupta, 2019; Pfeffer, 2020; Srisathan et al., 2020). Conversely, cultures resistant to change can significantly undermine AI initiatives, regardless of the resource availability. Process integration represents another critical element. Fragmented, inconsistent, or misaligned processes weaken the ability of organisations to harness AI's capabilities for decision-making and efficiency improvements (Tehrani et al., 2024). Advanced technology adoption may require automation and redesign of their existing processes to align with the capabilities of new digital tools.

Finally, the availability of financial and complementary resources such as time, IT competencies, and supporting assets are essential for sustaining readiness (Soomro et al., 2020). Organisational success depends on aligning available resources with the specific requirements of the external environment and the concerned technological task. Given that AI adoption often requires continuous updating of infrastructure, data systems, and human capabilities. Therefore, flexible and sufficient funding is essential for sustaining AI initiatives (Gorla et al., 2017). Weak financial resilience may force premature termination of projects, reducing both confidence and competitive strength.

Together, the interplay between leadership vision, cultural openness, structural coherence, process integration, and financial stability constitute organisational readiness. It is underpinned by the firm's ability to dynamically reconfigure its resource base. The organisation's capacity to transition from AI potential to realized value creation increases with a stronger synergy among these elements.

○ Environmental Readiness

The environmental context of AI readiness pertains to the external forces that shape and often compel organisations toward AI adoption (Oztemel and Polat, 2006; Huang and Rust, 2021). Prior literature highlights several factors influencing environmental readiness, including industry regulations, governmental support, and pressures exerted by markets, customers, and other stakeholders (Lee et al., 2018; Najdawi, 2020; Zhang et al., 2020). In increasingly dynamic environments, organisations must continuously monitor and respond to evolving customer expectations and competitive pressures in order to sustain performance and strategic positioning (Shabani-Naeeni and Ghasemy-Yaghin 2021). Customer demand is a critical external factor, compelling firms to leverage innovative technologies for personalized solutions, enhanced experiences, and market advantage (Tisdale, 2015; Lee et al., 2018; Garcia-Machado and Martínez-Avila, 2019; Liao and Tsai, 2019; Najdawi, 2020).

TOE framework positions environmental conditions among the three central domains influencing the adoption and diffusion of innovations. From this perspective, AI readiness is about establishing internal capabilities and aligning them with institutional, regulatory, and market requirements. Similarly, institutional theory emphasises that organisational behaviour is not purely rational or efficiency-driven. Instead, it is also shaped by pressures to conform to societal norms, regulatory requirements, and industry expectations. These include regulatory compliance, imitation of competitors, professional standards, customer expectations, and ethical norms etc (Oztemel and Polat, 2006; Tisdale, 2015; Lee et al., 2018; Liao and Tsai, 2019; Najdawi, 2020; Zhang et al., 2020; Huang and Rust, 2021; Shabani-Naeeni and Ghasemy-Yaghin, 2021). Together, these institutional forces create both pressures and avenues for environmental readiness for AI adoption. Governments and policy bodies play a particularly important role in strengthening environmental readiness. Government policies and actions shape the broader ecosystem fostering AI adoption and innovation. Regulatory frameworks with intelligent monitoring enable experimentation. Governments directly influence the pace and scale of AI adoption by safeguarding ethical boundaries (Liao and Tsai, 2019; Kellogg et al., 2020; Najdawi, 2020; Murray et al., 2021). Such supportive mechanisms can lower entry barriers and reduce uncertainty for firms contemplating AI investment.

A further dimension of environmental readiness is data governance and regulatory compliance. Since AI applications particularly those related to personalization, recommendation, and predictive analytics depend heavily on the processing of extensive datasets, environmental readiness is profoundly shaped by the regulatory frameworks governing data usage (Kaplan and Norton, 2004; Tisdale, 2015; Aboelmaged and Hashem, 2019; Garcia-Machado and Martínez-Avila, 2019; Jun et al., 2021). Drawing on contingency theory, firms must adapt their strategies and practices to align with jurisdictional contexts. It is essential as stricter data protection regimes impose significant compliance burdens in areas such as cloud computing, cross-border data storage, and the deployment of intelligent agents. Conversely, in regions with more lenient regulatory environments, firms may face fewer immediate constraints but potentially greater reputational risks if customer trust and ethical standards are compromised (Naujokaitiene et al., 2015; El-Kassar and Singh, 2019; Najdawi, 2020; Fast et al., 2023; Kokshagina et al., 2023). Thus, external regulations simultaneously act as both constraints and safeguards that shape the feasibility and the legitimacy of AI adoption.

Finally, market and competitive dynamics play a critical role in defining environmental readiness. Firms failing to respond to market signals risk strategic redundancy. Whereas the adaptive and well-aligned firms can establish differentiation, resilience, and long-term value creation. The more adaptive an organisation is in interpreting and responding to the environmental elements, the stronger its readiness to strategically adopt and integrate AI.

- **Human readiness**

While the human element has traditionally been considered a subset of organisational readiness, the increasing complexity of the human-technology interface necessitates treating human readiness as a distinct and more comprehensive dimension. Employees' individual and collective skillsets to operate, adapt to, and collaborate with AI technologies are critical determinants of adoption success (Lee et al., 2019; Najdawi, 2020; Flavian et al., 2022; Minkkinen et al., 2023; Tehrani, 2024). Consistent with the concept of absorptive capacity, it reflects an organisation's capacity to acquire, assimilate, and apply new knowledge. It hugely relies on the knowledge base and learning orientation of its workforce. Prior experience with digital and advanced technologies further strengthens employees' potential to leverage AI effectively. Experiential learning contributes to both individual competence and organisational learning loops (Chen et al., 2017). Employees' perceptions and attitudes toward AI adoption are equally decisive as the technical proficiency is. Theories such as the TAM emphasise perceived usefulness and ease of use as key drivers of adoption behaviour. The Unified Theory of Acceptance and Use of Technology (UTAUT) highlights performance and effort expectancy as key determinants of successful technology adoption (Dasgupta and Gupta, 2019; Najdawi, 2020). Thus, the willingness of employees to engage with AI, regardless of low technological literacy, is a critical readiness factor. Moreover, the sustained integration of AI necessitates a proactive learning orientation and a culture of continuous skill development. Structured training and capability-building initiatives are critical in supporting this objective (Dasgupta and Gupta, 2019). From the dynamic capabilities' perspective, human readiness reflects an organisation's ability to reconfigure its workforce in response to technological change. Dasgupta and Gupta (2019) highlighted that AI systems increasingly require adaptive human-machine collaboration, underscoring human readiness as a strategic enabler for long-term digital transformation

Table 4.2: TOEH based AI readiness assessment framework

<table>
<tr><th>Dimensional element</th><th>Attributes</th><th>References</th></tr>
<tr><td colspan="3">Technological dimension</td></tr>
<tr><td>Technology info. management</td><td>Analysis of all related AI technology to choose the best possible solution; Knowledge about the impact of AI systems on business processes; Development of clear technology management strategies for the implementation of AI; Analysis of the concerned technology in terms of compatibility; Analysis of the concerned technology in terms of technological maturity; Analysis of concerned technology in terms of impact on organisation’s day to day business; Analysis of the concerned technology in terms of ROI</td><td rowspan="4">(Star and Bowker, 2006; Tisdale, 2015; Nortje and Grobbelaar, 2020; Stenberg and Nilsson, 2020; Horvat and Heimberger, 2022; Holmstrom, 2022; Kinkel et al., 2022; Lada et al., 2023; Shang et al., 2023; Taherizadeh and Beaudry, 2023; Tehrani et al., 2024)</td></tr>
<tr><td>Data Access</td><td>Data availability across operational layers; Data flow across operational layers; Data access; Data quality</td></tr>
<tr><td>Security</td><td>Cyber and data security awareness and capabilities; Performing plans to control organisation’s records and information</td></tr>
<tr><td>IT infrastructure</td><td>Identification of communication requirements; Identification of computing requirements; Identification of network connectivity; Identification of information networks involved with implementation, operation, and management of AI; Organisational ability to develop technology sustainability map for AI</td></tr>
<tr><td colspan="3">Organisational dimension</td></tr>
<tr><td>Leadership support</td><td>Leadership commitment and support in terms of strategic assistance; Leadership commitment and support in terms of funding; Leadership commitment and support in terms of cooperation; Leadership’s understanding of AI technologies; Clarity in AI vision and strategy of leadership</td><td rowspan="4">(Gonzalez-Benito, 2006; Bhattacherjee and Hikmet, 2008; Gorla et al., 2017; Huang and Rust, 2018; Dasgupta and Gupta, 2019; Eljasik-Swoboda, 2019; Mahroof, 2019; Blut and Wang, 2020; Kellogg et al., 2020; Pfeffer, 2020; Soomro et al., 2020; Srisathan et al., 2020; Stenberg and Nilsson, 2020; Zhang et al., 2020; Murray et al., 2021; Tehrani et al., 2024)</td></tr>
<tr><td>Operational integration</td><td>Level of alignment of current processes with AI technologies; Integration capabilities of current AI technologies; Integration requirements of desired AI technologies</td></tr>
<tr><td>Culture</td><td>Organisational commitment to monitoring and continuously improve; Organisational attitude towards new technologies and its ability to exploit them; Organisational capability of taking initiative to develop an AI adoption strategy; Organisational capability of taking initiative to develop an AI adoption strategy</td></tr>
<tr><td>Structure</td><td>Hierarchy of organisation; Roles and responsibilities; Cooperation and interaction points among organisation units</td></tr>
</table>

Financial analysis	Financial feasibility for AI systems; Financial capacity of organisation to cover all expenses associated with the implementation, operation, and management of AI technology	
	Environmental dimension	
Competitors	Capability to carry out comprehensive competitor analysis; Aware of the possible competitor threats with regard to leveraging AI	(Kaplan and Norton, 2004; Oztemel and Polat, 2006; Naujokaitiene et al., 2015; Tisdale, 2015; Lee et al., 2018; Aboelmaged and Hashem, 2019; El-Kassar and Singh, 2019; Garcia-Machado and Martínez-Avila, 2019; Liao and Tsai, 2019; Kellogg et al., 2020; Najdawi, 2020; Zhang et al., 2020; Huang and Rust, 2021; Jun et al., 2021; Murray et al., 2021; Shabani-Naeeni and Ghasemy-Yaghin 2021; Fast et al., 2023; Kokshagina et al., 2023)
Ethics and regulations	Compatible of the desired AI tech with the existing values of the organisation; AI technology analysis for ethical and business values	
Govt. support	Govt. support for the initiative of AI adoption for SME's; Financial or other incentives from government for AI adoption	
Customers	Capability to carry out customer analysis; Strategy to assess the customer satisfaction and AI acceptance; Strategy to determine the impact of AI technologies on the customers	
Market	Capability to carry out efficient market analysis; Capability to determine potential market threats and opportunities with regard to leveraging AI for business growth	
Suppliers and collaborators	Supplier's willingness to collaborate and coordinate with regard to AI; Collaborator's willingness to collaborate and coordinate with regard to AI; Supplier's systems capability to integrate with AI systems; Collaborator's systems capability to integrate with AI systems	
	Human dimension	
Employees	Employee's awareness of AI technologies; Employee's involvement in strategic planning; Employee's perception of AI for the business; Employee's perception of AI in terms of their job security; Recruitment strategy to hire AI literate employees	(Chen et al., 2017; Clohessy and Acton, 2019; Dasgupta and Gupta, 2019; Lee et al., 2019; Najdawi, 2020; Flavian et al., 2022; Minkkinen et al., 2023; Tehrani, 2024)
Digital Skills	Skills and expertise to implement and manage AI; Training and other activities for skill development; Strategy to upskill employees with regard to AI	

4.3.2. Weighting scheme

As outlined in Section 4.2, the BWM proposed by Rezaei (2015), was employed to assess the relative importance of the dimensional elements and attributes by deriving their optimal weights. Beyond identifying the most and least critical factors, this approach also established a consistent ratio that reflects their comparative significance. Experts evaluated the significance of each dimensional element (DE) = {E1, E2, E3, E4, …, En} and its associated attributes DEAn = {A1, A2, A3, A4, …, Am} using a Likert scale. For each set, the experts identified the most significant (E-best or A-best) and least significant (E-worst or A-worst) items. To establish relative importance, two sets of pairwise comparisons were conducted on the basis of Likert scale ratings. The first comparison assessed the degree to which the most significant attribute was preferred over all others. Whereas the second comparison assessed the degree to which all attributes were preferred over the least significant attribute. The optimal weights were then derived by solving a minimization problem, which minimized the maximum absolute deviation between these two comparison sets, thereby ensuring consistency and robustness in the final significance values. In summary, the calculation can be represented as follows:

$Min\ \xi\ \ subject\ to$: (here ξ represent maximum absolute difference)

$$\left|\frac{s_b}{s_j} - a_{bj}\right| \leq \xi\ \forall j$$

$$\left|\frac{s_j}{s_w} - a_{wj}\right| \leq \xi\ \forall j$$

$$\sum_{j=1}^{n} s_j = 1 \qquad \text{- Equation 4.1}$$

$$s_j \geq 0\ \ \forall j$$

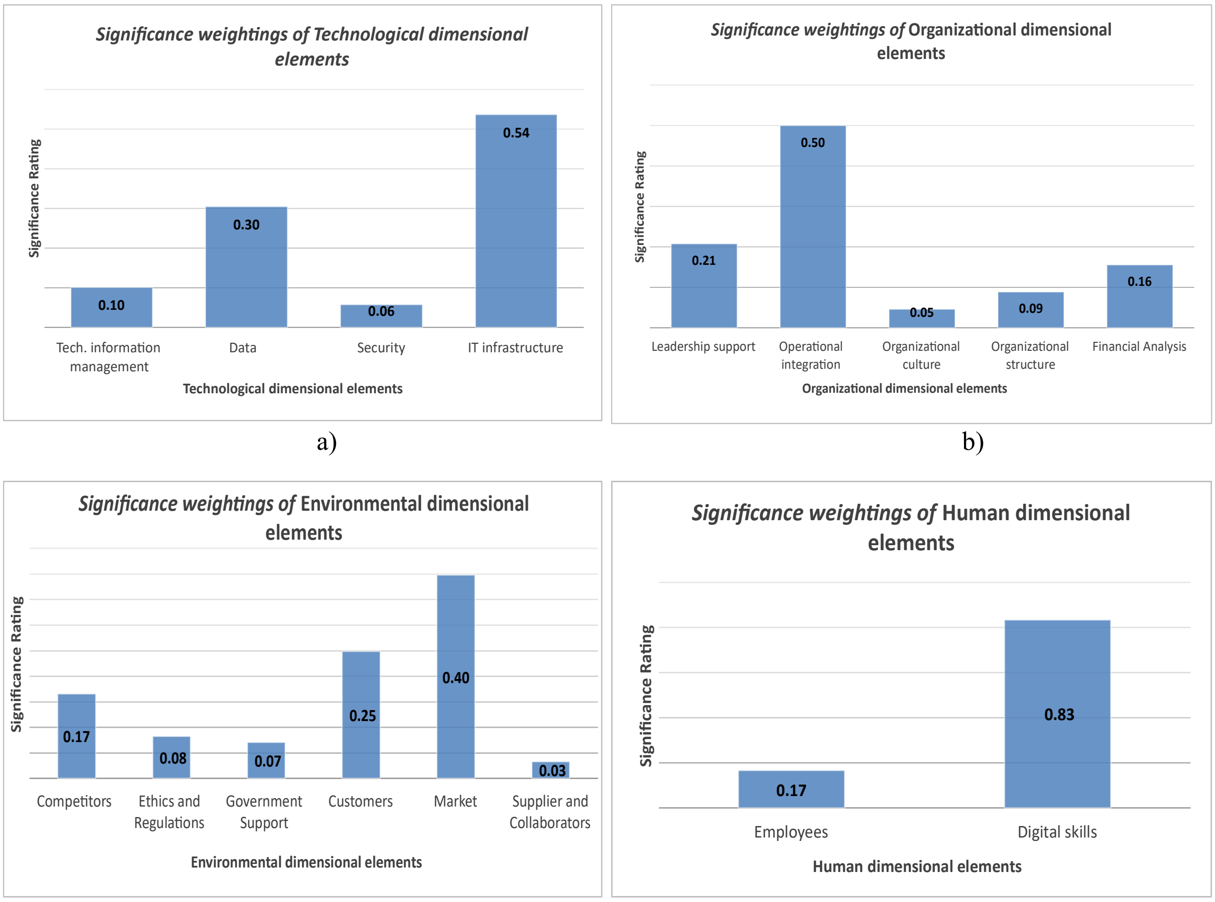
The final weights were obtained by averaging the individual weight ratings across the eight expert respondents, as expressed in Equation (4.2).

$$\frac{1}{n}\sum_{i=1}^{n} S_i \qquad \text{- Equation 4.2}$$

Each attribute was assigned a normalized significance weight to represent its relative contribution to the readiness of its corresponding dimensional element. The cumulative weight of attributes within each dimensional element equals one, ensuring that the significance of each attribute is expressed as a proportion of the total. A value of 1 denotes maximum importance, indicating full contribution, while a value of 0 reflects no contribution. Intermediate values between 0 and 1 represent the varying degrees of importance. This normalization procedure was also applied at the dimensional elements level. Thereby establishing a consistent and comparable weighting framework across both attributes and dimensions for the overall readiness assessment. The mean aggregation approach was employed to enhance the robustness of the results. This method reduces the influence of individual expert bias, balances extreme evaluations and produces a more representative consensus estimate. This is particularly important when dealing with subjective expert judgements in multi-criteria decision-making contexts.

4.3.3. Significance weightings

The proposed model is designed to evaluate the significance of AI readiness dimensions along with their constituent elements and micro-level attributes. Through the application of the Best-Worst Method, expert assessments were systematically elicited to assign relative weights across multiple levels. The resulting weighted rankings establish the comparative importance of each element and attribute. Thereby providing a structured basis for assessing readiness for AI adoption. These significance ratings serve as evaluative metrics for the measurement of an organisation's performance within each dimension and its subsequent aggregation into an overall readiness score. Figures 4.3a-4.3d present the cumulative significance ratings of the dimensional elements across the four primary readiness dimensions. These ratings are derived using Equation 2 (Section 4.3.2). The results demonstrate that within each dimension, one element consistently assumes a primary role, while the remaining elements contribute in a complementary, supporting capacity. For example, in the technology dimension, the element IT infrastructure accounts for 54% of the overall significance, whereas data positions it as a supporting component with 30%.



a) b)

c) d)

Figure 4.3: Significance weightings of dimensional elements

A more granular view is offered through the micro-level assignment of significance weightings across individual attributes (Figures 4.4–4.7). This reveals a similar distributional pattern. Within each dimensional element, one attribute typically emerges as the primary driver. Whereas others provide incremental but necessary support. For instance, in Figure 4.4, underscores the foundational role of the attribute Technology Sustainability Map for AI within the IT Infrastructure element. Similarly, Data Access within the Data element surpasses the substantial significance threshold, emphasizing its critical role in enabling effective AI adoption. The capability to strategically plan for organisational data management is also highlighted as exceptionally critical. In contrast, the Technology Information Management element demonstrates minimal variation across its attributes. It suggests that in some cases no single attribute dominates. Rather, each contributes relatively evenly, collectively constituting an area where balanced capability development is required. This distinction between primary drivers and distributed, complementary contributions offer a nuanced perspective on how individual capabilities shape AI readiness.

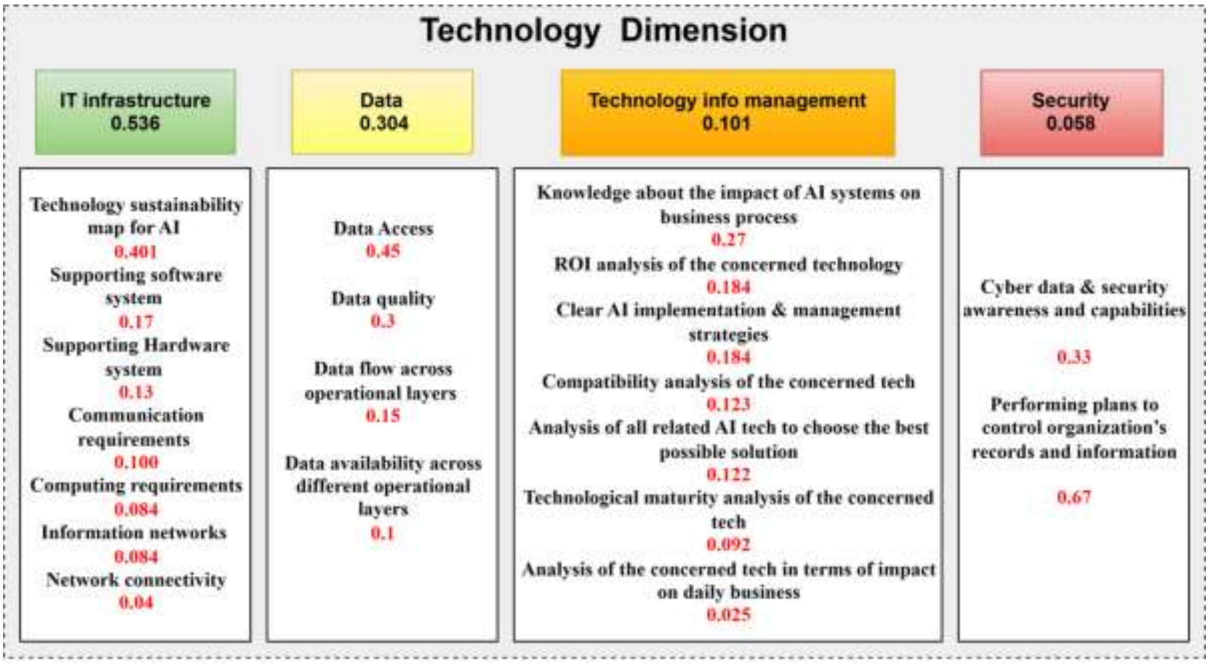


Figure 4.4: Significance weightings of technology dimension elements and their attributes

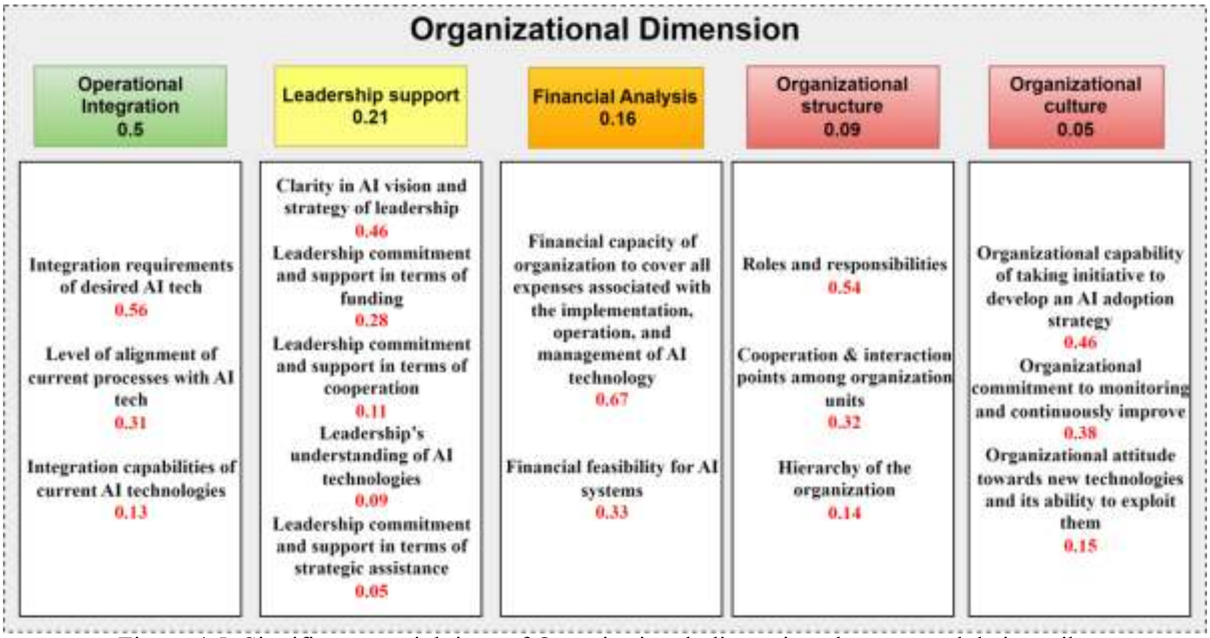


Figure 4.5: Significance weightings of Organisational dimension elements and their attributes

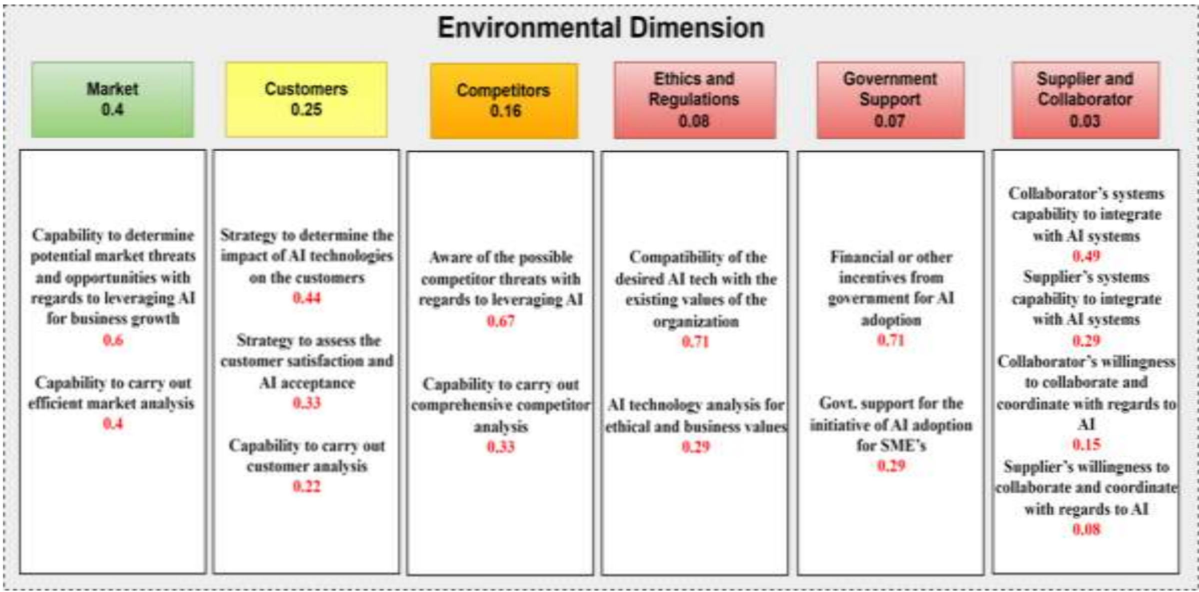


Figure 4.6: Significance weightings of environmental dimension elements and their attributes

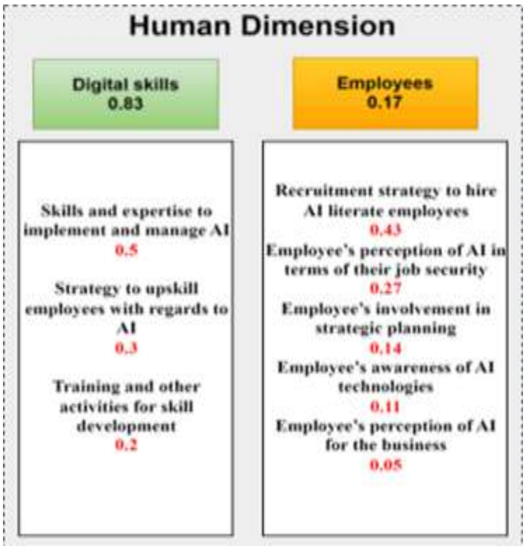


Figure 4.7: Significance weightings of Human dimension elements and their attributes

- ### Robustness of the weights

Since the readiness model relies on expert-derived weights obtained through the BWM, it is important to examine whether the resulting prioritisation of readiness elements is overly dependent on the exact numerical values assigned during the weighting process. In multi-criteria decision-making models, small variations in weights can sometimes lead to changes in ranking outcomes, which may raise concerns regarding the stability of the conclusions. For this reason, a sensitivity analysis was conducted to evaluate the robustness of the weighting structure.

In this analysis, a deterministic perturbation test was conducted in which each suitability weight was varied by ±10% while maintaining proportional normalization across the dimension set. This is a commonly used sensitivity technique in multi-criteria decision models to examine whether moderate variation in expert judgement would alter the relative ranking of criteria (Saltelli et al., 2008; Saaty & Vargas, 2012). It was complemented with Monte Carlo simulation in which random noise was introduced to the weight vectors across multiple iterations. Monte Carlo procedures are widely employed to evaluate the stability of weighted decision models under stochastic uncertainty (Kroese et al., 2014). This process was repeated across 500 iterations, allowing the distribution of ranking outcomes to be examined.

Table 4.3 reports the recalculated rankings using the ±10% weight perturbation approach. The results show that although minor numerical differences emerge after the perturbation, the relative ranking of elements remains unchanged across all readiness dimensions. In each dimension, the element identified as the primary contributor in the original model continues to occupy the top position, while the remaining elements maintain their supporting roles. Similarly, Table 4.4 presents the mean simulated weights, standard deviations, and the rank stability percentage in which each element retained its original ranking position. Together the results, demonstrate a high degree of stability in the prioritisation structure. Across all readiness dimensions, the elements identified as primary drivers in the original model consistently retained the top position in the vast majority of simulations. For example, IT infrastructure within the technology dimension maintained the first rank in approximately 96% of simulated cases, while the remaining elements largely preserved their relative positions with only minor fluctuations in average rank values. These findings indicate that the readiness prioritisation structure is not dependent on a narrowly defined set of parameter values. Instead, the hierarchy of capability importance remains stable even when the weighting scheme is subjected to substantial variation. From a methodological perspective, this suggests that the BWM-derived weights capture structural differences in capability relevance rather than artefacts of individual expert preferences.

Table 4.3: Sensitivity analysis of AI readiness dimensional element weights (±10% perturbation)

Readiness Dimension	Element	Original Weight	Rank	Weight (+10%)	Rank	Weight (−10%)	Rank
Technology	IT Infrastructure	0.536	1	0.5896	1	0.4824	1
	Data	0.305	2	0.3355	2	0.2745	2
	Tech. Info. management	0.101	3	0.1111	3	0.0909	3
	Security	0.058	4	0.0638	4	0.0522	4
Organisation	Operational integration	0.5	1	0.55	1	0.45	1
	Leadership Support	0.32	2	0.352	2	0.288	2
	Financial analysis	0.20	3	0.22	3	0.18	3
	Org. structure	0.09	4	0.099	4	0.081	4
	Org. culture	0.05	5	0.055	5	0.045	5
Environment	Market	0.4	1	0.44	1	0.36	1
	Customer	0.25	2	0.275	2	0.225	2
	Competitor	0.16	3	0.176	3	0.144	3
	Ethics & regulations	0.08	4	0.088	4	0.072	4
	Govt. support	0.07	5	0.077	5	0.063	5
	Suppliers & Collaborators	0.03	6	0.033	6	0.027	6
Human	Digital Skills	0.83	1	0.913	1	0.747	1
	Employees	0.17	2	0.187	2	0.153	2

Table 4.4: Monte Carlo Robustness Test of Readiness Element Weights

Dimension	Element	Original Weight	Mean Simulated Weight	Std. Dev.	Rank Stability (%)
Technology	IT Infrastructure	0.536	0.533	0.021	96.8%
	Data	0.305	0.307	0.018	94.7%
	Tech. Info. management	0.101	0.103	0.011	92.5%
	Security	0.058	0.057	0.009	91.9%
Organisation	Operational integration	0.50	0.498	0.024	95.6%
	Leadership Support	0.32	0.321	0.020	94.2%

	Financial analysis	0.20	0.199	0.016	93.1%
	Org. structure	0.09	0.091	0.011	92.4%
	Org. culture	0.05	0.049	0.009	91.6%
Environment	Market	0.40	0.401	0.023	95.8%
	Customer	0.25	0.249	0.020	94.3%
	Competitor	0.16	0.161	0.015	93.5%
	Ethics & regulations	0.08	0.079	0.011	92.1%
	Govt. support	0.07	0.070	0.010	91.8%
	Suppliers & Collaborators	0.03	0.030	0.006	90.9%
Human	Digital Skills	0.83	0.829	0.026	97.2%
	Employees	0.17	0.171	0.026	97.2%

Taken together, the deterministic sensitivity analysis and the Monte Carlo simulation provide complementary evidence that the readiness weighting model exhibits strong robustness and ranking stability. In practical terms, this implies that moderate variation in expert judgements would not significantly alter the interpretation of the readiness priorities. Consequently, the weighting scheme remains stable under moderate perturbations of the weighting structure, indicating that the framework's diagnostic outcomes are not parameter dependent.

4.3.4. AI readiness calculation

In the AI readiness calculation phase, a standardized assessment scheme is essential for ensuring consistency and comparability. This approach integrates each attribute's assigned significance (weight) with its corresponding performance rating, producing a composite score that reflects both importance and capability. The resulting values provide a systematic and actionable framework for readiness evaluation, enabling the identification of critical weaknesses and guiding targeted interventions to strengthen AI adoption at the attribute-specific level.

Indicating with,

- $\boldsymbol{R_D}$ the final readiness of a dimension
- $\mathbf{R_{DE}}$ the final readiness rating of a dimensional element,
- r_{dei} the rating of the i-th dimensional element of a dimension
- $\mathbf{r_{ai}}$ the rating of the **i**-th attribute of the dimensional element,
- c_{dei} the capability rating for the i-th dimensional element
- $\mathbf{c_{ai}}$ the capability rating for the **i**-th attribute,
- s_{dei} the weighted significance of the i-th dimensional element
- $\mathbf{s_{ai}}$ the weighted significance of the **i**-th attribute and
- **n** the number of attributes within the dimensional element

Then, $r_{ai} = (c_{ai} \times s_{ai})$ represent the readiness rating of each of the concerned attribute.

These attribute ratings were subsequently aggregated (as indicated in equation 4.3) to generate readiness scores for their corresponding dimensional elements. Equation 4.4 presents the formulation of the cumulative rating. It provides a consolidated measure of the organisation's preparedness within each dimension. These dimensional readiness scores establish a structured basis for assessment. These offer actionable insights into organisational strengths and weaknesses. In doing so, they guide targeted interventions and strategic initiatives aimed at advancing AI adoption across all readiness dimensions.

$$\boldsymbol{R_{DE}} = \sum_{i=1}^{n}(c_{ai} \times s_{ai}) \qquad \text{-Equation 4.3}$$

$$\boldsymbol{R_{D}} = \sum_{i=1}^{n}(r_{dei} \times s_{dei}) \qquad \text{- Equation 4.4}$$

To complement the quantitative assessment, a scheme of four predefined readiness states with associated evaluation criteria was introduced to assign descriptive readiness ratings. These states characterize structured and interpretable organisation's level of preparedness. The threshold range (1 to 5) and the corresponding scoring scheme were intentionally aligned with established technology maturity models. It ensures methodological consistency and facilitating comparability with existing digital transformation and innovation assessment frameworks. The approach provides an intuitive and actionable interpretation of readiness levels by adopting a familiar and widely applied maturity scale. Thereby enhancing its practical applicability for both researchers and practitioners.

- **Informal**: This state indicates that the organisation is at an initial and low level of readiness to support AI systems, requiring substantial focus and a strategic approach to advance. Informal state if $R < \mathbf{3.0}$
- **Struggling**: In this state, the organisation has begun making improvements to mitigate relevant risks and challenges, though significant development is still necessary. Struggling state if $\mathbf{3.0} \leq R < \mathbf{4.0}$
- **Approaching**: This state reflects that while the organisation is on the right path toward AI adoption, high risks persist, and additional efforts are required to reach full readiness. Approaching state if $\mathbf{4.0} \leq R < \mathbf{4.5}$ **.**
- **Desirable**: This state represents a well-established and robust foundation for AI systems, indicating that the organisation is optimally prepared for AI adoption. Desirable state if $R \geq \mathbf{4.5}$**.**

It is also pertinent to account for the disparities in the weightings and capability rating thresholds. Catering these disparities ensure a realistic and conservative readiness assessment. Stakeholder consultation and alignment with strategic priorities refine the weighting scheme. Whereas a pre-defined set of evaluative criteria provides a more structured and systematic approach. These criteria strengthen the model by preventing inflated readiness assessments and ensures the visibility of key deficiencies. For example, a single attribute accounting for approximately two-thirds (≈67% or 0.67) of a dimensional element's significance indicates that it is integral to the element's performance. In such cases, the readiness rating of this attribute should be treated as the decisive determinant of the element's overall readiness. This prevents undue dilution of its impact by less influential attributes and provides a clear, precise assessment.

Conversely, an attribute with a high influence (e.g., ≈40% or 0.40 weighting) but a low capability rating (e.g., the minimum threshold of 3 on the descriptive scale) should substantially downgrade the overall readiness score of the corresponding dimensional element. Averaging it with stronger yet less significant attributes could lead to misleading assessment. To address this, the model specifies that the dimensional elements containing highly influential but underdeveloped attributes are to be classified as not ready. This rule ensures that the final readiness state accurately reflects organisational limitations and provides a conservative, decision-relevant diagnostic.

If $\boldsymbol{s_{ai}} \geq \mathbf{0.67}$ (absolute significance) for any attribute i, then $\boldsymbol{R_{DE}} = \boldsymbol{c_{ai}}$ and

For any dimensional element with three or more attributes, if $\boldsymbol{s_{ai}} \geq \mathbf{0.4}$ (substantial significance) and $\boldsymbol{c_{ai}} < \mathbf{3}$ for its attribute i, then the final rating of that dimensional element is "**not ready**"

Same conditions are also followed for calculating the readiness of the four dimensions.

If $\boldsymbol{s_{dei}} \geq \mathbf{0.67}$ (absolute significance) for any dimensional element i, then $\boldsymbol{R_D} = \boldsymbol{c_{dei}}$ and

If $\boldsymbol{s_{dei}} \geq \mathbf{0.4}$ (substantial significance) and $\boldsymbol{c_{dei}} < \mathbf{3}$ for any dimensional element i of a dimension, then the final rating of that dimension is "**not ready**"

4.4.Model application and Evaluation

The proposed model is inherently iterative, requiring organisations to invest in targeted improvements until the desired readiness state is achieved. By assessing readiness at the attribute level of each dimensional element, the model enables the identification of specific scarcities or insufficiencies that may hinder an organisation's ability to fully benefit from AI adoption. This granular approach not only highlights existing gaps but also facilitates continuous monitoring across the technological, organisational, environmental, and human dimensions. Thereby supporting early detection of emerging issues.

To evaluate the robustness and practical effectiveness of the model, it was applied in real-world settings. Specifically, a capability-rating survey (explained in Section 4.2.3 and presented in Appendix 1) was administered to sixteen Italian SMEs. The survey used structured response options to capture firm-level AI capabilities, relevant to AI adoption. These options were deliberately framed to reflect a progression of requirements, each corresponding to specific readiness elements and attributes. They served a dual purpose, indicating firm's current preparedness within each readiness dimension and outlining the steps needed to advance to higher readiness levels. This dual orientation ensures that the assessment framework functions as a diagnostic tool along with a prescriptive guide for continuous improvement in AI readiness.

4.4.1. Characteristics of participating SMEs

To evaluate the effectiveness of the developed AI readiness assessment model, it was applied in real-world organisational contexts. Sixteen Italian SMEs from the manufacturing and services sectors participated in the study. As shown in Table 4.5, the majority of firms (n=11) employed between 20 and 35 workers, and the rest had between 35 and 50 employees.

This variation in workforce size reflects the typical scale of SMEs and offers a diverse basis for assessment. The participating firms also demonstrated varying levels of digital adoption, enabling targeted and comparative analysis. This cross-sectional diversity was crucial for evaluating the model's performance across different stages of technological maturity, providing a rigorous test of its robustness and generalizability.

To operationalize the assessment, organisational representatives, typically managers or executive were asked to complete the firm's capability rating questionnaire (Table 10.1 in appendix 1). The direct involvement of decision-makers in reporting organisational capabilities ensured authoritative and contextually grounded responses. Importantly, this evaluation approach provided an empirical basis for benchmarking readiness and validating the model's iterative mechanism. By comparing firms at different maturity stages, the analysis demonstrated how the model can diagnose gaps, inform targeted interventions, and track progression over time. Thus, it substantiates the model's positioning as an iterative readiness tool rather than a static diagnostic framework.

Table 4.5: Characteristics of the participating SMEs

SME	No. of employees	Business sector	Type of products	State of AI adoption	Area of AI adoption
SME1	20-35	Manufacturing	Food items	Initiated implementation	Supply chain
SME2	20-35	Manufacturing	Food items	Exploration	Not defined
SME3	20-35	Manufacturing	Sanitary items	Exploration to implementation	Supply chain
SME4	20-35	Manufacturing (Primary case)	Luxury Home décor items	Exploration	Not defined
SME5	20-35	Services	-	Exploration to implementation	Customer experience
SME6	35-50	Manufacturing	Sanitary items	Exploration	Supply chain
SME7	35-50	Manufacturing	Electrical items	Exploration to implementation	Supply chain
SME8	20-35	Services	-	Exploration	Customer experience
SME9	20-35	Manufacturing	Electrical items	Initiated implementation	Supply chain
SME10	20-35	Manufacturing	Food items	Exploration	Supply chain
SME11	20-35	Manufacturing	Food items	Initiated implementation	Supply chain
SME12	20-35	Manufacturing	Electrical items	Exploration	Not defined
SME13	20-35	Manufacturing	Sanitary items	Exploration to implementation	Not defined
SME14	35-50	Manufacturing	Sanitary items	Exploration	Not defined
SME15	35-50	Services	-	Exploration to implementation	Customer experience
SME16	20-35	Manufacturing	Food items	Exploration	Not defined

4.4.2. Results and Analysis

Based on the capability ratings collected through the completed survey questionnaires and the significance weights established by the study, readiness states were systematically calculated for all sixteen participating SMEs. These readiness scores represent aggregated quantitative outcomes derived from firm-level capability assessments weighted according to empirically established attribute importance.

To visualize these results, figures 4.8 and 4.9 present heatmaps that depict the readiness states of the four core dimensions and their respective dimensional elements across the sixteen SMEs. The visualization provides descriptive evidence of both cross-firm variation and intra-firm imbalance across readiness dimensions. This representation enables identification of relative strengths and deficiencies at different maturity stages. Importantly, the heatmaps function as an analytical representation of observed readiness distributions rather than independent validation of the model itself. Evidence from the heatmaps indicates substantial heterogeneity among SMEs, with some firms demonstrating balanced capability development while others exhibit uneven readiness profiles across technological, organisational , environmental, and human dimensions. This pattern suggests that AI readiness develops unevenly across capability domains rather than progressing uniformly. However, the visualization alone does not establish causal relationships between specific deficiencies and adoption outcomes, and should therefore be interpreted as diagnostic rather than explanatory evidence.

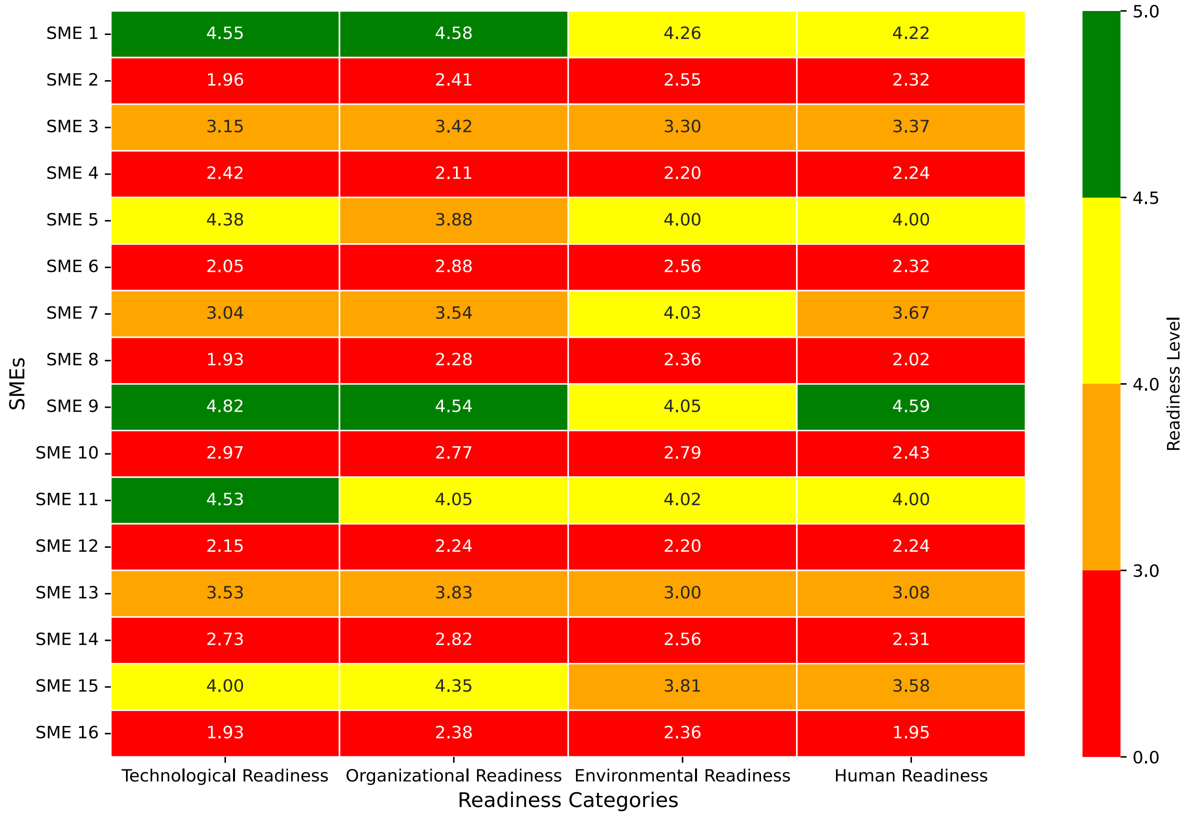


Figure 4.8: Heatmap representing the dimensional readiness of the participating SMEs

Dimensional elements	SME 1	SME 2	SME 3	SME 4	SME 5	SME 6	SME 7	SME 8	SME 9	SME 10	SME 11	SME 12	SME 13	SME 14	SME 15	SME 16
Tech info. management	4.00	2.15	3.27	1.78	4.25	2.29	3.30	1.76	4.63	2.82	4.61	1.78	4.12	2.29	4.00	1.76
Data	4.15	2.55	3.10	2.90	4.00	2.55	3.15	3.00	4.70	3.10	4.55	2.00	4.00	2.55	4.00	3.00
Security	4.33	2.00	3.67	2.00	3.00	2.00	3.67	1.33	5.00	3.33	4.33	2.00	3.00	2.00	4.00	1.33
IT infrastructure	4.92	1.60	3.11	2.32	4.78	1.74	2.87	1.41	4.92	2.89	4.51	2.32	3.22	3.00	4.00	1.41
Leadership support	4.54	2.15	3.15	1.99	4.00	1.99	3.07	3.00	4.26	2.78	4.24	2.90	3.62	2.04	4.00	3.10
Operational interation	4.56	2.19	3.19	1.75	4.00	2.88	3.56	2.00	4.56	2.75	4.00	1.63	3.88	2.88	4.56	2.00
Oragnizational culture	4.85	3.54	4.54	2.54	4.00	3.38	3.54	3.00	5.00	3.54	4.15	2.54	3.54	2.92	4.45	2.54
Oragnizational structure	4.54	2.32	3.32	2.32	4.00	3.00	3.86	2.00	4.71	2.32	4.00	2.32	3.46	3.00	4.07	2.00
Financial analysis	4.33	3.00	4.00	3.00	3.00	3.67	3.67	2.00	4.33	2.67	3.67	3.00	4.00	3.33	4.00	2.67
Competitor	4.00	2.00	3.00	2.00	4.00	3.33	3.00	2.67	4.33	2.00	4.00	2.00	3.00	3.33	4.00	2.67
Ethics and regulations	3.71	3.00	3.29	2.00	4.00	3.00	3.00	4.00	4.00	3.71	4.00	2.00	3.00	3.00	4.00	4.00
Govt. support	3.29	2.57	3.29	3.00	4.00	3.00	4.29	3.00	4.00	3.29	4.29	3.00	3.00	3.00	4.00	3.00
Customers	4.67	2.00	3.00	1.78	4.00	2.00	4.00	2.00	4.00	2.44	3.67	1.78	3.00	2.00	3.33	2.00
Market	4.40	3.00	3.60	2.40	4.00	2.40	4.60	2.00	4.00	3.00	4.00	2.40	3.00	2.40	4.00	2.00
Suppliers and collaborators	4.37	2.74	3.37	2.45	4.00	2.93	4.21	2.51	4.00	3.22	3.95	2.45	3.00	2.93	3.15	2.51
Employees	4.32	1.46	2.73	1.46	4.00	1.46	3.51	2.14	5.00	2.11	4.00	1.46	3.56	1.41	3.00	1.73
Digital skills	4.20	2.50	3.50	2.40	4.00	2.50	3.70	2.00	4.50	2.50	4.00	2.40	3.00	2.50	3.70	2.00

Figure 4.9: Heatmap representing the AI readiness elements of the participating SMEs

Further, the relationship of AI readiness scores with the state of AI adoption, and the area of AI adoption was analysed. Normality tests were conducted to identify the appropriate statistical approach. Given the relatively small dataset, the Shapiro-Wilk test was applied and indicated non-normality in readiness dimension scores (table 4.6). This deviation can be attributed to multiple factors such as the small sample size and potential skewness in the data. This is also consistent with heterogeneous SME adoption stages.

Because normality assumptions were not satisfied, non-parametric tests were employed. The Chi-square test examined associations between AI adoption state and dimensional readiness scores, while Spearman’s rank correlation assessed relationship strength and direction. The statistical results (Tables 4.7 and 4.8) show that readiness scores were similarly distributed across identified adoption areas, indicating no statistically significant association between readiness level and functional adoption domain. In contrast, a positive association was observed between higher readiness scores and more advanced AI adoption stages. These indicate that progression in AI adoption is more closely related to overall organisational preparedness than to the specific domain in which AI is implemented. Technological and human readiness dimensions exhibited relatively stronger associations with adoption advancement. While this suggests their potential importance in supporting implementation progress, the study does not establish their dominance over other dimensions across different SME contexts.

Table 4.6: Shapiro-Wilk test results

Readiness Dimensions	W	p-value
Technological readiness	0.894	0.045
Organisational readiness	0.911	0. 049
Environmental readiness	0.856	0.017
Human readiness	0.885	0.046

Table 4.7: chi square test

Statistic	Value (AI adoption state)	Value (Area of AI adoption)
Chi2 Statistic	16.0	0.0000
p-value	0.0003	1.0000

Table 4.8: Spearman Rank Correlation analysis results

Readiness Dimensions	Spearman Correlation with AI Adoption State	Spearman Correlation with Area of AI adoption
Technological readiness	0.918	0.0348
Organisational readiness	0.904	0.1216
Environmental readiness	0.906	0.0348
Human readiness	0.913	0.0348

Further, figure 4.10 presents a detailed breakdown of low-level attribute readiness scores for three SMEs, each representing a distinct AI adoption state. SME 4 (the primary industrial case) is positioned in the exploration stage, SME 3 is progressing towards implementation, and SME 9 has entered the implementation stage. The heatmap provides empirical evidence that attribute-level readiness scores increase progressively alongside adoption maturity. Differences across firms demonstrate how capability development manifests at micro-attribute level rather than solely at aggregated dimensional scores. The observed progression supports the interpretation that adoption maturity is reflected in increasingly developed readiness profiles across multiple attributes. However, since the comparison relies on illustrative cases rather than longitudinal observation, it cannot confirm developmental sequencing or temporal progression of readiness capabilities.

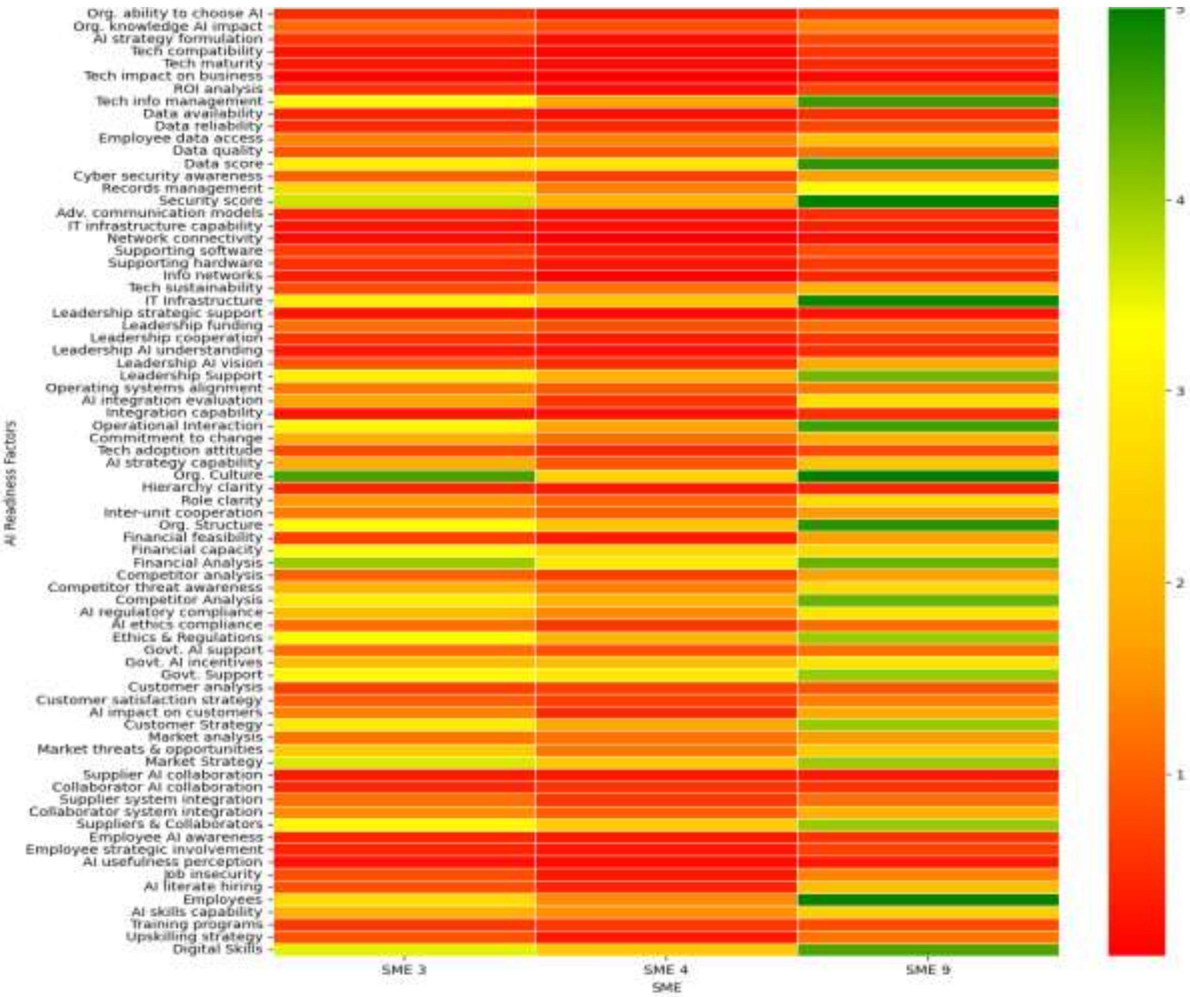


Figure 4.10: Comparison of the states of AI readiness attributes for SMEs 3,4 and 9

4.5.Conclusion

The primary objective of this phase was to conceptualize and operationalize a multidimensional AI readiness assessment model tailored for SMEs. Building on the TOEH framework, the model defined AI readiness dimensions and decomposed them into elements and low-level attributes. It allows structured measurement of organisational preparedness across technological, organisational , environmental, and human domains. An empirical study established the relative importance of readiness components and introduced a structured readiness calculation scheme comprising four readiness states. This scheme provides a diagnostic classification mechanism intended to support capability assessment rather than predict adoption outcomes. Application across sixteen SMEs demonstrated a statistically supported association between higher readiness levels and more advanced AI adoption stages, while no significant relationship was observed between readiness and adoption area. These findings suggest that adoption maturity may depend more on systemic organisational capability than on sector-specific application choices within the studied sample. Among readiness dimensions, technological and human readiness showed comparatively stronger associations with adoption progression. This observation indicates contextual salience within the studied sample but does not imply universal priority across all SME ecosystems. Since, the conclusions are derived from a limited SME sample operating within specific industrial and governance contexts, and therefore cannot be generalized to large enterprises or substantially different institutional environments without further validation.

Chapter 5. AI enablers and strategic performance improvement (Phase 2)

The literature review further elucidated that the majority of the work concerned with the impact of AI adoption on performance outcomes adopt a generalized perspective. It lacks empirically justification for the identification of the specific contributions of distinct AI enablers to the performance outcomes. This phase therefore addresses CIRQ2 (PERQS 2.1 & 2.2) by investigating the relationship between distinct enabling factors and different strategic performance outcomes. It addresses the 'Why AI is to be pursued?' aspect of AI adoption lifecycle (as depicted in figure 5.1). This can assist SMEs with the development of contextualized strategies for achieving specific performance outcomes.

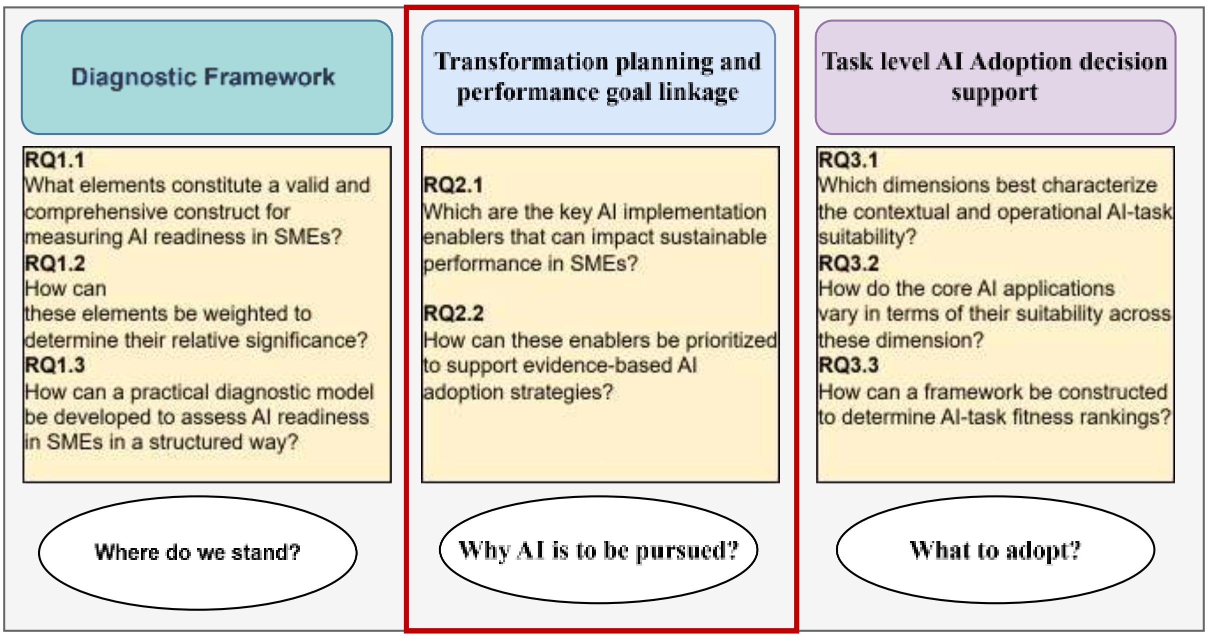


Figure 5.1: 'Why' aspect of AI adoption lifecycle

5.1.Introduction

The rapid advancement of technology to enhance sustainable business performance has become a prominent focus for both scholars and industry practitioners. Whilst organisations increasingly recognize the strategic importance of innovative technologies for achieving competitive advantage, novel solutions aimed at strengthening organisational capabilities continue to emerge. SMEs often face constraints related to technological know-how, strategic planning capabilities, and financial resources (Buer et al., 2020; Lassen and Waehrens, 2021; Hansen et al., 2024). These limitations result in fragmented or suboptimal transformation initiatives. Addressing these challenges require SMEs to develop a comprehensive understanding of the strategic and operational roles of AI enablers.

Drawing upon the Resource-Based View (RBV) and TOE theories, this phase intends to conceptualize AI enablers as strategic resources and capabilities whose value, rarity and inimitability can drive performance outcomes. Together, these frameworks underscore that AI adoption success relies upon the firm's ability to integrate technological infrastructure, it's internal & external capabilities, and their strategic alignment into a coherent system of resources (Malik, 2023). This induces that AI adoption is not merely a technological implementation but a capability-building process. Here the synergy between different AI implementation enablers like digital skills, data management, and human expertise determines performance outcomes.

Consequently, this research emphasises the context-dependent value of these AI enablers across different performance dimensions. By analysing their influence of AI enablers across different performance dimensions, SMEs can design targeted and high-impact strategies for specific enhancement contexts. Despite growing interest in AI adoption, empirical studies systematically linking AI enablers to distinct performance outcomes in SMEs remain scarce. Existing research focuses on general success factors, adoption drivers, or potential benefits, with few studies, such as Usmani et al. (2023), empirically connected specific enablers to performance impacts, particularly in resource-constrained SME settings. Similarly, Badghish and Soomro (2024) investigated the determinants of AI adoption for achieving sustainable business performance in Saudi SMEs. They employed a quantitative approach to evaluate the significance of these factors on AI adoption and its impact on economic and operational performance dimensions. While their study aligns conceptually with the proposed work, their work analysed how AI enablers shape AI adoption and then analysed its resulting impact on two performance dimensions. In contrast, the proposed research aims to examine the direct influence of AI enablers across multiple sustainable business performance dimensions. The focus of the research is on enabling SMEs to establish aligned and context-specific goals for performance enhancement.

5.2. TOEH-framework based AI enablers

It builds upon the extended TOEH framework that was first operationalised in phase 1. By employing the same conceptual foundation, the research ensures both continuity and coherence across the different phases of analysis. Maintaining this shared lens allows the enablers to be examined in direct relation to the organisational conditions that were previously diagnosed. These enablers (enlisted in table 5.1) play a dual role. Firstly, they create the infrastructural, organisational , and human capacities necessary for AI integration. Secondly, they shape the extent to which such integration can be converted into tangible and sustainable performance improvements. In this sense, the TOEH-guided analysis uncovers the drivers of successful AI adoption and provides insight into how these drivers underpin the long-term value realization of AI initiatives.

5.2.1. Technological enablers

Technology related factors influencing AI adoption and implementation encompass both internal organisational elements (such as technological infrastructure, cybersecurity, and related systems) and external resources (including governmental technology initiatives, incentives, and third-party IT service providers). In the proposed framework, internal technological factors are categorized as technological enablers. Whereas all external factors, including external technological resources, are positioned under the environmental dimension. This distinction is grounded in the TOE framework, which asserts that organisational adoption of technology is shaped by technological readiness, organisational capabilities, and external environmental pressures (Tornatzky and Fleischer, 1990).

From the RBV perspective, effectively leveraged internal technological resources constitute valuable, rare, and non-substitutable assets capable of generating sustained competitive advantage (Barney, 1991). These key enablers in this context include software platforms, hardware, and networking and communication systems. These infrastructural components represent strategic resources that strengthen an organisation's ability to leverage AI for competitive advantage. Equally critical is the alignment between existing technological infrastructure and AI system requirements, as misaligned or inadequate systems can disrupt operations and reduce AI effectiveness (Taherizadeh and Beaudry, 2023; Hu et al., 2024). Formal endorsement and validation of technology and information management plans further ensure optimal utilization of resources, reflecting the RBV principle that effective resource orchestration is essential for value creation

Data, as the foundational element of AI, is another critical internal technological enabler. TOE emphasises that technological readiness includes access to reliable and relevant data. Whereas RBV conceptualizes data as an intangible yet strategic resource that underpins the organisation's ability to create AI-driven capabilities (Barney, 1991; Taherizadeh and Beaudry, 2023). Whilst, high-quality, abundant, and relevant data enables AI models to perform effectively, its deficiency, low quality or security issues can undermine performance. However, increasing data volume, complexity, and sensitivity pose challenges in knowledge management, including security, privacy, storage, and retrieval etc. Breaches from cyberattacks, human error, or weak governance can erode trust in AI systems (Bandari, 2023). SMEs, constrained by limited finances, skilled personnel, and digital experience, may struggle to implement effective data management strategies (Bhuiyan et al., 2024).

5.2.2. Organisational enablers

The organisational context provides critical enablers for AI adoption, encompassing structural, operational, financial, and managerial factors. Prior studies highlight the importance of cooperation across organisational units, inter-organisational interaction points, innovation-oriented culture, continuous monitoring practices, integration of processes with AI technologies, and financial capacity as central drivers of effective transformation (Aboelmaged and Hashem, 2019; Clohessy and Acton, 2019; Zhang et al., 2020).

Operational and process integration is a key enabler that ensures seamless functioning across organisational processes and units. Misaligned or fragmented workflows can hinder AI adoption by creating inefficiencies and obstructing implementation (Tehrani et al., 2024). Effective integration enhances operational performance through optimized processes, improved workflow efficiency, and more accurate AI-supported decision-making.

Continuous monitoring and learning culture enable organisations to refine, update, and optimize operations in alignment with evolving AI technologies (Aldoseri et al., 2024). By embedding learning and improvement mechanisms into organisational routines, firms can increase their adaptability to new AI tools. This in turn may strengthen performance and ensure that AI implementation contributes to sustained competitiveness.

Collaboration and interaction points facilitate the steady flow of information and data across departments and operational layers (Han and Trimi, 2022). This enhances the functionality of AI systems by ensuring access to accurate, timely, and comprehensive data inputs. Strong collaboration is founded upon shared reliable data streams that supports the technical and operational success of AI adoption. Along with that it helps with improving decision-making quality.

Organisational attitude and technological orientation act as cultural enablers by fostering openness and adaptability toward technological change (Viterouli et al., 2024). A positive orientation lowers resistance, accelerates adoption, and fosters a culture conducive to experimenting with AI. This cultural readiness enhances performance by boosting employee acceptance and engagement, while improving operational efficiency through reduced resistance to new workflows.

Financial resources are another critical enabler, as sustained investment is necessary to support infrastructure upgrades, system maintenance, and ongoing technological alignment (Kulkov et al., 2024). Adequate financial commitment ensures AI systems remain up to date and effective, directly improving economic performance through cost savings, efficiency gains, and potential revenue growth. However, constrained financial capacity in SMEs limits their ability to sustain such investments. This uncertainty in digital transformation returns due to technological volatility and market dynamics further exacerbates the risk (Kraus et al., 2021).

5.2.3. Environmental enablers

All potential external variables influencing AI adoption can be broadly categorized as environmental enablers. Within the TOE framework, the environmental dimension reflects the external conditions, pressures, and supports that shape the organisation's adoption decisions. From a resource-based view (RBV) perspective, environmental enablers function less as internal firm specific resources and more as external contingencies and constraints. These define how firms can acquire, access, and exploit valuable resources for competitive advantage. These include external data, customer insights and collaborative networks etc.

Among these, data emerges as the most critical enabler for the effective functioning of AI technologies. A substantial portion of organisational data is sourced externally from customers, markets, competitors, and collaborators. Therefore, environmental factors are central to data accessibility and quality. de Almeida et al. (2021) described that effective data exchange is often influenced by privacy regulations and data protection laws. Failure to comply with these regulations risks legal sanctions, damages reputation and impact customer trust. This can have a direct impact on performance and can undermine the quality of AI-driven decision-making. Similarly, adherence to ethical standards and corporate values is essential for sustaining legitimacy and brand trust (Agu et al., 2024). These elements indirectly strengthen performance, as they influence customer acceptance and stakeholder confidence in AI-enabled offerings.

Customer demand and market requirements represent another critical external enabler. Kelly et al. (2023) elucidated that customer satisfaction and acceptance are essential for value realization. Therefore, AI adoption must align with evolving customer expectations. The success of AI implementation is not only measured in terms of internal efficiency but also in its ability to enhance customer satisfaction and business growth. Finally, compatibility of external systems, particularly those of suppliers and collaborators, significantly affects AI-enabled operational workflows. Lack of integration between partner systems and organisational AI platforms can reduce efficiency, increase errors, and limit scalability (Zhang et al., 2020). Conversely, strong external compatibility enhances performance by improving supply chain coordination, data sharing, and responsiveness.

Market competition may also exert pressure on firms to pursue AI adoption as a strategic necessity. High market saturation requires organisations to continuously analyse competitor advancements and remain vigilant against potential AI-driven competitive threats (Malik et al., 2023). Competitors digital growth can also act as a motivating factor that compels firms to explore AI capabilities. However, their direct role in determining the success of AI implementation is limited in scope and thus has been excluded from this analysis.

Governmental support, in the form of financial incentives, subsidies, or policy frameworks acts as an enabling condition that reduces entry barriers and accelerates the adoption of AI (Cheng et al., 2024). This support enhances the investment feasibility and creates a more favourable adoption climate. However, it does not directly determine the success of AI implementation. Similarly, as explicated above, the impact of ethics and regulations is closely related to an organisation's ability to manage and leverage data effectively. Though they have been excluded here to avoid redundancy as these considerations have already been addressed within the technological variables' context.

5.2.4. Human enablers

The human-technology relationship represents a critical organisational enabler in AI implementation. It reflects the interaction between technological innovation and the workforce's perception, trust, and skill readiness. Within the TOE framework, these factors fall under the organisational dimension. They reflect internal resources, culture, and human capital that condition AI adoption. From the lens of the resource-based view (RBV), workforce capabilities, trust, and openness to change constitute valuable, rare, and inimitable resources that can determine whether AI becomes a source of sustainable competitive advantage or remains underutilised.

Human perception of AI is a fundamental determinant of the adoption climate. Employees' perception of AI's role in business operations and its impact on job security often shape their trust in these systems (Glikson and Woolley, 2020; Bhargava et al., 2021). Distrust may demonstrate resistance to adoption, lower engagement, or active opposition. Involving employees in planning and maintaining transparent communication about AI adoption helps mitigate these concerns, fostering psychological safety and building confidence in AI-enabled transformation (Tortorella et al., 2021). In turn, this enhances social performance by improving employee well-being and governance performance through greater alignment between human and technological decision-making (Habbal et al., 2024).

Beyond perception, workforce skills and competencies are equally critical. Employees' prior experience with innovative technologies directly influences their ability to interact productively with AI (Yu et al., 2023). Targeted training and opportunities for upskilling enables employees to acquire the necessary technical literacy and adaptive expertise to integrate AI into daily workflows (Leoste et al., 2021). From an RBV standpoint, these skillsets and learning capacities can be seen as human capital resources that are both firm-specific and difficult to imitate. Thereby supporting long-term competitive differentiation.

The performance implications of these enablers are multidimensional. Improved workforce trust and confidence facilitate performance by reducing adoption resistance and ensuring smoother integration of AI systems into processes (Tariq et al., 2021). Enhanced skillsets and adaptive learning directly support innovation performance. As employees become active contributors to the design and refinement of AI-supported tasks. Moreover, engaged and skilled employees improve economic performance by driving efficiency gains, reducing the costs of failed implementation, and accelerating return on investment (Tariq et al., 2021).

Table 5.1: AI enablers

Types	Enabling factors
Technological	Technology infrastructure
	Data management
	Interoperability
	Security
Organisational	Workflow alignment
	Cross-functional co-operation and interactions
	Change management strategy
	Sustained financial capability
Environmental	Compatibility with the external systems
	Customer and market conformation
Human	Employees' skill level
	Employees' experience
	Employees' involvement in strategic planning
	Employees' perception about AI

5.3. Sustainable performance dimensions

Organisational performance has traditionally been assessed in terms of profitability and the achievement of strategic objectives defined by management. However, sustainability-oriented performance evaluation has gained prominence in the recent years. It allows organisations to assess progress across multiple dimensions and levels. This broader perspective facilitates the effective realization of organisational objectives. It ensures long-term resilience by integrating economic, social, and environmental considerations. Consequently, sustainable performance evaluation increasingly emphasises multidimensional frameworks that capture both strategic contributions and wider societal impacts.

Several frameworks have been proposed in this regard. For instance, the Environmental, Social, and Governance (ESG) model assesses performance in environmental, social, and governance domains (Rajesh, 2020). Similarly, the Triple Bottom Line (TBL) framework incorporates economic, environmental, and social dimensions (Hourneaux et al., 2018), while Xu et al. (2019) advance a three-dimensional structure based on economic, operational, and environmental outcomes. Table 5.2 enlists the collective business performance dimensions proposed by these frameworks along with their metrics.

The economic dimension reflects a firm's financial health, including profitability, cost-efficiency, and growth. AI technologies have demonstrated significant potential in this area, particularly in reducing operational costs through intelligent management and predictive maintenance (Putha, 2020). Moreover, automation of routine tasks contributes to resource optimization and improved profitability (Acemoglu and Restrepo, 2019). Advanced AI applications further support revenue generation by effectively identifying of market opportunity, forecasting customer behaviour, optimization price, and developing personalized marketing strategies (Okeleke et al., 2024; Rane et al., 2024).

The operational dimension emphasises efficiency in processes, product development, time-to-market, and quality improvement. Organisations are increasingly leveraging AI to automate repetitive processes, detect potential bottlenecks, and dynamically adapt workflows to enhance productivity and minimize disruptions (Acemoglu and Restrepo, 2018; Czarnitzki et al., 2023).

The governance dimension relates to leadership's role in ensuring responsible, ethical, and transparent business practices. This includes risk management, regulatory compliance, and accountability. AI contributes to governance through predictive risk analytics, anomaly detection, and continuous monitoring, thus equipping organisations with robust tools for proactive decision-making (Biolcheva and Molhova, 2022; Arumugam and Manida, 2024).

The social dimension focuses on employee well-being, workplace safety, and opportunities for capability development. AI has been shown to enhance skills, support equitable evaluation systems, and improve workplace conditions (Morandini et al., 2023). Yet, risks remain: AI-enabled surveillance may foster negative employee perceptions, heighten concerns about job security, and strain human-technology relationships (Hughes et al., 2019; Bhargava et al., 2021).

The environmental dimension seeks to minimize the ecological footprint of organisational activities. While this study does not consider environmental aspects of AI adoption, it introduces an additional innovation dimension, reflecting adaptability, creativity, and R&D capacity. Emerging GenAI technologies, for example, are being harnessed to produce novel marketing content, design new products, and support complex problem-solving. Thus, enhancing both efficiency and originality in organisational processes (Amankwah-Amoah et al., 2023; Pagani and Champion, 2023). Innovation, as argued by Babina et al. (2024), further strengthens operational quality and accelerates sustainable competitiveness.

Table 5.2: Sustainable Business Performance dimensions

Sustainable Business Performance dimensions	Metrics
Economic	Return on investment
	Cost savings
Operational performance	Enhanced quality
	Operational efficiency
Governance	Enhanced and strategic decision-making
	Regulation and compliance
Social performance	Employee well-being
	Customer satisfaction
Innovation	Novel solutions
	Novel tech utilization

5.4. AI implementation contexts

Digital transformation (DT) aspects represent distinct organisational aspects, directly or indirectly shaped by the adoption of digital technologies. Adlmaier and Schildhauer (2017) introduced the Digital Strategy Framework (DSF), delineating these critical aspects of digital transformation. Similarly, several studies (Feichtinger, 2018; Wilaisakoolyong et al., 2018; Schildhauer et al., 2019; Schallmo and Rusnjak, 2021) have discussed these aspects, commonly including processes and operations, employees, data and technological infrastructure, organisational structure, business models and strategies, products and services, and customers.

Brodny and Tutak (2022) emphasised that the integration of disruptive technologies (such as the Internet of Things (IoT), digital twins, virtual reality, and artificial intelligence) within these DT aspects creates opportunities for value generation. At the same time, Ghobakhloo and Ching (2019) highlighted different internal and external challenges with the incorporation of such technologies within SMEs. These impact the effectiveness and sustainability of implementation efforts. Given this complexity, it becomes essential to analyse the role of AI enablers across different DT aspects. It helps understand their level of contribution to different sustainable business performance dimensions. Accordingly, this work adopts digital transformation aspects as control variables. It enables a systematic evaluation and comparison of AI enablers across various business functions. This approach supports a nuanced understanding by identifying patterns and variations in how AI enablers interact with and influence organisational processes under transformation. The scope of work is restricted to two commonly observed AI implementation contexts (business processes and operations, and customer services) for maintaining the analytical focus. This delineation is informed by empirical evidence from the participating SMEs, which largely concentrate their AI adoption efforts within these domains (as illustrated in figure 5.3). Guerra et al. (2025) described that business processes and operations often serve as the foundation for internal efficiency-oriented transformation, where AI supports automation, process optimization, and decision enhancement. Conversely, customer services embody an externally oriented application area, demanding personalization, responsiveness, and experience enhancement (Piccoli et al., 2017). This targeted selection ensures the analysis remains relevant to the organisational domains most affected by AI adoption. The conceptual model guiding this investigation is presented in Figure 5.2.

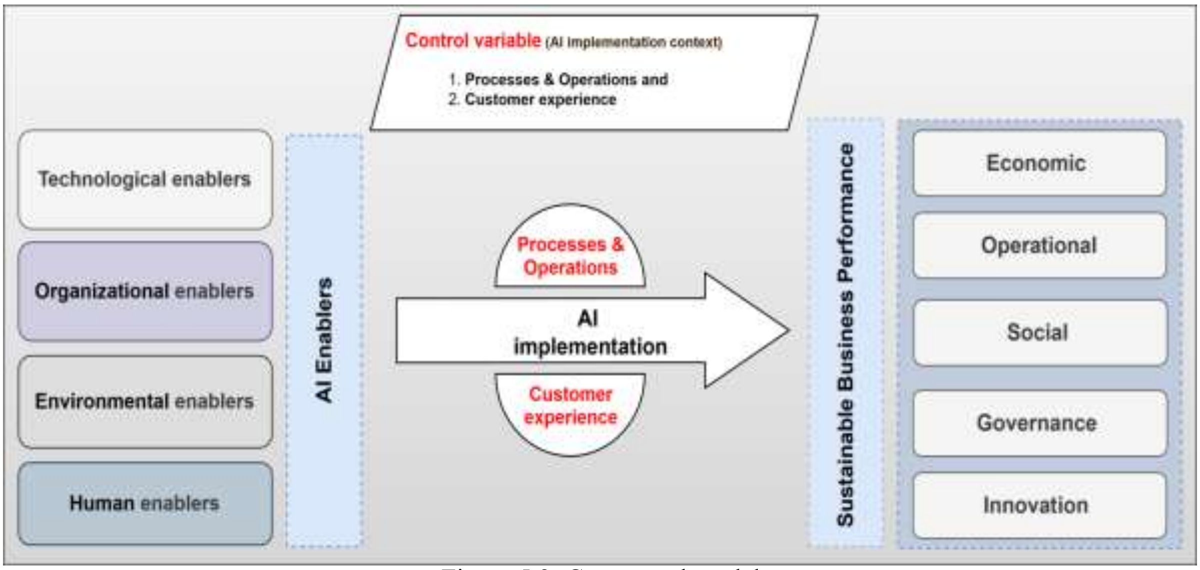


Figure 5.2: Conceptual model

5.5.Methodology

The work adopted a primary research design to reflect its exploratory orientation. A survey questionnaire (attached as appendix 2 in section 10.2) directly addressing the research questions was designed. It was administered to collect firsthand data for mapping the impact strength of the AI enablers on different business performance dimensions. The questionnaire uses a 5-point Likert scale to quantify the influence of AI enablers on specific performance dimensions. This impact-matrix format enables a multivariate analysis of the relationships between AI enablers and performance outcomes.

The survey was administered using a systematic sampling method rather than random sampling. It allows for greater precision in identifying patterns and variations across implementation contexts (Mostafa and Ahmad, 2018). The Italian SMEs that were either in the process of adopting AI or had already implemented AI solutions were specifically targeted. To capture both implementation contexts, the sample included respondents with direct experience in AI-enabled business processes and operations as well as customer experience transformation. This structured sampling approach ensured that the research questions were addressed in a focused and contextually relevant manner. In total, 119 validated responses were incorporated into the analysis.

The reliability of the dataset was tested using Cronbach's alpha. For analytical rigor, a hybrid feature selection methodology was applied, combining the Random Forest regressor and Partial Least Squares Structural Equation Modelling (PLS-SEM). The Random Forest regressor was first employed to filter out less significant variables and identify the most influential ones. Given its capacity to model complex, non-linear relationships and provide empirical rankings without assumptions about data distribution (Abdulhafedh, 2022). The top-ranked variables were then subjected to PLS-SEM which enabled both cross-validation and an interpretable, relative assessment of the selected features. PLS-SEM was particularly suited for this study due to its robustness with smaller datasets and its ability to simultaneously handle multiple dependent variables (Hair et al., 2019).

5.6. Results and analysis

5.6.1. Characteristics of the participants

Participants were recruited through direct engagement with physical visits made to twenty-three SMEs to encourage participation in the survey. As illustrated in Figure 5.3, among these SMEs, six had already implemented and four were in the process of implementing AI solutions specifically for customer experience enhancement. Similarly, five SMEs had implemented and eight were in the process of implementing AI solutions for the improvement of processes and operations.

The questionnaire was disseminated to 337 potential participants from these SMEs through both in-person distribution and email. From these, 119 valid responses were obtained and analysed. Figures 5.4 and 5.5 present the breakdown and characteristics of the respondents. The sample included individuals from diverse functional areas within SMEs; 28 from HR, 43 from IT support, 28 from management, and 20 from production. Moreover, the respondents possessed one to seven years of AI implementation experience. This diversity across both functional roles and levels of experience provided a comprehensive perspective on AI adoption within SMEs. Experienced professionals contributed informed insights drawn from practice, while less experienced participants offered fresh viewpoints, often highlighting emerging trends and novel relationships. The blend of perspectives enriched the dataset, enabling a balanced, nuanced, and refined analysis of how AI implementation variables influence different dimensions of business performance.

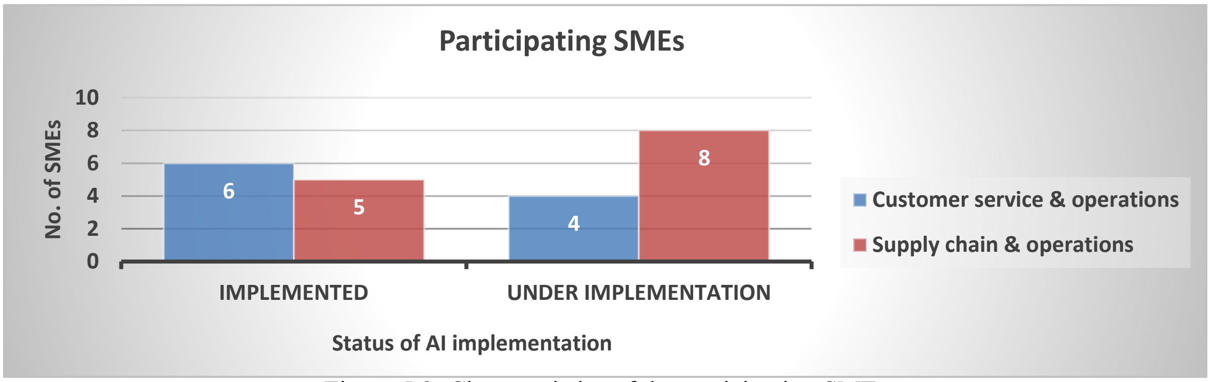


Figure 5.3: Characteristics of the participating SMEs

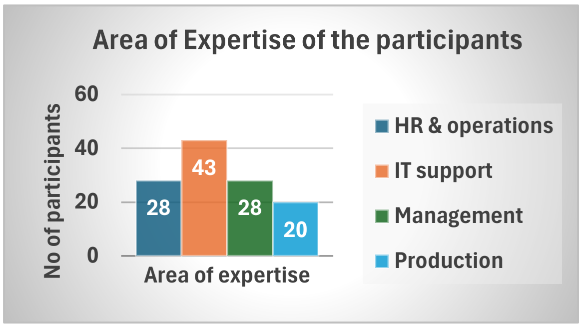


Figure 5.4: Area of Expertise of the participants

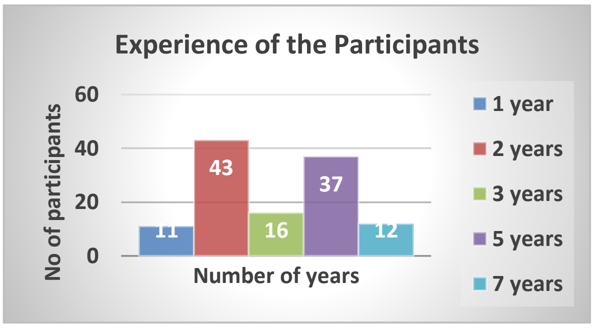


Figure 5.5: Experience of the participants

5.6.2. Data reliability

For a comprehensive understanding of the results, two complementary analytical approaches were employed. The first involved a generalized analysis of the complete dataset (N = 119). It provided an overarching view of the patterns and relationships across all cases. In parallel, a contextualized analysis was conducted. It examined the two AI implementation contexts (processes and operations (N = 66) and customer experience (N = 53) separately. This dual approach enabled both a broad evaluation of

AI enablers and a context-specific assessment. It facilitated the identification of similarities and differences in their influence across distinct transformation domains.

The reliability of the collected data was assessed using Cronbach's alpha test. Both the complete dataset and the two transformation-specific samples were analysed, with the results presented in tables 5.3 and 5.4. According to Gupta et al. (2023), values of $\alpha \geq 0.8$ indicate high internal consistency, while $0.7 \leq \alpha < 0.8$ denote acceptable consistency. As shown in the tables, all Cronbach's alpha values exceeded 0.7, indicating that the variables and metrics reliably measured the intended enablers and performance dimensions. The overall dataset exhibited slightly higher alpha scores than the separate subsamples, suggesting minor variability when the data were divided. However, all values remained above the acceptability threshold.

Small differences in alpha values were also observed across the two implementation contexts, with the innovation performance dimension showing a slightly larger variation. These differences likely reflect contextual variations between the transformation settings rather than issues with data heterogeneity or measurement alignment, as all alpha scores for innovation remained above 0.7.

Table 5.3: Reliability Cronbach's alpha test for AI enablers

AI enablers	**Cronbach's Alpha**		
	Whole data	**Contextual data**	
		Processes and Operations data	**Customer Experience data**
Technology infrastructure	0.77	0.752	0.784
Data management	0.811	0.80	0.831
Interoperability	0.702	0.701	0.704
Security	0.713	0.72	0.704
Workflow alignment	0.814	0.87	0.754
Co-operation and interactions	0.742	0.783	0.70
Change management strategy	0.76	0.82	0.7
Sustained financial capability	0.85	0.851	0.863
Compatibility with external systems	0.812	0.772	0.844
Customer and market conformation	0.814	0.820	0.811
Employees' skill level	0.77	0.79	0.72
Employees' experience	0.741	0.74	0.743
Employees' involvement in planning	0.754	0.77	0.743
Employees' perception about AI	0.733	0.751	0.724

Table 5.4 :Reliability Cronbach's alpha test for Performance dimensions

Performance dimension	**Cronbach's Alpha**		
	Whole data	**Contextual data**	
		Processes and Operations data	**Customer Experience data**
Economic performance	0.873	0.720	0.742
Operational performance	0.920	0.869	0.901
Governance performance	0.873	0.809	0.775
Social performance	0.79	0.729	0.742
Innovation performance	0.910	0.725	0.976

As previously described, a hybrid feature selection approach combining the Random Forest regressor and PLS-SEM was employed, ensuring statistical robustness, theoretical coherence and enhanced interpretability of the findings. Model performance was evaluated using the coefficient of determination (R^2) and the Root Mean Squared Error (RMSE). While R^2 captures the proportion of variance in the dependent variable explained by the independent variables, RMSE quantifies the average magnitude of prediction error by comparing actual versus predicted values. Taken together, these complementary metrics provide a rigorous assessment of both model accuracy and prediction error. Model performance metrics (Table 5.5) show comparable explanatory power across generalized and contextual datasets. The R^2 coefficients remain consistently high across performance dimensions, particularly for operational and economic performance, while RMSE values remain within comparable ranges. This stability indicates that predictive relationships between AI enablers and performance outcomes persist under different contextual data conditions

Table 5.5: Metrics for evaluation of the predictive validity

Dependent variable	Model Performance					
	R^2 Coefficient of Determination			RMSE Root Mean Squared Error		
	Whole data	Contextual data		Whole data	Contextual data	
		Processes & Operations data	Customer Experience data		Processes & Operations data	Customer Experience data
Economic performance	0.81	0.732	0.754	0.179	0.214	0.252
Operational performance	0.92	0.91	0.872	0.12	0.19	0.185
Governance performance	0.754	0.647	0.623	0.23	0.342	0.413
Social performance	0.89	0.641	0.864	0.153	0.23	0.218
Innovation performance	0.82	0.632	0.715	0.166	0.221	0.471

5.6.3. Robustness and sensitivity

To verify that the prioritisation of AI implementation enablers was not driven by specific modelling assumptions, an additional robustness assessment was conducted. In this study, the analytical results are expressed primarily as ranked priorities of influential enablers, derived from feature importance scores generated by the Random Forest algorithm and effect-size estimates obtained through PLS-SEM. As a consequence, the interpretation of the model relies more on the relative ordering of factors than on precise numerical coefficients. In Random Forest models, feature importance values are generated internally through repeated sampling and the aggregation of multiple decision trees rather than through weights defined by the researcher (Breiman, 2001; Liaw and Wiener, 2002). For this reason, robustness was examined by evaluating whether the prioritisation of enablers remained stable when the analysis was performed under different contextual data conditions. To assess this stability formally, Spearman's rank correlation coefficient (ρ) was calculated between the ranked lists of influential enablers identified in the two transformation contexts considered in the study (processes and operations and customer experience) across each performance dimension. Spearman's correlation is particularly suitable for this purpose because it measures the degree of agreement between ranked variables without requiring assumptions of linear relationships or normally distributed data (Zar, 2005). The method is commonly used in robustness checks when model outcomes are expressed as ordered rankings rather than continuous parameter estimates.

The coefficients reported in Table 5.6 reveal differing levels of agreement across the performance dimensions. Operational performance shows a strong correspondence between contexts (ρ = 0.70), while innovation performance demonstrates substantial stability (ρ = 0.60). Governance and social performance display moderate agreement (ρ = 0.50), suggesting that although the order of certain enablers shifts, the overall group of influential factors remains largely consistent. By contrast, economic performance presents almost no rank correspondence (ρ = 0.00), indicating that the prioritisation of enablers within this dimension is highly dependent on the transformation context. Taken together, these results suggest that the model captures a stable underlying structure in most performance dimensions, while also reflecting meaningful contextual variation in their relative importance of enablers. In other words, the prioritisation outcomes do not appear to be artefacts of a single modelling configuration but instead reflect a combination of robust structural relationships and context-specific differences in AI implementation priorities.

Table 5.6: Spearman Rank Correlation between contextual prioritisations

Performance Dimension	Spearman Rank Correlation (ρ)	Stability Interpretation
Economic performance	≈ 0.00	High contextual sensitivity
Operational performance	≈ 0.70	Strong stability
Governance performance	≈ 0.50	Moderate stability
Social performance	≈ 0.50	Moderate stability
Innovation performance	≈ 0.60	Substantial stability

5.6.4. Elimination of variables

It was necessary to reduce the dimensionality of the dataset to address the challenges of complexity and potential multicollinearity arising from the large number of independent variables (AI enablers). However, non-systematic or subjective elimination of variables was unsuitable, as the relevance of enablers may differ across dependent variables. Hence, a systematic feature selection process was required to ensure both analytical rigor and the preservation of comprehensiveness.

For this purpose, the Random Forest regression algorithm was employed. Given its proven capability to effectively manage multicollinearity while ranking variables based on their predictive contribution (Liaw and Wiener, 2002; Wies et al., 2023). It is a supervised ensemble learning method that builds upon the principles of decision trees, aggregating them to enhance their stability and predictive performance. It generates a large number of decision trees, each trained on a random subset of the data and a random selection of predictor variables at each split (Breiman, 2001). Further, it aggregates these multiple predictions through averaging, minimizes overfitting and identifies the most influential enablers (Agarwal et al., 2023; Wies et al., 2023). If the correlation is high, it distributes the importance among the features rather than inflating the effect of a particular variable (Wies et al., 2023). Thus, it enables to effectively manage interrelated variables by ranking them according to their contribution to prediction accuracy (Yuan et al., 2023).

Feature importance scores were computed using the permutation importance method that quantifies the decline in model predictive performance when the values of each predictor are randomly permuted. The magnitude of this decline reflects the predictor's contribution to the model's explanatory power. A greater drop indicates a higher importance score signifying a greater influence on the predicted outcomes (Yuan et al., 2023). Therefore, the feature importance scores presented in table 5.7 indicate the relative contribution of each enabler to overall model accuracy. These ensure the retention of a core set of consistently significant enablers, while also allowing flexibility for context-specific selection. The table lists the top ten most influential variables for the combined performance dimensions. These importance scores generated by the random forest regressor offer an evidence-based prioritisation of the factors most influential in shaping performance outcomes.

Table 5.7: Top ten features for business performance dimensions using Random Forest repressor (Combined results)

No.	Factors	Feature Importance
1.	Data management	0.271
2.	Technology capability	0.160
3.	Employees’ skill level	0.112
4.	Customer and market conformation	0.100
5.	Sustained financial capability	0.091
6.	Security	0.080
7.	Change management	0.093
8.	Workflow efficiency	0.061
9.	Employees’ involvement in strategy	0.020
10.	Co-operation and interactions	0.033

5.6.5. Top influencers across dimensions

The top-ranking variables extracted through random forest regressor were subsequently used as inputs for PLS-SEM analysis. It was used to cross-validate their selection and for a more interpretable, relative assessment of their influence. As outlined earlier, the analysis was carried out for both the generalized case (whole dataset) and the contextual cases (separate analyses for processes & operations and customer experience). This approach helped examine the sensitivity further, by comparing the recurrence of influential enablers across performance dimensions and transformation contexts (Tables 5.8-5.12). Contextual datasets function as natural perturbations of the modelling environment, enabling assessment of whether prioritisation outcomes remain stable under plausible variation.

- **Generalized case**

Figure 5.6 presents the most influential variables along with their importance scores across the five performance dimensions in the generalized context. Several enablers emerged as consistently significant across multiple dimensions, demonstrating their multifaceted role in shaping organisational performance. For example:

- Data management exerted influence across all five dimensions,
- Technology capability and employee skill levels appeared across four,
- Security featured across three, and
- Employee involvement in strategic decision-making and change management was significant across two dimensions.

This consistency highlights their systemic significance, suggesting that these enablers serve as foundational drivers for performance improvement across transformation domains. At the same time, the relative importance scores varied across dimensions. It reflects the differential dependency of each performance outcome on specific enablers. For instance, data management exhibited importance ratings of 0.20, 0.50, 0.30, 0.29, and 0.35 for the economic, operational, governance, social, and innovative dimensions, respectively. This pattern indicates that while data management is universally relevant, its impact is most pronounced on operational performance. Whereas its effect on economic performance is comparatively modest. Furthermore, several dimension-specific variables emerged as critical steering factors. For instance, workflow efficiency was a key determinant of operational performance. Cooperation and interaction played a pivotal role in governance performance, and customer and market orientation was uniquely significant for the social performance dimension. These localized drivers emphasise their role alongside universally relevant enablers. These suggest that performance outcomes are also shaped by variables whose influence is tightly bound to the characteristics of the respective dimension.

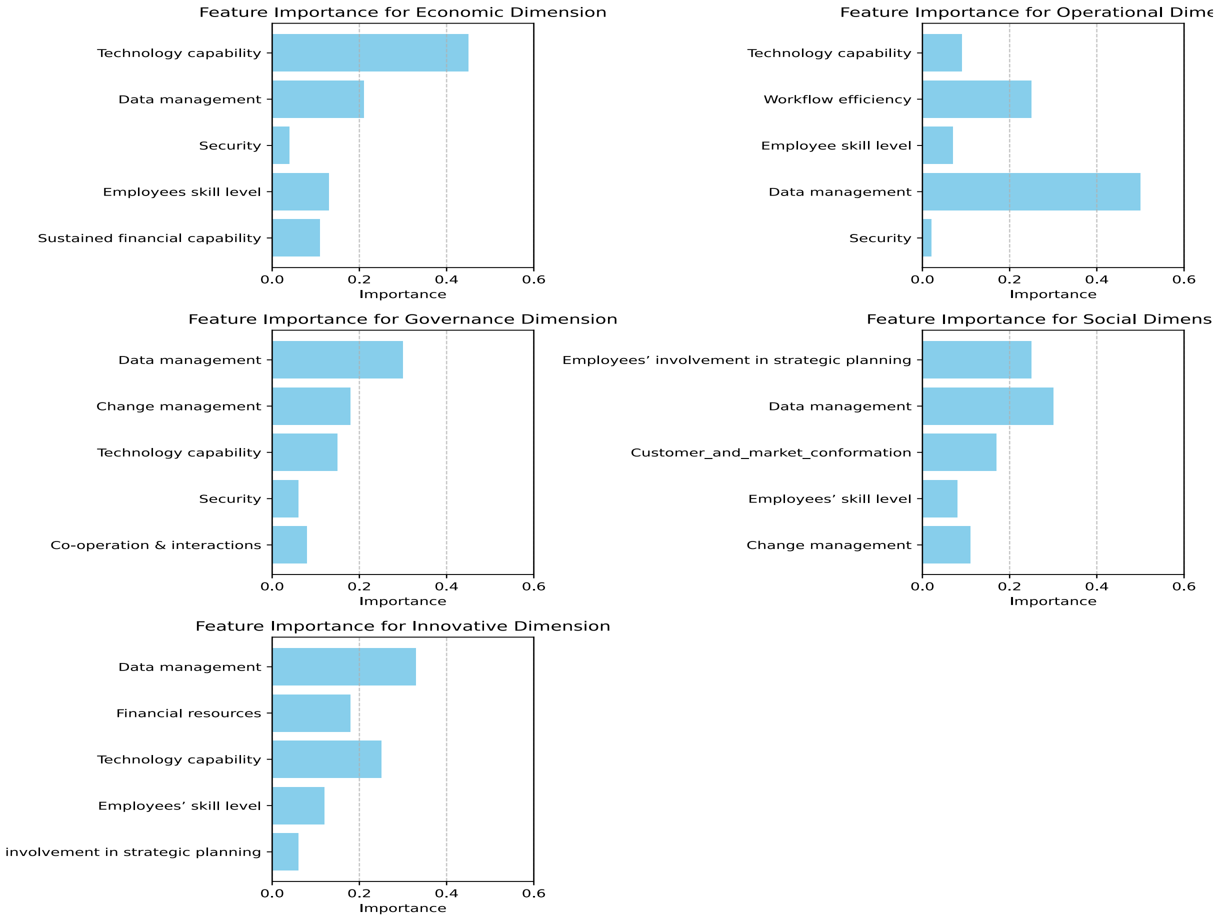


Figure 5.6: Top 5 influential variables across the performance dimensions (generalized/ non-contextual)

- **Contextualized case**

As shown in Tables 5.8-5.12, nearly all of the influential variables identified in the generalized case remain consistent across both transformation contexts. This reinforces the robustness of the baseline findings. The key enablers for each performance dimension broadly align with those already observed. The sole exception is the addition of customer & market conformation to the processes and operations context under the economic performance dimension. However, given its relatively low importance rating (0.024435), this factor can be considered marginal and does not materially affect the broader patterns.

The contextualized case therefore extends the findings of generalized case by illustrating that the influence of these multifaceted enablers is not uniform. Instead, it varies according to both (a) the specific performance dimension under consideration and (b) the transformation context. For example, the relative importance of data management diverges significantly across contexts: in the processes and operations context, its importance ratings for the economic and social dimensions are 0.083423 and 0.154559, whereas in the customer experience context, the corresponding values rise sharply to 0.298507 and 0.385697. This demonstrates that while data management is a consistently critical enabler, its magnitude of influence is considerably heightened when the transformation is directed toward customer-facing outcomes.

Similarly, the three localized variables identified in the generalized case, workflow efficiency for operational performance, cooperation and interaction for governance, and customer and market for social performance continue to exert influence on the same specific dimensions across both contexts. This alignment suggests that these factors act as cross dimensionally anchored drivers. Their role remains consistent, regardless of AI adoption efforts towards internal process optimization or customer experience enhancement.

Taken together, the contextualized case analysis demonstrates that while the set of influential variables across contexts is largely stable, the relative weightings of these enablers shift significantly. It underscores the importance of adopting a context-sensitive perspective in AI transformation strategies.

Table 5.8: Top influential variables for Economic performance (Processes & Operations vs Customer Experience)

No.	Top variables for Economic performance			
	Variables for Processes & Operations	**f^2 effect size**	**Variables for Customer Experience**	**f^2 effect size**
1.	Technology capability	0.690839	Data management	0.298507
2.	Sustained financial capability	0.092695	Technology capability	0.223881
3.	Data management	0.083423	Employees' skill level	0.223881
4.	Employees skill level	0.064138	Sustained financial capability	0.179104
5.	Customer & market conformatio	0.024435	Security	0.074627

Table 5.9: Top influential variables for Operational performance (Processes & Operations vs Customer Experience)

No.	Top variables for Operational performance			
	Variables for Processes & Operations	**f^2 effect size**	**Variables for Customer Experience**	**f^2 effect size**
1.	Data management	0.546295	Data management	0.551983
2.	Workflow efficiency	0.330951	Workflow efficiency	0.131524
3.	Technology capability	0.060724	Security	0.127062
4.	Employees skill level	0.030493	Technology capability	0.101772
5.	Security	0.030197	Employees skill level	0.120268

Table 5.10: Top influential variables for Governance performance (Processes & Operations vs Customer Experience)

No.	Top variables for Governance performance			
	Variables for Processes & Operations	**f^2 effect size**	**Variables for Customer Experience**	**f^2 effect size**
1.	Data management	0.286561	Data management	0.2929
2.	Change management	0.219723	Technology capability	0.194414
3.	Cooperation & Interactions	0.176859	Change management	0.12649
4.	Technology capability	0.094236	Security	0.090102
5.	Security	0.073208	Cooperation & Interactions	0.072515

Table 5.11: Top influential variables for social performance (Processes & Operations vs Customer Experience)

No.	Top variables for social performance			
	Variables for Processes & Operations	**f^2 effect size**	**Variables for Customer Experience**	**f^2 effect size**
1.	Customer & market conformation	0.286552	Data management	0.355697
2.	Employee's involvement in S.P	0.185743	Employee's involvement in S.P	0.32645
3.	Data management	0.154559	Customer & market conform.	0.279943
4.	Change management	0.111093	Employees' skill level	0.021787
5.	Employees skill level	0.098654	Change management	0.020097

Table 5.12: Top influential variables for innovative performance (Processes & Operations vs Customer Experience)

No.	Top variables for Innovation performance			
	Variables for Processes & Operations	**f^2 effect size**	**Variables for Customer Experience**	**f^2 effect size**
1.	Technology capability	0.260974	Data management	0.445209
2.	Data management	0.250965	Technology capability	0.333569
3.	Sustained financial capability	0.209375	Employees skill level	0.094446
4.	Employees skill level	0.138379	Employees' involvement in SP	0.039506
5.	Employee's involvement in S.P	0.119064	Sustained financial capability	0.037657

5.7. Discussion

The objective of this research was to develop a prioritisation model of AI enablers for sustainable performance improvement in SMEs. Drawing on expert-based evaluation of enabler-performance relationships, the study examines relative influence patterns rather than empirically observed performance outcomes. A systematic understanding of how these enablers contribute across performance dimensions is vital for ensuring the alignment between the AI initiatives and the transformation context. Figure 5.7 provides a visual representation of the scope and strength of influence of the top-ranked variables across business performance dimensions in both contextualized settings. Based on their sphere of influence, AI implementation variables are classified into three broader categories that are universal, multidimensional, and local influencers. This classification reflects comparative influence patterns derived from the analysis and serves as an interpretative structuring device rather than a causal hierarchy.

5.7.1. Universal influencers

Universal influencers are defined as the variables exerting relatively high influence across all five performance dimensions in both contexts. Data management emerges as the sole universal influencer. Its impact scores were consistently high, with comparatively lower influence observed in driving social performance within the process and operations context. This pattern suggests that data management functions as a foundational enabling condition within the evaluated model. In practical terms, this indicates that SMEs may benefit from strengthening data infrastructure and governance before scaling other AI initiatives, particularly where cross-dimensional performance objectives are pursued. From an academic perspective, the finding aligns with prior literature emphasizing data as a foundational digital resource (Mikalef et al., 2019; Wamba et al., 2021).

5.7.2. Multidimensional influencers

Multidimensional influencers are variables that shape several but not all performance dimensions in both contexts. These include technology capability, employee skill level, employee involvement in strategic planning, change management, and security.

Extensive multidimensional influencers: Technology capability, employee skill level, and security impact three or more performance dimensions.

Moderate multidimensional influencers: Employee involvement in strategic planning and change management impact two dimensions.

The results indicate that these variables exhibit cross-dimensional relevance, though not universal dominance. They may, therefore be interpreted as supporting enablers that can amplify the influence of universal factors such as data management. For example, technology capability demonstrates strong influence across operational, governance, and innovation outcomes, while showing comparatively weaker influence on economic performance. This pattern suggests a layered capability configuration rather than a linear maturity path, where strengthening foundational capabilities may create enabling conditions for complementary technological, organisational , and human factors, positioning within the influence structure.

5.7.3. Local influencers

Local influencers are variables demonstrating strong influence on a single specific performance dimension across both contexts. These include:

- Workflow efficiency for operational performance
- Cooperation and interaction for governance
- Customer and market conformation for social performance

While their overall impact is moderate, these variables demonstrate concentrated influence within specific dimensions of business performance. This indicates that certain enablers may disproportionately affect specific performance objectives, depending on strategic emphasis (e.g., workflow efficiency for operational excellence or customer-market conformation for social legitimacy). Importantly, this does not imply that local enablers are less important overall; rather, their impact is contextually bounded within the evaluated model.

Taken together, this three-tier classification reflects a layered system of enablers. Universal influencers (e.g., data management) exhibit cross-dimensional prominence. Multidimensional influencers (e.g., technology capability, employee skill levels) demonstrate broader but selective relevance and local influencers (e.g., workflow efficiency, cooperation and interaction) fine-tune outcomes within targeted domains. Whilst the generalized case demonstrated the consistent appearance of these enablers across performance dimensions, the contextualized analysis revealed shifts in influence magnitude depending on transformation focus (process & operations vs. customer experience). These shifts indicate contextual sensitivity in influence patterns, rather than structural reconfiguration of the enabler system. Theoretically, this contributes to understanding AI adoption as a structured configuration of enabling conditions whose relative prominence varies with performance orientation.

Practically, SMEs can use this categorization as a structured decision-support reference for staged capability development:

- First, prioritise strengthening universal enablers (e.g., data management).
- Next, reinforce multidimensional enablers (e.g., technology capability, employee skill levels, change management) to broaden cross-functional impact.
- Finally, target local enablers to optimize context-specific objectives.

This staged approach ensures that SMEs invest scarce resources where they create the broadest value, while still accommodating context-specific performance needs.

5.7.4. Category-Level Synthesis

The analysis indicates a predominance of internal enabling factors in facilitating AI-assisted performance outcomes within SMEs. Specifically, three factors within each of the technological, organisational , and human categories were identified as influential, whereas only one environmental factor demonstrated comparable prominence. In terms of relative magnitude, technological factors, particularly data management received the highest influence scores across performance dimensions and contextual settings. This aligns with prior research emphasizing the foundational role of technological infrastructure in AI-driven transformation (Mikalef et al., 2019; Wamba et al., 2021).

However, the strength of influence varies depending on performance dimension and implementation context. Technological enablers demonstrated greater relative influence in the customer experience context whereas organisational , human, and environmental factors hold a supporting role as indicated by the results in Figure 5.7. This pattern may reflect the central role attributed in prior literature to data analytics and digital platforms in enabling personalized and adaptive customer interactions (Chatterjee et al., 2021; Kumar et al., 2023). However, the present study does not directly examine these mechanisms and therefore cannot establish them as causal explanations. On the other hand, organisational enablers were comparatively more prominent in process and operations settings. These observations point to context-dependent differences in enabler salience; however, they do not provide evidence of causal dominance across contexts. The environmental variable Customer and Market Conformation showed consistent influence across both contexts, likely reflecting the embedded customer-centric orientation of the social performance dimension (Dwivedi et al., 2021). However, this interpretation is inferential and derived from pattern alignment rather than direct measurement of customer-centric outcomes. Overall, the results illustrate that while technological enablers occupy a structurally central position within the evaluated model, AI adoption in SMEs reflects a configuration shaped by the interplay of technological, organisational , human, and environmental factors. The evidence supports a context-sensitive prioritisation approach rather than a universal sequencing model. Taken together, these findings suggest a layered and context-dependent configuration of AI enablers.

Finally, it is important to acknowledge that these findings are based on structured expert judgement rather than direct firm-level implementation data; therefore, influence relationships represent perceived importance rather than validated performance causality. Second, participants primarily consisted of academics, IT managers, and consultants, reflecting analytical and cross-industry perspectives rather than sector-specific operational experience. Third, the analysis captures relative influence structures at a single point in time and does not account for longitudinal capability development. Accordingly, the proposed prioritisation should be interpreted as structured guidance rather than a prescriptive implementation sequence.

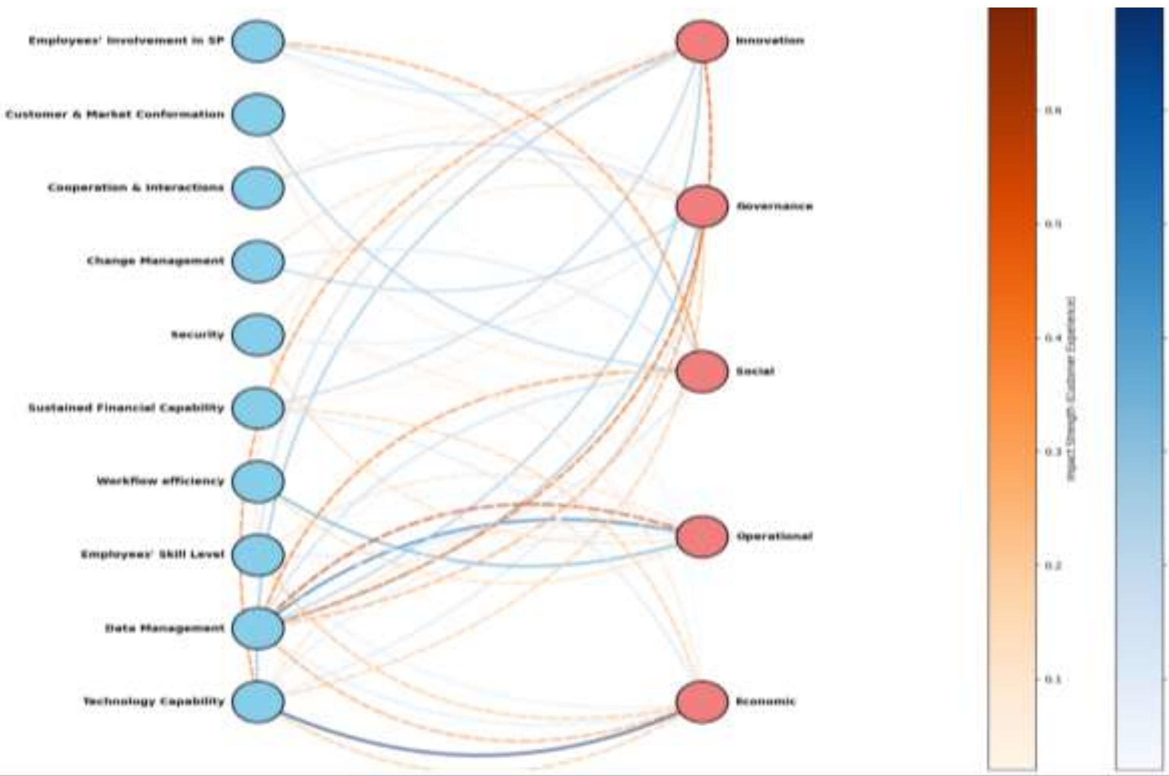


Figure 5.7: Network graph: AI implementation variables on business dimensions (both context)

5.8.Conclusion

The findings of this work underscore the differentiated impact of AI enablers on business performance dimensions across distinct transformation contexts. Unlike prior research, it examined the direct role of multidimensional enablers in shaping performance outcomes. This focus provides practitioners with a structured, evidence-based foundation for crafting context-specific and performance-aligned AI adoption strategies. Its key contribution lies in its classification of AI enablers into three categories based on their sphere of influence. Thereby offering a systematic lens for aligning implementation priorities with intended outcomes. It challenges the adequacy of one-size-fits-all approaches. Instead, it demonstrates the necessity of tailored strategies that can calibrate adoption efforts according to specific organisational goals. By directing the transformation initiatives toward high impact areas, this approach mitigates the risks of misaligned goal-setting and inefficient resource allocation.

Chapter 6. Identification of Sales and Operations planning (S&OP) Tasks to Be Supported by Artificial Intelligence and Generative AI

Having examined readiness and enablers, the third phase turns to the heart of operational practice: aligning AI applications with task requirements. It was recognized that the existing literature on understanding AI-task fitness remains fragmented and underdeveloped. These overlook the nuanced interplay between task characteristics and technological capabilities. Furthermore, most models remain generic and adopt "one-size-fits-all" approach that limits their practical utility. This creates a knowledge gap in understanding the "fit" between AI capabilities and the contextual requirements of the real-world organisational tasks. Consequently, this phase addresses CIRQ 3 (PERQs 3.1-3.3) by analysing the suitability of different AI applications for nineteen S&OP tasks, offering practical guidance on what AI solution can be most effectively deployed addressing the 'What' aspect of AI adoption lifecycle (as illustrated in figure 6.1).

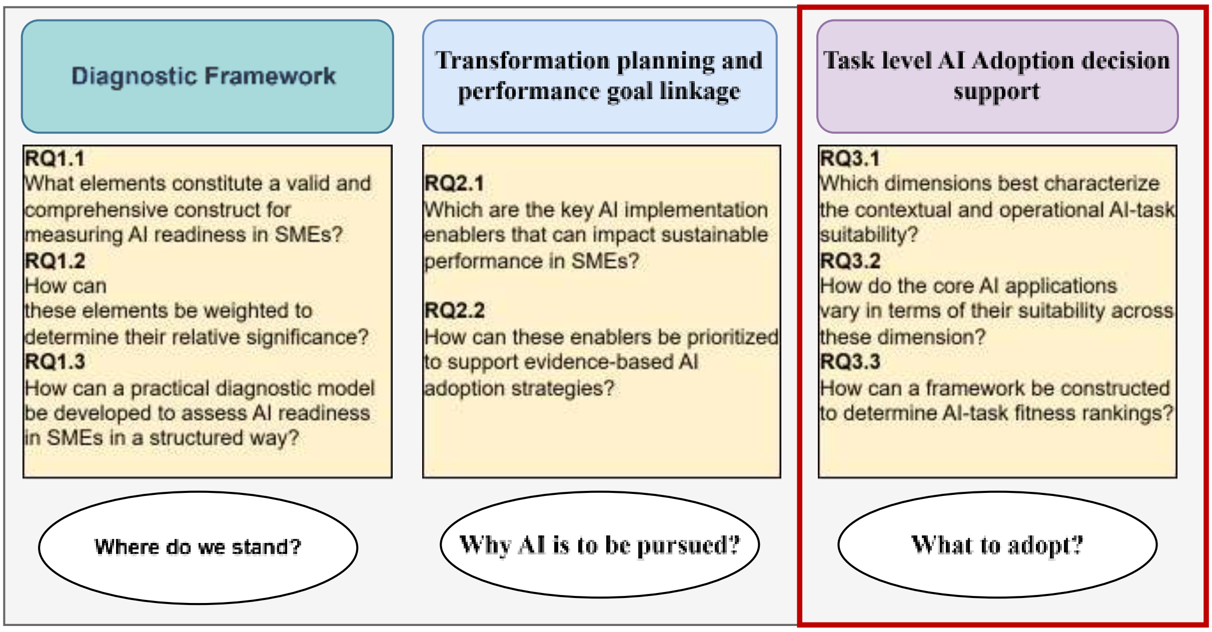


Figure 6.1: 'What' aspect of AI adoption lifecycle

6.1. Introduction

SMEs operate in an increasingly competitive environment, marked by rapidly evolving customer expectations and volatile market demands. This dynamic context necessitates that SMEs remain agile, proactive, and customer-focused to sustain competitiveness (Gupta et al., 2020). Responsiveness, service quality, and personalized offerings have become critical determinants of long-term viability (Mazzarol, 2015). Consequently, SMEs often provide customized products with high variability. This, in turn increases the complexity of their planning processes. Such complexity demands robust strategic, tactical, and operational planning systems capable of optimizing resources and ensuring performance (Jonsson and Holmström, 2016).

To address these challenges, several planning systems have been proposed in literature and adopted in practice, including S&OP, Production Planning and Control (PPC), Collaborative Planning, and Advanced Planning and Scheduling (APS) (Lapide, 2005; Pereira et al., 2020). These systems differ in scope and function, addressing high-level strategic alignment planning (e.g., S&OP) to operational execution (e.g., PPC and APS). Collectively, they enable organisations to manage complexity, enhance flexibility, and align resources with market demands. Thereby improving overall performance through analytics-driven decision-making.

In parallel, AI has emerged as a transformative technological paradigm, reshaping business operations through intelligent decision-making, analytical forecasting, and dynamic optimization (Davenport and Ronanki, 2018; Wamba-Taguimdje et al., 2020). Within the domain of planning systems, AI has attracted attention for its potential to enable data-driven demand forecasting and support complex, interdependent decision-making (Choi et al., 2018). Existing studies such as Jonsson and Holmstrom (2016), Choi et al. (2018) and Wamba-Taguimdje et al. (2020) highlighted AI's prospective role in technology-assisted planning. However, these remain general in emphasizing far-reaching benefits rather than its specified role in enhancing planning systems. Limited attention has been devoted to examining how the capabilities of AI may best address the nuanced requirements of distinct activities embedded within comprehensive planning frameworks such as S&OP, PPC, or APS. The interrelated and complex components of planning systems demand a more granular investigation into how AI can complement these planning activities for enhanced outcomes. Consequently, this research intends to address this gap to enhance both theoretical understanding and practical guidance.

Instead of addressing the broad domain of planning systems, this research narrowed its focus specifically to S&OP. The selection of this functional context was primarily determined by organisational access and industrial collaboration conditions, rather than emerging as a diagnostic outcome of the proposed framework. As an MTO SME, they demand a critical coordination mechanism linking demand forecasting, design, and production planning etc. S&OP integrates functionally interrelated and decision-intensive tasks that vary in complexity, adaptability, repetitiveness, and decision risk, thereby providing an analytically robust context for demonstration of the framework. Accordingly, the case study should be interpreted as a demonstrative application designed to evaluate the operational applicability of the framework rather than as a framework-prescribed identification of a priority adoption domain. The predefined organisational context enabled in-depth exploration of task-level decision processes and facilitated access to domain experts necessary for detailed suitability assessment.

This positioning has two methodological implications. First, the case illustrates how the framework can be applied within a complex planning environment, thereby demonstrating feasibility and interpretability under realistic organisational constraints. Second, because the functional scope was contextually bounded, findings should not be interpreted as evidence that S&OP represents a universally optimal AI adoption entry point for SMEs. The purpose of the case study is therefore evaluative rather than confirmatory: it examines whether the framework can systematically translate strategic adoption considerations into operational deployment guidance within a real organisational setting.

To systematically investigate the alignment of AI applications with the diverse S&OP tasks, the work adopts the Task-Technology Fit (TTF) theory (Goodhue and Thompson, 1995). It emphasises that the effectiveness of a technology in supporting tasks depends on its fitness or alignment with the task's inherent requirements. It provides a robust foundation for evaluating the suitability of different AI applications for diverse S&OP activities. It provides a novel contribution through the development of an AI-for-task suitability framework tailored to S&OP. Specifically, it advances the literature by (i) identifying and categorizing core S&OP activities, (ii) systematically mapping these tasks against distinct AI applications, and (iii) establishing a structured ranking of AI-task fitness. It offers context-specific, fit-for-purpose AI integration that enriches theoretical understanding of AI adoption in complex planning contexts. It can also help delivering actionable insights for practitioners seeking to optimize S&OP performance. Through this approach, the work contributes to both theory and practice by advancing insights into where and how AI can generate the most value in complex planning environments. This AI-task suitability framework can play a vital role in guiding more targeted and effective AI adoption strategies.

6.2. Methodology

As outlined above, the primary aim of this phase is to determine the suitability of distinct AI applications for S&OP tasks. It adopts the Task-Technology Fit (TTF) lens as the guiding framework, to ensure analytical rigor. TTF underscores that technological effectiveness is not universal but depends on the degree of alignment or "fit" between technology capabilities and task characteristics. In this context, a task-level suitability analysis grounded in TTF provides the most appropriate theoretical basis for answering the central research question, that is *"Which AI application fits which S&OP task?"*

Recognizing the limitations of relying solely on literature assessment or expert judgement in a rapidly evolving technological domain, this study adopts a hybrid methodological approach. As illustrated in Figure 6.2, the approach integrates literature-driven conceptual insights with empirical validation and is structured in three phases.

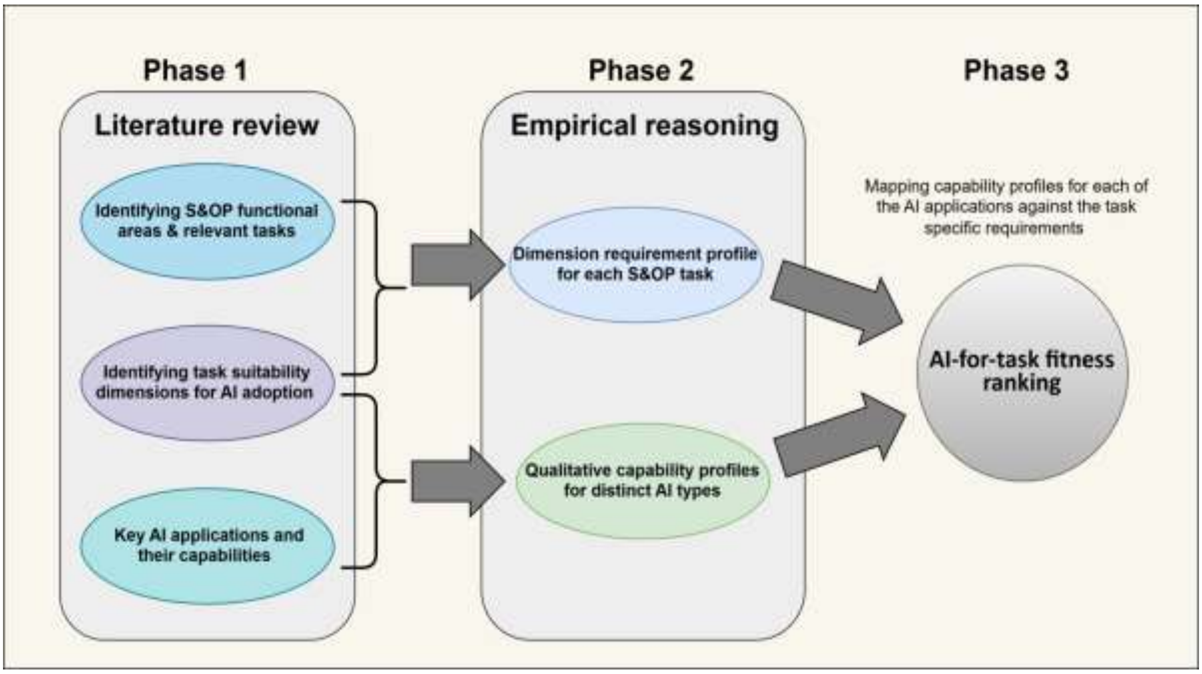


Figure 6.2: Conceptual research model

6.2.1. Phase 1: Literature Review and Conceptual Grounding

The first phase building directly on the primary systematic literature review presented in Chapter 2, involved a targeted literature review to define the conceptual foundation of the study. While the SLR provided a broad understanding of AI suitability frameworks, this structured but non-systematic review focuses on domain-specific refinement, supporting task-AI suitability modelling. These include identification of key S&OP functional areas and their associated tasks, delineation of core AI applications and their characteristic capabilities, and extraction of task suitability dimensions relevant to AI adoption.

To map the functional areas and relevant planning tasks, a structured review of S&OP frameworks was conducted. Simultaneously, the capabilities of distinct AI applications were examined to establish their comparative strengths and limitations. Additionally, literature addressing task suitability for AI adoption was reviewed to generate a comprehensive set of evaluative dimensions. Distinct but complementary search strategies were applied to each thematic area. For AI-related literature, focused keyword-based searches (e.g., “core AI applications,” “reinforcement learning adaptability”) were sufficient to retrieve directly relevant research. By contrast, literature on S&OP tasks was more fragmented. Accordingly, iterative techniques such as keyword expansion, backward/forward citation tracking, and domain-specific cross-referencing were employed. The same iterative approach was applied to refine the list of task suitability dimensions. This phase thus established a methodologically robust conceptual foundation for subsequent empirical validation.

6.2.2. Phase 2: Expert Elicitation and evaluation

The second phase operationalised the conceptual insights by synthesizing them into capability profiles for AI applications and requirement profiles for S&OP tasks. To ensure reliability, an expert elicitation approach was employed using a structured survey questionnaire. A multi-criteria decision-making technique, Best-Worst Method (BWM) proposed by (Rezaei, 2015) was used to analyse expert responses. It avoids oversimplification by deriving the optimized weights, that capture the relative importance of criteria. In this study, it provided nuanced insights into (i) the relative capabilities of AI applications across the predefined suitability dimensions, and (ii) the criticality of each dimension for the effective execution of individual S&OP tasks. Fifteen experts including both academics and industry professionals participated in the study. To ensure domain relevance and diversity of perspectives, participants with substantial experience in AI adoption within manufacturing planning contexts were sampled. The survey was divided into two sections. In section 1, experts rated the capabilities of AI applications (e.g., ML, RL, Simulation, GenAI) against each suitability dimension. It generated capability profiles for each AI application. Whereas, section 2 assessed the dependency of each S&OP task on the suitability dimensions, formulating requirement profiles. Responses were then aggregated and analysed to construct composite profiles, ensuring methodological rigor while minimizing individual bias.

6.2.3. Phase 3: Mapping and Suitability Ranking

In the final phase, the capability profiles of AI applications and the requirement profiles of S&OP tasks were systematically matched using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) proposed by (Hwang and Yoon, 1981). This method was chosen because it is well-suited for multi-criteria decision-making problems where alternatives must be evaluated against an “ideal” set of requirements (Rehman et al., 2024). It complements the BWM used in the previous phase as it also accounts for both the best and worst possible scenarios. It allows for a balanced and discriminative ranking of options, making it particularly appropriate for aligning AI capabilities with the nuanced requirements of S&OP tasks.

The initial normalization was established in the previous phase by ensuring that the scales across both capability and requirement profiles were consistent. Subsequently, the BWM was applied to capture the relative importance of each criterion in determining task suitability. Using these weighted profiles, the distance of each AI application’s capabilities from the ideal solution (perfect task alignment) and the negative-ideal solution (complete misalignment) was calculated. A closeness coefficient was then computed for each application, forming the basis of a structured fitness ranking. This ranking systematically determines the suitability of AI technologies for individual S&OP planning tasks. Suitability is classified into four categories: Primary Fit, Supporting Fit, Shared Fit, and Peripheral Fit. Primary Fit represents the AI application that most effectively meets a task’s core requirements, offering the highest potential for direct performance gains, such as superior accuracy, scalability, or adaptability in critical task dimensions. Supporting provides complementary strengths that enhance task execution when integrated alongside the primary fit. Such technologies can bolster specific aspects of performance (such as improving interpretability, mitigating risks, or supporting adaptability). Thereby creating synergistic value. In addition, Shared Fit arises when two or more AI technologies demonstrate closely comparable levels of suitability for the same task. It suggests that either these may serve as viable primary solutions on their own or their combined use could enhance robustness. Finally, Peripheral Fit designates AI applications that are not the most suitable but still exceed a minimum threshold of acceptability. Thereby remaining relevant as secondary or contingency options. A formal mathematical formulation of the repeated TOPSIS procedure for computing AI-task-fitness scores for a set of AI methods across multiple S&OP tasks is provided below.

Let,
A = {1,...,m} be the set of AI methods (alternatives),
D = {1,...,n} the set of suitability dimensions (criteria), and
T = {1,...,p} the set of S&OP tasks.
x_{sd}= The capability score of AI method s, on dimension d
$w_d^{(t)}$= the weight of dimension d for task t with $\sum_{d=1}^{n} w_d^{(t)} = 1$
$X = [x_{sd}] \in R^{m\times n}$= capability matrix (rows = AI methods, columns = dimensions)
$R^{(t)} = \left[r_{sd}^{(t)}\right] \in R^{m\times n}$= normalized decision matrix for task t
$V^{(t)} = \left[v_{sd}^{(t)}\right]$= weighted normalized matrix for task
A^{+t}= ideal vector for task t
A^{-t}= negative-ideal vector for task t
$S_s^{+(t)}$= Euclidean distances of alternative s to ideal and negative-ideal for task t
$S_s^{-(t)}$= Euclidean distances of alternative s to negative-ideal for task t
$C_s^{(t)}$= TOPSIS closeness coefficient (fitness score) of AI s for task t
$rank_t(s)$= ranking position of AI s for task t

For a given task **t,** each AI option **s = (1,2, … , m)** is evaluated on criteria **d = (1,2, … , n)**

Step 1: Normalization

Skipped this step since same scale was used for both the profiles in the previous phase

Step 2: Weighted normalized decision matrix (per task t)

$$\boldsymbol{v_{sd}^{(t)} = w_d^{(t)}\, r_{sd}} \text{ ---------------------------- Equation 6.1}$$

Step 3: Ideal and negative-ideal solutions (per task t)

$$\boldsymbol{A_d^{+(t)} = max_s v_{sd}^{(t)}} \text{ ---------------------------- Equation 6.2}$$

$$\boldsymbol{A_d^{-(t)} = min_s v_{sd}^{(t)}} \text{---------------------------- Equation 6.3}$$

Step 4: Distances to the ideal and negative-ideal (per task t)

For each AI s= (1,…..,m)

$$\boldsymbol{S_d^{+(t)} = \sqrt{\textstyle\sum_{d=1}^{n}(v_{sd}^{(t)} - A_d^{+(t)})^2}} \text{ ---------------------------- Equation 6.4}$$

$$\boldsymbol{S_d^{-(t)} = \sqrt{\textstyle\sum_{d=1}^{n}(v_{sd}^{(t)} - A_d^{-(t)})^2}} \text{ ---------------------------- Equation 6.5}$$

Step 5: Closeness coefficient (AI–task fitness score)

$$C_s^{(t)} = \frac{S_d^{-(t)}}{S_d^{+(t)} + S_d^{-(t)}} \textbf{ with } 0 \leq C_s^{(t)} \leq 1 \text{------------------------------ Equation 6.6}$$

Step 6: Ranking

$$rank_t(s) = 1 + \#\{k: C_k^t > C_s^t\} \text{------------------------------ Equation 6.7}$$

$$PrimaryFit = \arg \boldsymbol{max}_s C_s^{(t)} \text{------------------------------ Equation 6.8}$$

$$SupportingFit = \arg \boldsymbol{max}_{s:s \notin PrimaryFit} C_s^{(t)} \text{------------------------ Equation 6.9}$$

$$SharedFit = if C_s^{(t)} \geq \max\left(C_s^{(t)}\right) - \delta \text{ } and \text{ } s \neq \arg \boldsymbol{max}_s C_s^{(t)} \text{ ------ Equation 6.10}$$

$$PeripheralFit = if C_s^{(t)} < \max\left(C_s^{(t)}\right) - \delta \text{ } and \text{ } C_s^{(t)} \geq \in \text{ ------------ Equation 6.11}$$

6.3. Conceptual grounding

6.3.1. Sales and Operation planning (S&OP): key areas and activities

The core S&OP system is to integrate sales and operations plans in order to achieve a balance between production capacity and market demand (Nemati et al., 2017). S&OP establishes a cross-functional tactical plan that consolidates diverse business plans (such as sales, manufacturing, procurement, and marketing) into a single cohesive strategy. Its objective is to ensure that operational tactics are consistently aligned with an organisation's strategic objectives. Thereby driving overall business success. Moreover, long-term business strategies are embedded into the S&OP process to inform and support decision-making in shorter-term, daily operations. Palmatier (2002) further conceptualised S&OP as a unified process consisting of multiple interdependent sub-processes, each responsible for carrying out fundamental planning activities.

Over the past two decades, several researchers Thome et al. (2012), Meyr et al. (2015), Kristensen and Jonsson (2018), Pereira et al. (2020), and Bhalla et al. (2023), have conducted literature reviews to examine S&OP from varying perspectives. Functional domains provide a more practical framework for assessing AI suitability, as they reflect where planning tasks are actually executed. By shifting the focus from abstract planning to functional contexts, this research identifies tasks where AI can meaningfully enhance operational decision-making, adopting a functional-domain lens for reviewing S&OP activities. Whilst these studies provide valuable insights into strategic alignment and decision-making, much of the literature continues to address S&OP at an abstract planning level. Key planning domains such as demand planning, supply planning, financial planning, and executive review are widely discussed. Yet these often overlook the operational complexity and functional nuances that define real-world execution. Without identifying and understanding the specific tasks carried out in functional areas, the identification of opportunities for AI application remains largely conceptual. Consequently, the present research adopts a functional-domain lens to review S&OP activities. Thereby offering a contextually grounded basis for evaluating AI application and transformation potential.

In parallel, organisations employ varying production strategies (such as Make-to-Stock (MTS), Make-to-Order (MTO), Configure-to-Order (CTO), and Engineer-to-Order (ETO)) to manage supply chains according to their business models. Each manufacturing environment is characterized by unique configurations of customization levels, production volumes, lead times, demand variability, and inventory strategies (Christogiannis, 2014, Koenen, 2017). These characteristics in turn create distinct S&OP planning requirements. For instance, prior studies have emphasised on balancing standardized production with demand variability within MTS and MTO contexts (e.g., Ivert et al., 2015; Pereira et al., 2020). Conversely, recent research has highlighted the greater complexity of ETO and CTO environments, where high product variability and customer-specific customization necessitate the expansion of traditional S&OP frameworks. Bhalla et al. (2023), for example, extended Pereira et al.'s (2020) conceptual framework to the ETO context. Their study introduced an engineering planning domain to capture custom design and technical requirements. It excluded distribution planning, since ETO products are typically shipped directly to customers without the need for advanced logistics. Such work underscores the need to refine S&OP frameworks in order to adequately capture the planning realities of high-customization environments.

Building on these insights, the present study seeks to systematically review S&OP functional areas across all major manufacturing environments (MTS, MTO, CTO, and ETO). This analysis provides a comprehensive scheme of S&OP planning domains by incorporating both commonalities and context-specific requirements (see Table 6.1). This refined framework ensures that the key planning activities across diverse environments are captured and an operationally relevant basis for evaluation is provided. By doing so, it directly manages the abstract S&OP planning limitation. It addresses its operational tasks and context-specific requirements where AI can deliver tangible decision-making support.

Table 6.1: Key S&OP planning areas and activities

No.	Planning areas	Planning activities	References
1.	**Sales planning**	Demand forecasting	(Lapide, 2005; Grimson and Pyke, 2007; Baumann, 2010; Godsell et al., 2010; Olhager and Prajogo, 2012; Thome et al., 2012; Feng et al., 2013; Tuomikangas and Kaipia, 2014; Ivert et al., 2015; Pereira et al., 2020; Bhalla et al., 2023)
		Order conformation and commitments	
		Order prioritisation	
		Sales promotions planning	
2.	**Configuration/ Engineering Planning**	Requirements/Configurations validation	(Chen-Ritzo et al., 2010; Christogiannis, 2014; Carvalho, et al. 2015; Bhalla et al., 2023)
		BOM generation/ configuration	
		Lead time/cost estimation	
3.	**Procurement planning**	Material Requirements Planning	(Lapide, 2005; Grimson and Pyke, 2007; Baumann, 2010; Olhager and Prajogo, 2012; Thome et al., 2012; Feng et al., 2013; Tuomikangas and Kaipia, 2014; Ivert et al., 2015; Cunha et al., 2018; Pereira et al., 2020; Bhalla et al., 2023)
		Supplier selection and scheduling	
		Cost, Lead Time and Risk Analysis	
		Safety Stock and Reorder Point Planning	
4.	**Production planning**	Master production scheduling	Bhalla et al. (2023); Pereira et al. (2020); (Cunha et al., 2018); Ivert et al. (2015); Tuomikangas and Kaipia (2014); (Feng et al., 2013); Baumann (2010); Olhager and Prajogo (2012); Thome et al. (2012); Lapide (2005)
		Capacity planning	
		Routing and sequencing	
		Load Balancing	
5.	**Distribution planning**	Inventory deployment	(Lapide, 2005; Baumann, 2010; Olhager and Prajogo, 2012; Thome et al., 2012; Feng et al., 2013; Tuomikangas and Kaipia, 2014; Ivert et al., 2015; Pereira et al., 2020)
		Transport and logistic planning	
		Route optimization	
		Delivery prioritisation	

o Sales planning

Sales planning is widely recognized as one of the critical pillars of S&OP that functions as the key interface between the market and organisational operations (Thome et al., 2012; Pereira et al., 2020; Bhalla et al., 2023). It translates sales forecasts, market signals, and demand insights into actionable inputs for supply chain activities. By doing so, it enables alignment between supply and demand. It ensures that organisational resources and capacities are synchronized with market expectations (Grimson and Pyke, 2007; Ivert et al., 2015). Sales planning encompasses several core activities that together provide a foundation for integrated business decision-making (see Table 6.1).

- **Demand forecasting**

Demand forecasting relies on historical sales data, market insights, seasonal patterns, promotions, and external factors to project future product demand (Lapide, 2005; Grimson and Pyke, 2007; Thome et al., 2012). Accurate forecasts help firms synchronize supply chain resources in advance, reducing costs, preventing stockouts, and enhancing responsiveness. Conversely, poor forecasting can result in excess inventory, missed sales, or operational inefficiencies.

- **Order conformation and commitments**

Order confirmation is particularly critical in ETO and CTO environments, where products are customized and resources must be carefully allocated (Adrodegari et al., 2015; Shurrab et al., 2020). This process evaluates both technical feasibility and resource availability before accepting orders. This ensures that only viable projects are pursued. By aligning commitments with capacity and inventory constraints, organisations reduce delivery backlogs, improve on-time performance, and build customer trust (Grimson and Pyke, 2007).

- **Order prioritisation**

Order prioritisation enables firms to rank and select orders based on criteria such as profitability, projected sales volume, and strategic value (Tuomikangas and Kaipia, 2014). Structured prioritisation ensures that resources are directed toward the most economically and strategically important opportunities. This not only improves efficiency and decision-making but also enhances long-term competitiveness and profitability (Adrodegari et al., 2015).

- **Sales promotions planning**

Sales promotion planning involves designing and timing marketing campaigns in alignment with operational capacity. By integrating demand forecasts into promotional decisions, firms can anticipate demand fluctuations, optimize inventory levels, and synchronize production schedules. This proactive alignment prevents overstocking or shortages and supports both revenue growth and supply chain stability (Thome et al., 2012).

o Configuration/ Engineering planning

Configuration and engineering planning encompass the definition, management, and validation of technical specifications to ensure alignment with customer requirements, feasibility constraints, and supply capabilities (Bhalla et al., 2023). These activities are particularly critical in ETO, CTO, and ATO manufacturing environments. Here product offerings must balance customization with standardization while safeguarding cost efficiency and reliability (Christogiannis, 2014; Carvalho et al., 2015; Bhalla et al., 2023). By enabling the early translation of customer needs into feasible and manufacturable solutions, configuration planning strengthens responsiveness and competitiveness.

- **Requirements/Configurations validation**

Requirements and configuration validation ensure that proposed product specifications are feasible and conform to predefined engineering and design constraints (Bhalla et al., 2023). This process assesses the alignment of features and components with established technical rules and organisational capabilities, allowing only viable configurations to proceed. Early validation minimizes the risk of design errors, reduces rework, and ensures accurate communication with production and procurement teams (Carvalho et al., 2015; Bhalla et al., 2023).

- **BOM generation/ configuration**

Automated BOM configuration translates customized orders into precise lists of components and subassemblies required for production (Christogiannis, 2014; Carvalho et al., 2015). By ensuring seamless integration between sales commitments, procurement needs, and manufacturing operations. BOM configuration reduces errors, accelerates order processing, and supports mass customization. This capability enhances responsiveness to customer demands while maintaining operational efficiency.

- **Lead time/cost estimation**

Lead-time and cost estimation involve forecasting production expenses and delivery timelines for configured products based on resource availability, scheduling, and procurement conditions (Carvalho et al., 2015; Bhalla et al., 2023). Accurate estimation enables realistic quoting, strengthens customer trust, and minimizes the risk of overpromising. By improving quoting precision and delivery reliability, these practices enhance overall planning accuracy and customer satisfaction (Chen-Ritzo et al., 2010; Christogiannis, 2014; Bhalla et al., 2023).

○ Procurement planning

Procurement planning is a central element of the S&OP process that ensures the timely and reliable availability of materials required for production. Its primary objective is to secure supply continuity while avoiding excess inventory and unnecessary costs. By translating operational demand forecasts into executable sourcing strategies, procurement planning balances material availability, cost efficiency, and risk management (Thome et al., 2012). Key activities include material forecasting, supplier selection, contract negotiation, procurement scheduling, and contingency planning. When effectively integrated, procurement planning aligns with sales and production requirements, enhances supply chain efficiency, and supports seamless order fulfilment (Tuomikangas and Kaipia, 2014; Ivert et al., 2015).

- **Material Requirements Planning (MRP)**

Material Requirements Planning encompasses the preparation of purchase requisitions to ensure the timely procurement of raw materials essential for scheduled production. It aligns material inflows with manufacturing needs by considering production plans, inventory levels, and supplier lead times. By minimizing holding costs, preventing stockouts, and ensuring uninterrupted production flow, MRP strengthens the link between planning and execution (Cunha et al., 2018; Pereira et al., 2020).

- **Supplier selection and scheduling**

Supplier selection and scheduling involve strategic evaluation of supplier capabilities against organisational requirements. Factors such as cost efficiency, risk exposure, reputation, and strategic alignment inform the prioritisation of dependable suppliers who can reliably meet forecasted demand. This activity ensures continuity in component supply, supports timely order fulfilment, and mitigates risks of disruption. Moreover, cultivating long-term supplier partnerships fosters stability, enhances trust, and contributes to the resilience of the supply chain (Thome et al., 2012; Ivert et al., 2015; Bhalla et al., 2023).

- **Lead Time, cost and Risk Analysis**

  This activity focuses on assessing supplier reliability, identifying potential bottlenecks, and evaluating variability in lead times and costs. Regular monitoring of these factors enables proactive anticipation of delivery risks and cost fluctuations. Such analysis feeds into scenario planning within the broader S&OP framework. It allows organisations to design contingency strategies, alternative sourcing plans, and adaptive pricing mechanisms. As a result, organisations enhance agility, strengthen supply chain resilience, and improve their ability to withstand uncertainty (Tuomikangas and Kaipia, 2014; Adrodegari et al., 2015; Bhalla et al., 2023).

- **Safety Stock and Reorder Point Planning**

  Safety stock and reorder point planning are critical for mitigating demand variability and supply uncertainties. By systematically determining safety stock levels, organisations safeguard against production interruptions and demand surges. This activity addresses the fundamental trade-off between holding costs (such as capital investment, storage, and obsolescence) and the risks associated with stockouts, including lost sales and production delays. Effective planning in this area optimizes operational resilience and ensures balanced, cost-effective inventory management (Thome et al., 2012; Pereira et al., 2020).

o Production planning

Production planning constitutes one of the core pillars of the S&OP framework, tasked with transforming demand forecasts into executable and resource-efficient manufacturing plans. Within the S&OP context, its primary contribution lies in determining how best to allocate and utilise manufacturing resources to meet the consensus demand plan (Grimson and Pyke, 2007). It ensures close alignment between organisational objectives, customer requirements, internal capacity, and material availability. Functioning as the interface between commercial ambitions and operational capabilities, production planning facilitates evidence-based decision-making while ensuring responsiveness and balance across the supply chain (Thome et al., 2012; Pereira et al., 2020).

- **Master production scheduling (MPS)**

  MPS represents a central element of production planning in the S&OP process. It specifies time-phased production of individual products derived from aggregate demand forecasts (Pereira et al., 2020). MPS defines precise quantities and production timings by converting high-level projections into actionable manufacturing activities. This coordination ensures that sales demand, existing inventories, and production capacity remain synchronized. Thereby reducing overproduction and stockouts, improving resource utilization, and enhancing customer satisfaction (Lapide, 2005; Tuomikangas and Kaipia, 2014; Pereira et al., 2020).

- **Capacity planning**

  Capacity planning evaluates the adequacy of organisational resources (both human and technological) for supporting projected production schedules. Typically, this involves a two-stage process: Rough-Cut Capacity Planning to provide a high-level assessment, followed by detailed Capacity Requirements Planning (CRP) to match resource availability with MPS execution (Thome et al., 2012; Tuomikangas and Kaipia, 2014). Such assessments help identify capacity bottlenecks, support realistic scheduling, and promote operational efficiency by aligning production targets with feasible resource constraints.

- **Routing and sequencing**

  Routing and sequencing determine the operational order and scheduling of production tasks. This activity enhances productivity by streamlining workflows, reducing idle time, and ensuring adherence to production schedules. By coordinating task execution at a detailed level, routing and sequencing contribute to efficient resource utilization and timely order fulfilment, thereby reinforcing alignment between planning objectives and execution performance (Grimson and Pyke, 2007; Thome et al., 2012).

- **Load Balancing**

  Load balancing seeks to distribute workloads evenly across planning periods to avoid production variability. By aligning demand with capacity in a phased and predictable manner, it minimizes excessive inventory buildup, mitigates resource strain (e.g., labour, machinery, and materials), and avoids the disruptions associated with sudden peaks or troughs in production. This smooth production flow enhances operational efficiency, improves system stability, and ensures resilience across the supply chain (Lapide, 2005; Thome et al., 2012; Tuomikangas and Kaipia, 2014).

o Distribution planning

Distribution planning encompasses a set of strategic and tactical processes dedicated to managing the storage, movement, and delivery of finished goods across the supply chain (Thome et al., 2012; Pereira et al., 2020). Its primary objective is to ensure the timely and cost-effective delivery of the right products to the right customers. Functioning as the critical interface between organisational operations and market demand. It aligns manufacturing outputs and inventory availability with customer requirements. Effective distribution planning enhances the agility and resilience of the supply chain by streamlining product flows, optimizing inventory placement, mitigating logistical risks, and improving cost efficiency (Grimson and Pyke, 2007; Tuomikangas and Kaipia, 2014; Pereira et al., 2020).

- **Inventory deployment**

  Inventory deployment involves determining the optimal locations and quantities of stock across the supply chain network (Pereira et al., 2020). By balancing availability with cost efficiency, it minimizes stockout risks, reduces lead times, and ensures reliable product accessibility. A well-designed inventory deployment strategy strengthens operational flexibility, mitigates disruption risks, and contributes to customer satisfaction while improving financial performance (Thome et al., 2012; Tuomikangas and Kaipia, 2014).

- **Transport and logistic planning**

  Transportation and logistics planning play a pivotal role in scheduling, routing, and executing the physical movement of goods. This activity encompasses fleet management, carrier selection, route design, and mode optimization. These ensure timely, reliable, and cost-effective deliveries (Tuomikangas and Kaipia, 2014). Decisions are guided by trade-offs among cost, speed, and service quality, with the aim of aligning transportation operations with broader supply chain objectives. Effective logistics planning reduces costs, shortens transit times, and enhances service levels, thereby strengthening overall supply chain performance (Thome et al., 2012).

- **Route optimization**

  Route optimization emphasises synchronizing transportation activities with warehouse and distribution centre operations to maximize efficiency (Pereira et al., 2020). It seeks to minimize dwell time, reduce congestion, and align inbound and outbound flows for smoother operations. Improved coordination results in higher vehicle utilization, shorter turnaround times, and reduced operational bottlenecks. Ultimately, route optimization enhances responsiveness, lowers costs, and supports agile supply chain performance (Lapide, 2005; Thome et al., 2012).

- **Delivery prioritisation**

  Delivery prioritisation involves determining the order in which customer demands are fulfilled, especially under conditions of limited capacity or fluctuating demand (Thome et al., 2012; Ivert et al., 2015). Criteria such as profitability, contractual obligations, strategic partnerships, and service-level agreements guide prioritisation decisions. By systematically aligning order fulfilment with business value, delivery prioritisation strengthens customer satisfaction while ensuring operational execution remains consistent with strategic objectives (Tuomikangas and Kaipia, 2014; Ivert et al., 2015).

6.3.2. Key AI applications

AI is a broad and evolving domain of computer science concerned with developing systems capable of emulating human intelligence. Scholars and practitioners alike have highlighted its transformative potential for industrial productivity and organisational growth (Ivanov et al., 2021; Sheff, 2023). The capabilities and interpretations of AI vary across disciplines, experts, and industries, reflecting differences in priorities, competencies, and contexts of use.

For instance, the European Commission (2018) defines AI as a system or program that is capable of observing its environment, learning from it, and recommending actions based on acquired knowledge. Similarly, a European Union study group describes AI as a system capable of addressing complex tasks in digital or physical domains by collecting structured or unstructured data, analysing it, acquiring knowledge, and recommending optimal actions (Samoili et al., 2020). Industry leaders also articulate AI's capabilities through the lens of their operational contexts. Google (2023) emphasises its role in perception, language translation, data processing, and forecasting. McKinsey (2023) frames AI as data-trained systems that identify patterns, forecast outcomes, and dynamically adapt to new information. Whilst, Amazon (2023) highlights AI's problem-solving abilities in learning and pattern recognition, Tesla (2023) stresses perception and reasoning as core enablers of autonomous vehicles and robotics. Collectively, these interpretations converge around five foundational AI capabilities including learning, prediction, reasoning, perception, and adaptation (see Table 6.2).

Table 6.2: AI capabilities and their description

Capability	Description
Learning	It allows the systems to learn from data that can help to make learned and intelligent predictions. Learning can be Supervised, semi-supervised or unsupervised.
Perception	It allows the system to recognize and interpret the scenario by imitating human senses.
Prediction	It is the ability to analyse data and identify historical patterns to predict future trends.
Reasoning	It allows proving rationale and make decisions in complex scenarios.
Adaptation	The capability to adjust adapt and tune itself dynamically to accommodate new data.

Building on these capabilities, AI can be categorized into several core application domains (Table 6.3). Among them, ML is particularly prominent, employing algorithms that extract patterns from data to make predictions or decisions without explicit programming (Sarker, 2021). Learning and prediction form the foundation of ML. It enables tasks such as predictive maintenance (Kamat and Sugandhi, 2020), customer behaviour analysis (Segun-Falade et al., 2024), and anomaly detection (Omol et al., 2024). ML also integrates reasoning, perception, and adaptability to extend its functionality across diverse contexts. Other essential subfields include Natural Language Processing (NLP), Computer Vision (CV), RL, Simulation, Robotics and GenAI (Abioye et al., 2021). These domains often overlap with and are built upon ML, leveraging advanced architectures such as deep learning and neural networks to deliver state-of-the-art solutions (Striuk et al., 2021; Zheng et al., 2023; Younesi et al., 2024). They also provide the foundation for emerging paradigms such as Digital Twins, Agentic AI, and Explainable AI etc. (Koskinen, 2024).

Table 6.3: Core AI sub-fields and their strengths

Core AI fields	Learning	Prediction	Reasoning	Perception	Adaptation
ML	Learn patterns from data	Predict outcomes	Uses basic logic	Need clean data	Improve with new data
NLP	Learns language rules	Predict next words	Understand intent	Process text/speech	Adapt to new language
CV	Learn to identify objects	Predict image content	Understand scenes	Process images/videos	Adjust to environment
RL	Learn by trial and error	Predict best action	Balance risks/rewards	Sense environment	Change strategy
Simulation	Learn behaviour of the system	Make scenario-based predictions	What-if scenario reasoning	Often but not always	Based on changing inputs
Robotics/ Autonomous system	Learn from the feedback	Predict consequences	Complex reasoning	Sense environment	Adjust actions in real time
GenAI	Learn to create content	Predict next element	Keep logic coherent	Analyse data patterns	Adapt style

NLP and CV play a critical role and offer significant value across a wide range of AI applications. However, their core strengths lie in data understanding, perception and content generation rather than decision-making or process optimization. Given that the current study focuses on evaluating the suitability of AI for S&OP tasks, where the emphasis is on planning and decision-making, NLP and CV are not considered core AI subfields for direct application in this domain. Similarly, Robotics/Autonomous systems are also excluded as they are predominantly concerned with operational automation, which falls outside the planning and decision-making focus of S&OP processes. Consequently, this work will focus on ML, Simulations, RL and GenAI AI as the core AI applications for evaluating their suitability in addressing the requirements of S&OP planning tasks. By focusing on these domains, the study ensures alignment between AI capabilities and the requirements of planning-intensive, decision-oriented tasks central to S&OP.

6.3.3. Task suitability assessment framework for AI adoption

The development of a structured and effective framework for assessing AI adoption requires a clear understanding of the critical factors that determine the suitability of AI applications for organisational decision-making. To this end, existing literature was systematically reviewed to identify relevant factors and dimensions and explained in section 2.3.3 (under theme 4). The review was conducted with the objective of extracting and synthesizing relevant factors to develop a comprehensive and context-sensitive set of dimensions suited to the specific requirements of S&OP planning tasks. Since many existing frameworks are either tailored to particular AI applications (such as ML or GenAI) or confined to specific industry contexts, an aggregated list was compiled by consolidating and merging overlapping dimensions (as presented in table 6.4). This consolidated set serves as the foundation for constructing a structured task suitability assessment framework tailored to S&OP planning.

Table 6.4: AI Suitability Differentiation Framework

Suitability dimension	ML	Simulation models	RL	GenAI
Task Complexity	High suitability for moderately complex tasks (LeCun et al., 2015; Brynjolfsson et al., 2017)	High suitability for complex tasks (Siegfried 2014; Fujimoto et al., 2017)	High suitability for complex tasks involving sequential decision-making (Sutton and Barto, 2018; Nguyen et al., 2020)	Ideal for moderately complex tasks (Brown et al., 2020; Gartner, 2023)
Task Objectivity	High suitability for highly objective and quantifiable outcomes (Scott, et al., 2021; Kunze et al., 2022)	High task objectivity and clarity increase suitability (Birta and Arbez, 2013; Xu et al., 2014)	High task objectivity increases suitability (Liu et al., 2014; Arulkumaran et al., 2017)	Good at generating subjective outputs (Weidinger et al., 2022; OpenAI, 2023)
Data Availability and quality	High suitability for environments with large volumes and high-quality data (Brynjolfsson et al., 2017; Scott, et al., 2021)	High suitability for structured and high-quality data. (Fujimoto et al., 2017; Kritzinger et al., 2018)	High suitability for data-rich environments but can also function with limited data (Silver et al., 2017; Fu et al., 2022)	High suitability for data-rich environments with quality prompts. (Mandvikar and Achanta., 2023; OpenAI, 2023)
Repetitiveness	High suitability for highly repetitive tasks (Brynjolfsson et al., 2017; Liu et al., 2023)	High suitability for modeling repeatable scenarios (Birta and Arbez, 2013; Tsao et al., 2020)	Thrives in dynamic environment (Arulkumaran et al., 2017; Padakandla, 2021)	Good at generating consistent and repetitive output (Brown et al., 2020; Mandvikar and Achanta., 2023)
Adaptability	Improves with new data (Scott, et al., 2021; Taye, 2023)	Multiple iterative runs allow planners to adjust (Fernandes et al., 2022; Chernikova et al., 2024)	Learns optimal actions over time (Sutton and Barto, 2018; Kurte et al., 2020)	Improved output with prompt engineering (Bommasani, 2021; Mandvikar and Achanta., 2023)
HMI	Limited interpretability (Ribero, et al., 2016; Brynjolfsson et al., 2017)	Visual interaction (Matkovic et al., 2010; Pedersen et al., 2017)	Limited interaction (Cruz and Igarashi, 2020; Puiutta and Veith, 2020)	High interaction (Bommasani, 2021; OpenAI, 2023)
Creativity	Limited (Brown et al., 2020; Hughes et al., 2021)	Supports informal creative decision-making (Cohen and Zhang, 2016; Calder, et al., 2018)	Not ideal but can discover novel strategies (Silver et al., 2017; Colin, 2020)	Strong fit (Gartner, 2023; OpenAI, 2023)
Risk Impact	Suitable for low to moderate risk tasks (Ribero, et al., 2016; Scott, et al., 2021)	Excellent for testing decisions in risk-free virtual settings (Barat et al., 2022; Kulkarni et al., 2022)	Suitable for trial-and-error in high-risk tasks (Arulkumaran et al., 2017; Dong et al., 2020)	Suitable for low to moderate risk tasks (Mandvikar and Achanta., 2023; OpenAI, 2023)

6.4. Empirical Reasoning

Building on the theoretical foundations synthesized from the literature, empirical reasoning was employed to operationalize the framework and validate its applicability. This process involved developing qualitative capability profiles for distinct AI applications and requirement profiles for S&OP tasks. Fifteen experts from both academia and industry, each possessing relevant experience in AI applications, were selected through purposive sampling. This ensured the required breadth of expertise and diversity in perspectives. The panel included six university lecturers with research specialization in digital transformation and related domains, alongside nine industry professionals comprising two IT team leaders, five IT managers, and two consultants (participant characteristics are summarized in the table 6.5 below). Whilst, academic representation contributed theoretical depth and alignment with current scholarly discourse, the multi-level industry composition enabled the integration of strategic, technical, and operational perspectives. Consultants brought cross-industry and cross-context exposure, IT managers provided organisation-level strategic and managerial understanding, and team leaders contributed hands-on knowledge grounded in day-to-day implementation realities. This composition reduced the likelihood of single-perspective dominance and strengthened the comprehensiveness of the elicited judgements. As a result, the derived weights reflect substantial domain expertise and offer a well-informed representation. However, the relatively small panel size limits statistical generalizability. The findings should therefore be interpreted as contextually grounded expert judgements with strong indicative value, while broader empirical testing would be beneficial to confirm their stability across a wider spectrum.

Table 6.5: Resulting profiles and related participant insights

Code	Sector	Role	Experience	Expertise
1	Industry	IT Manager	7	Technical support & strategic planning
2	Industry	IT Manager	13	Technical support & strategic planning
3	Industry	IT Manager	4	Technical support & strategic planning
4	Industry	IT Manager	4	Technical support & strategic planning
5	Industry	IT Manager	3	Infrastructure management
6	Industry	Team leader	4	Solution implementation expert
7	Industry	Team leader	4	Solution implementation expert
8	Industry	Consultant	7+	Project management
9	Industry	Consultant	16+	Project management
10	Academia	Teaching/ Research	2	Planning and Control
11	Academia	Teaching/ Research	2	Planning and Control
12	Academia	Teaching/ Research	3	Smart applications for the industry
13	Academia	Teaching/ Research	5	Digital supply chain
14	Academia	Teaching/ Research	8	Smart applications for the industry
15	Academia	Teaching/ Research	12	HCI expert

Data collection was conducted using a structured questionnaire divided into two sections, each aligned with the specific objectives of capability and requirement assessment. The resulting profiles and related participant insights are presented below in table 6.5.

6.4.1. Qualitative capability profiles

As outlined in Table 6.3 and described in Section 6.2.2, the literature review helped formulate preliminary capability profiles for the four AI application. These profiles highlight their strengths across multiple task suitability dimensions. These were subsequently validated through expert evaluation to account for the rapid pace of technological advancements. The results presented in Figure 6.3, demonstrate a strong convergence between expert judgement and academic findings. This consistency not only reinforces the credibility of the framework but also strengthens confidence in its reliability for assessing AI capabilities in organisational contexts.

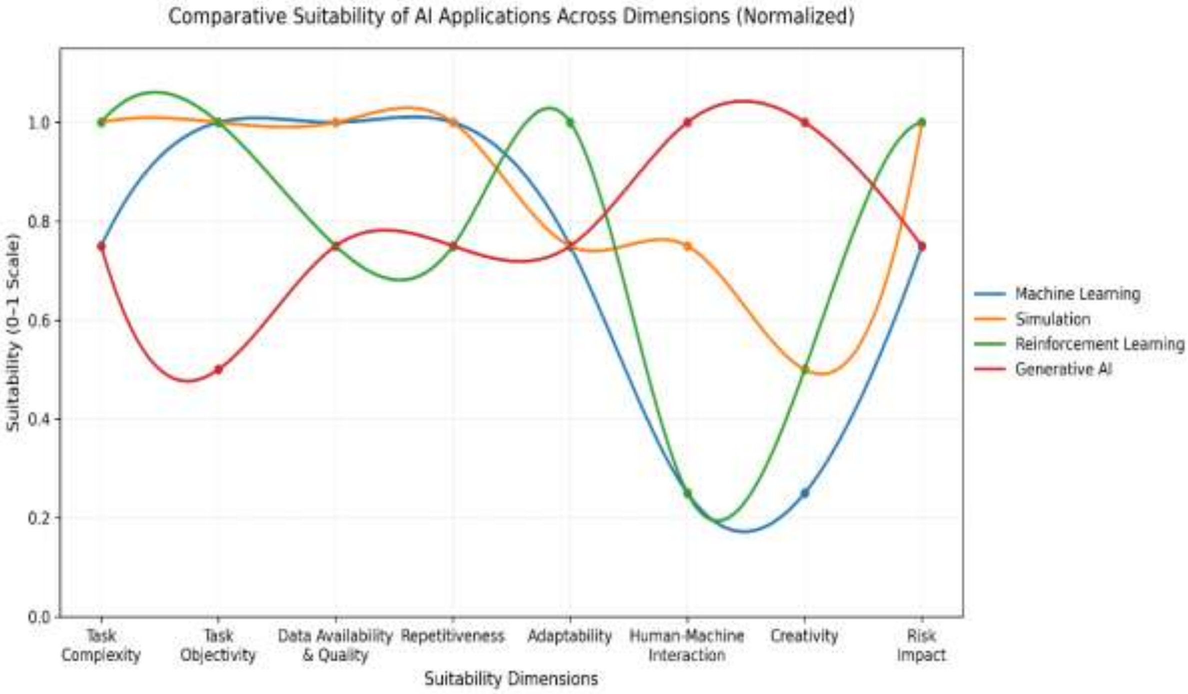


Figure 6.3: AI capability profiles across task suitability dimension

6.4.2. Requirement profiles for S&OP tasks

Sections 6.3.1 and 6.3.3 outlined the core tasks within S&OP domains and the task suitability assessment dimensions derived from literature. To establish which dimensions are most critical for each task, expert review was employed to compile requirement profiles. These profiles, presented in Figures 6.4a and 6.4b, highlight the degree of criticality of suitability dimensions across different S&OP tasks. Together, they provide a structured foundation for systematically matching AI capabilities to task requirements. Thereby advancing a more context-specific and practically grounded framework for AI adoption in planning environments.

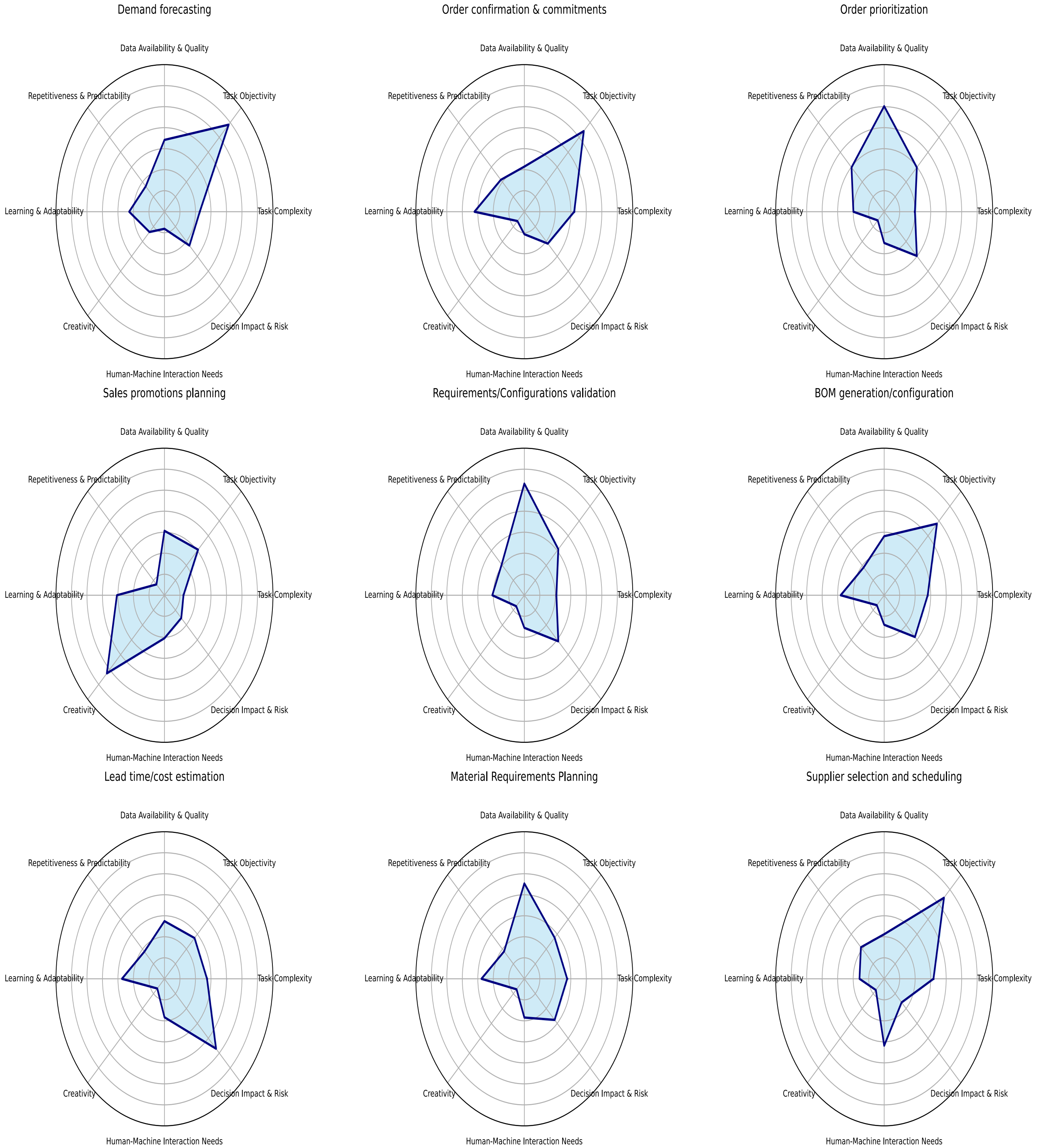


Figure 6.4a: Requirement profiles for S&OP tasks

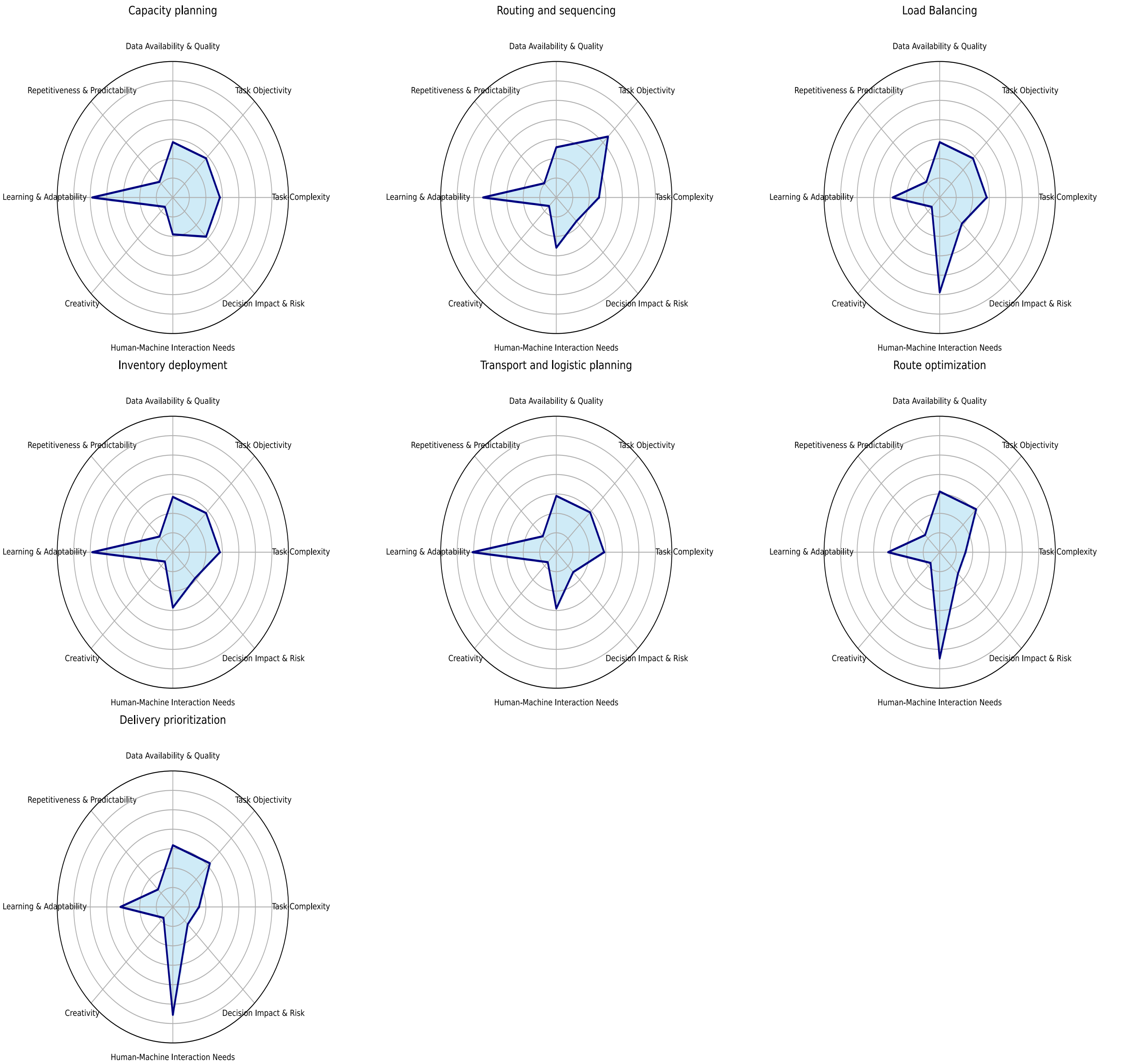


Figure 6.4b: Requirement profiles for S&OP tasks

Since the requirement profiles were derived from expert assessments, a limited sensitivity, as recommended by researchers (Saaty, 2008; Saltelli et al., 2008) was conducted. Rather than serving as a statistical validation technique, the sensitivity analysis functions as a robustness check, ensuring that the results are not disproportionately driven by individual judgements or minor variations in expert input. This enhances the transparency and credibility of the findings while remaining consistent with the interpretive nature of the research design (Saaty, 2008).

A similar hybrid robustness assessment used in phase 1 was conducted to examine the stability of the task-dimension importance structure in this phase. The results presented in Table 6.6 indicate a high degree of stability across the requirement profiles. For the majority of tasks, the three most influential suitability dimensions retained their original ranking positions in more than 90-97% of perturbation and simulation runs. For instance, task objectivity and data availability consistently remain dominant drivers for tasks such as demand forecasting and material requirements planning, while adaptability and HMI maintain their prominence for logistics and routing activities. Only minor fluctuations were observed in lower-ranked dimensions, suggesting that the prioritisation structure remains largely unchanged under plausible variations in expert assessments. Taken together, these results indicate that the requirement profiles capture structural characteristics of S&OP task demands rather than artefacts of a particular weighting configuration. Consequently, the framework's task-dimension mappings can be considered robust and suitable for supporting the subsequent matching of AI capabilities to planning tasks.

Table 6.6: Robustness of Task Requirement Profiles

Task	Rank	Suitability Dimension	Original Weight	Perturbation Stability (±10%) rank	Monte Carlo Stability percentage
Demand forecasting	1	Task Objectivity	0.293	1	95%
	2	Data Availability	0.171	2	93%
	3	Task Complexity	0.114	3	90%
Order confirmation & commitments	1	Task Objectivity	0.271	1	96%
	2	Task Complexity	0.161	2	93%
	3	Adaptability	0.161	3	92%
Order prioritisation	1	Data Availability	0.251	1	95%
	2	Repetitiveness	0.149	2	91%
	3	Task Objectivity	0.149	3	91%
Sales promotions planning	1	Creativity	0.263	1	96%
	2	Adaptability	0.153	2	93%
	3	Task Objectivity	0.153	3	93%
Requirements / Configurations validation	1	Data Availability	0.266	1	96%
	2	Task Objectivity	0.155	2	92%
	3	Risk Impact	0.155	3	92%
BOM generation / configuration	1	Task Objectivity	0.241	1	95%
	2	Task Complexity	0.140	2	91%
	3	Data Availability	0.140	3	91%
Lead time / cost estimation	1	Risk Impact	0.235	1	95%
	2	Task Complexity	0.137	2	90%
	3	Task Objectivity	0.137	3	90%
Material Requirements Planning	1	Data Availability	0.227	1	96%
	2	Task Complexity	0.138	2	91%
	3	Task Objectivity	0.138	3	91%
Supplier selection & scheduling	1	Task Objectivity	0.273	1	96%
	2	HMI	0.159	2	93%
	3	Task Complexity	0.159	3	93%
Cost, Lead Time & Risk Analysis	1	Risk Impact	0.241	1	96%
	2	Task Complexity	0.140	2	91%
	3	Data Availability	0.140	3	91%
	1	Task Objectivity	0.288	1	96%
	2	Data Availability	0.168	2	93%

Safety Stock & Reorder Point Planning	3	Adaptability	0.112	3	89%
Master production scheduling	1	Task Objectivity	0.255	1	95%
	2	Task Complexity	0.150	2	92%
	3	Risk Impact	0.150	3	92%
Capacity planning	1	Adaptability	0.244	1	96%
	2	Task Complexity	0.142	2	91%
	3	Task Objectivity	0.142	3	91%
Routing & sequencing	1	Task Objectivity	0.222	1	95%
	2	Adaptability	0.222	2	95%
	3	Task Complexity	0.129	3	91%
Load balancing	1	HMI	0.244	1	96%
	2	Task Complexity	0.142	2	91%
	3	Data Availability	0.142	3	91%
Inventory deployment	1	Adaptability	0.244	1	96%
	2	Task Complexity	0.142	2	91%
	3	Task Objectivity	0.142	3	91%
Transport & logistics planning	1	Adaptability	0.254	1	96%
	2	Task Complexity	0.145	2	92%
	3	Task Objectivity	0.145	3	92%
Route optimization	1	HMI	0.273	1	96%
	2	Task Objectivity	0.156	2	91%
	3	Data Availability	0.156	3	91%
Delivery prioritisation	1	HMI	0.278	1	96%
	2	Task Objectivity	0.159	2	91%
	3	Adaptability	0.159	3	91%

6.4.3. AI-for-task fitness ranking using TOPSIS

TOPSIS proposed by (Hwang and Yoon, 1981) was employed to systematically assess the suitability of different AI applications for distinct S&OP tasks. This method orders the alternatives based on their closeness coefficient, with higher values indicating stronger suitability. This way each AI application was assessed for its distance from the ideal (best) and negative-ideal (worst) solutions and ranked according to its relative closeness. The resulting AI-to-Task Fitness Ranking was computed using equation 6.7 provided in section 6.3.3. It provides a quantified measure of alignment between AI capabilities and task requirements. The ranking values range from 0 to 1, where higher scores indicate stronger fitness and, consequently, greater potential for effective task support. In this way, the approach translates qualitative capability and requirement profiles into a structured, comparable, and decision-oriented metric for guiding AI adoption in S&OP contexts.

As explained above, TTF suggests that an optimal alignment between the technological capabilities and the characteristics of the task realize performance benefits. However, in the context of this study, this concept of "fit" is expanded beyond a simple binary match to a more nuanced view. Four fitness rankings categorized as Primary fit, Shared Fit, Supporting Fit and Peripheral fit are introduced that are described in section 5.2.3 above. This multi-tiered understanding enables a more nuanced interpretation of how different AI technologies can be strategically integrated within complex S&OP

processes to maximize the strategic value. By recognizing how different technologies can contribute in complementary roles, a more effective alignment between task requirements and technological capabilities is possible.

Equations 6.6- 6.11 are used to evaluate the fitness scores and develop the final rankings of the AI application for each S&OP task. The figure 6.5 shows the AI-for-S&OP tasks fitness scores and the table 6.7 present the rankings for each task.

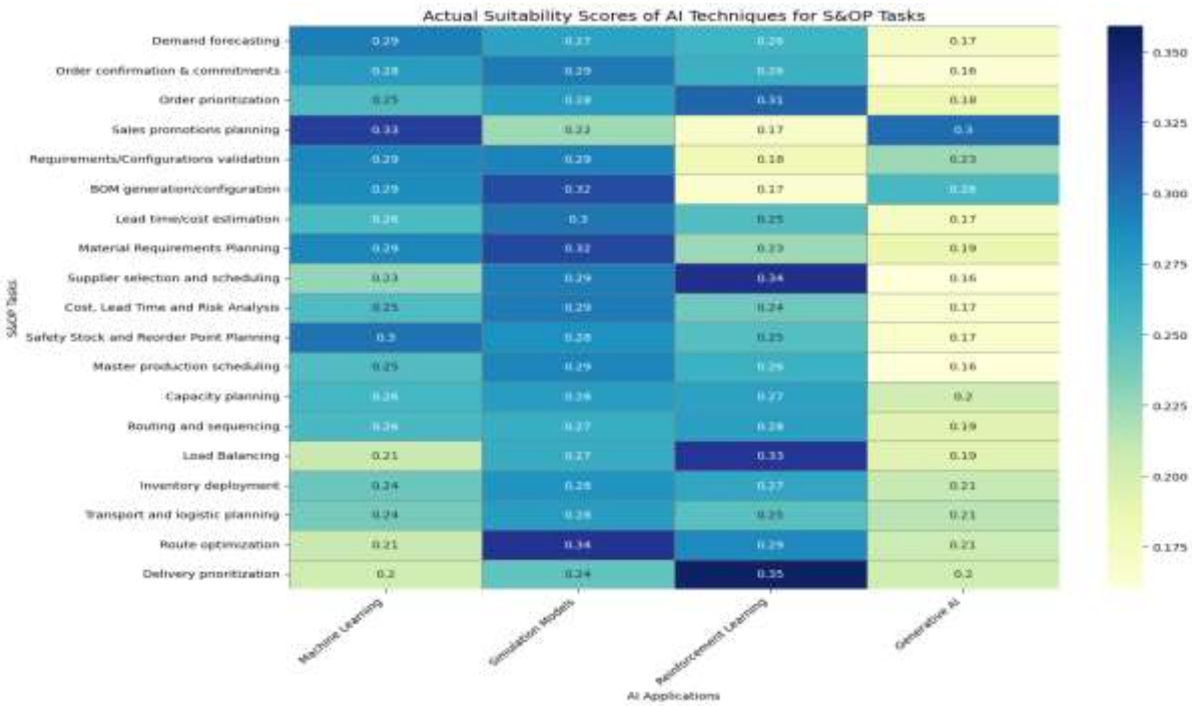


Figure 6.5AI-for-Task Fitness scores

Table 6.7: AI-for-S&OP tasks fitness ranking

S&OP Task	Primary Fit	Shared Fit	Supporting Fit	Peripheral
Demand forecasting	-	ML, RL, Sim	-	GenAI
Order Confirm. and commitment	-	ML, Sim	RL	GenAI
Order prioritisation	RL	-	ML, Sim	GenAI
Sales promotions planning	-	ML, GenAI	Sim	RL
Requirements / config. validation	-	ML, Sim	GenAI	RL
Bom generation / configuration	Sim	-	ML, GenAI	RL
Lead time / cost estimation	Sim	-	ML, RL	GenAI
Material requirements planning	Sim	-	ML	RL, GenAI
Supplier Selection and Scheduling	RL	-	ML, Sim	GenAI
Cost, lead time and Risk analysis	Sim	-	ML, RL	GenAI
Safety Stock and Reorder Point	ML	-	Sim, RL	GenAI
Master production scheduling	Sim	-	ML, RL	GenAI
Capacity planning	-	-	ML, Sim, RL	GenAI
Routing and Sequencing	-	-	ML, Sim, RL	GenAI
Load balancing	RL	-	Sim	ML, GenAI
Inventory deployment	-	RL, Sim	ML	GenAI
Transport and Logistics Planning	Sim	-	ML, RL	GenAI
Route optimization	Sim	-	RL	ML, GenAI
Delivery Prioritisation	RL	-	Sim	ML, GenAI

6.5. Discussion

TTF theory asserts that performance gains arise when technology aligns with task characteristics. In the empirical context of this study, TTF was operationalised across multiple S&OP task categories to examine how different AI technologies align with distinct task characteristics. The task-level suitability scoring conducted extended the notion of 'fit' to a multidimensional perspective, allowing a nuanced understanding of how different AI technologies can be strategically positioned. The results suggest that AI adoption in S&OP should not be conceptualised as a single-technology optimisation problem, instead AI technologies operate as complementary components within complex S&OP processes for enhanced decision quality, efficiency, and adaptability. This approach enables organisations to align technological capabilities with varying task requirements, fostering resilient, flexible, and high-performing S&OP systems, while providing granular guidance on selectively or jointly deploying AI for context-appropriate integration.

Forecasting and demand-oriented tasks demonstrate a layered and complementary technological interaction rather than dominance by a single AI approach. In demand forecasting, ML, RL and Simulation received comparable suitability ratings, resulting in a Shared Fit classification. Whilst, ML contributes predictive precision, Simulation enables scenario-based sensitivity analysis and RL introduces adaptability to evolving market conditions. GenAI adds value by integrating unstructured insights such as market sentiments; although its lower reliability in quantitative forecasting resulted in its classification as a Peripheral Fit.. Similarly, in order confirmation and commitment processes, ML and Simulation again form a Shared Fit. This classification reflects their complementary strengths in pattern recognition (ML) and modelling operational constraints (Simulation). RL can play a supporting role by fine-tuning commitments in uncertain or volatile contexts, whereas GenAI's peripheral role could be due to lower process transparency and limited verifiability.

Tasks with a strong optimization orientation generally exhibit a single, dominant Primary Fit. For instance, order prioritisation aligns most closely with RL as the Primary Fit. RL received the highest task-technology alignment score for sequential trade-off optimization. This suggests that RL may be particularly suited for dynamic trade-off environments involving urgency, profitability, and capacity constraints. ML and Simulation were assigned a supporting role, providing input parameters such as demand probabilities and process variability, whereas GenAI remains peripheral due to its limited contribution to core optimization logic. Similarly, RL's adaptive learning of sequential allocation strategies within dynamic environment emphasise RL-driven Primary fit for load balancing and delivery prioritisation tasks. Simulation reinforces outcomes through policy stress-testing, and ML enhances predictive output. Once again, GenAI plays a peripheral role, only capable of offering narrative or visualization support rather than contributing to the core optimization logic. It should be noted that RL applicability assumes sufficient historical and real-time data availability, a condition not uniformly present across all SMEs

In contrast, ML and Simulation suitability for configuration and validation-oriented tasks may be largely due to high reliance of these tasks on analytical precision and structured process logic. Both technologies demonstrated strong alignment scores in compliance-intensive tasks such as requirements validation. This suggests that ML can facilitate compliance checking by identifying patterns and anomalies across extensive historical datasets, whereas simulation can help testing the feasibility of configurations under practical operational constraints. Thus, together forming a Shared Fit. GenAI in this context is ranked as a supporting fit due to its ability to translate complex technical rules into interpretable, user-friendly representations. However, RL's limited applicability in deterministic validation contexts made it a Peripheral fit for such tasks. Similarly, for BOM generation and product configuration, Simulation emerges as the Primary Fit. This likely reflects its capability to model complex interdependencies and production pathways. ML and GenAI offer Supporting Fits.

Planning and scheduling activities illustrate deafferented technology roles. Tasks such as MRP and master production scheduling showed Primary Fit with Simulation due to modelling of temporal dependencies and capacity constraints. ML provides Supporting Fit by refining demand inputs. RL appears Peripheral due to high data and exploration requirements. Conversely, supplier selection and scheduling find its Primary Fit in RL. RL's dynamic allocation capabilities aligned strongly with tasks involving adaptive supplier performance learning. ML and Simulation offer supporting roles whereas GenAI remains peripheral. Simulation's strengths play a leading role within tasks involving multidimensional evaluation such as lead time, cost, and risk analysis. ML also supports by capturing historical performance patterns, whereas RL can add adaptability in uncertain contexts. Safety stock and reorder point determination align primarily with ML, reflecting its ability to learn demand variability and forecast patterns. Simulation and RL play a supporting role by stress-testing policies and adjusting to changing service levels.

Certain tasks demonstrate multi-technology complementarities through shared fit. For instance, in sales promotion planning, ML demand forecasts can help uplift the novel campaign content generated by GenAI and Simulation can help evaluate alternative promotional strategies for effective results. Similarly, inventory deployment exhibits a shared Fit between RL and Simulation. As RL can optimize allocation policies and Simulation can test their robustness across scenarios. Routing and logistics tasks also align predominantly with Simulation and RL. Simulation-driven transport planning and route optimization can help model complex networks, capacities, and time variability whereas RL enhances adaptability by learning policies under stochastic disruptions. ML can also play a part in by enhancing input accuracy through demand and lead-time predictions.

Overall, this classification emphasises that AI technologies operate as interdependent and complementary layers. Primary fits denote the most directly aligned technology that may require assistance from supporting fits to enhance stability and performance. Shared fits capture synergistic potential of different AI applications that reinforce one another. Whereas, peripheral fits signal limited yet contextually relevant contributions. The empirical results demonstrate differentiated suitability patterns across task categories within the studied SME context. Recognizing these layered roles prevents oversimplifying AI adoption as a 'winner-takes-all' decision. This asserts that AI transformation strategies should prioritise task-contingent alignment rather than universal technological standardization. Instead, it highlights how integrated portfolios of ML, Simulation, RL, and GenAI can jointly enable more adaptive, resilient, and value-generating S&OP processes.

However, the interpretations are derived from structured evaluations provided by domain experts, including academics, IT managers, and industry consultants with experience in AI and S&OP-related processes. The identified task-technology fit patterns therefore reflect aggregated expert judgement rather than direct observation of implementation outcomes within a single organisational setting. As such, the classifications represent analytically informed assessments of technological suitability, not empirically measured performance effects.

The findings are consequently bounded by the expertise, professional backgrounds, and experiential frames of the participating experts. While this enables cross-sectoral and cross-organisational generalizability at a conceptual level, it does not substitute for longitudinal implementation evidence within specific firms. Contextual factors such as organisational culture, governance structures, data infrastructure maturity, and sector-specific process complexity may moderate the practical realization of the identified fits. Furthermore, the categorization into Primary, Shared, Supporting, and Peripheral

Fits reflects relative alignment based on expert consensus rather than deterministic technological superiority. The results should therefore be interpreted as a theoretically grounded decision-support framework rather than prescriptive implementation guarantees.

Importantly, these limitations primarily concern empirical realisation rather than the broader applicability of the approach itself. With regards to the generalizability and methodological transferability of framework beyond S&OP, it can be replicated in other contexts. As it is grounded in a task-level, requirement-driven logic rather than domain-specific assumptions. By decomposing processes into discrete tasks, assessing their characteristics, and mapping them to suitable AI capabilities, However, its application requires context-specific adaptation, including redefining task structures, validating requirement dimensions, and re-evaluating weights through expert input. While S&OP serves as the initial application domain, the approach can be viewed as a generalizable decision-support methodology for AI-task alignment, provided these adjustments are made.

6.6.Conclusion

This study presents a structured assessment of the suitability of four AI technologies including ML, Simulation, RL, and GenAI across 19 S&OP tasks. Guided by TTF framework, the analysis draws on expert-based suitability rankings to examine the extent to which different technological capabilities align with specific task characteristics. The results demonstrate that the alignment is neither uniform nor exclusive. Instead, AI technologies assume differentiated roles defined as Primary Fit, Shared Fit, Supporting Fit and Peripheral Fit. These layered roles reflect varying degrees of relative suitability as assessed by the expert panel.

The findings indicate that ML dominates data-driven forecasting and inventory control whereas Simulation is ranked the strongest fit for modelling, planning, and risk evaluation tasks. RL was evaluated as practically suitable for adaptive decision-making contexts such as prioritisation, allocation, and supplier scheduling. GenAI, by contrast was positioned as complementary technology, contributing mostly to interpretive, communicative, and creative augmentation tasks. In several cases such as demand forecasting, sales promotions planning, and inventory deployment multiple technologies received comparable suitability rankings, indicating Shared Fits. These patterns suggest the importance of integrating complementary AI technologies in complex planning environments, rather than reliance on a single dominant method. Overall, the study advances the scholarship by operationalizing TTF within a multi-technology context and by conceptualizing technological fit as multidimensional rather than singular. Specifically, the framework extends conventional interpretations of fit by incorporating collaborative and supporting roles alongside primary alignments

For practitioners, the framework provides a structured decision-support tool for comparing technological options across heterogeneous task environments and for identifying potential complementarities. The suitability rankings represent relative alignment assessments derived from academic and industry experts, not observed firm-level performance effects. Accordingly, the framework offers structured guidance rather than prescriptive guarantees. Further, the study's insights on Shared Fits and technological complementarities remain limited as these do not model integration complexity, interaction effects, or governance constraints that may arise in hybrid AI systems. Future work may address this by explicitly modelling or quantifying the interaction effects and integration challenges that may emerge within hybrid AI systems.

Chapter 7. Synthesis of insights from the three phases

Though the three phases were conducted as distinct studies, they were not intended as parallel or independent investigations but were designed as analytically cumulative layers addressing progressively deeper decision questions within the AI adoption journey. These converge to form an integrated understanding of AI adoption roadmap for SMEs. This chapter presents an integrated discussion, combining the insights from the three phases of the study, outlining how the conceptual alignment, rather than empirical dependency extends the existing knowledge into a coherent adoption pathway. It discusses, how the framework supports SMEs in pursuing strategically aligned and sustainable AI-driven transformation and how they can inform both academic inquiry and managerial practice.

This chapter synthesizes the individual contributions within a broader narrative to demonstrate how they contribute to the overarching research aim of developing a strategic AI adoption roadmap for SMEs. While each phase has generated distinct insights, this chapter distils their collective value when considered as complementary layers of a coherent adoption pathway. Whilst Phase 1 produced a structured readiness profile identifying weighted capability gaps and development priorities, **the empirical results indicated organisational preparedness but did not determine which AI investments would most strongly contribute to performance improvement**. **This analytical limitation informed the design focus of Phase 2**, which introduced a performance-contingent prioritisation logic linking AI implementation enablers to multidimensional performance outcomes. However, strategic prioritisation alone does not specify where AI should be deployed at the task level. Accordingly, Phase 3 translated strategic alignment into operational guidance by evaluating task-technology suitability. **In this way, each phase addresses a different level of decision abstraction rather than refining identical constructs**, resulting in **cumulative conceptual refinement** of the adoption roadmap. Complementing this conceptual integration, continuous engagement with Pinetti served as the empirical thread ensuring contextual relevance. It ensured that each analytical layer remained grounded in practical realities. However, the industrial case did not function as a cross-phase construct validation mechanism. Its advancing digital knowledge permitted sequential execution of the framework's phases from AI readiness assessment, to aligning AI implementation enablers with performance objectives, and finally to evaluating AI-Task suitability. The integration therefore occurs at the level of decision logic where Phase 1 addresses capability feasibility, Phase 2 strategic prioritisation, and Phase 3 operational configuration.

7.1. Overview of the research questions

The initial phase centred on the diagnostic assessment of organisational readiness for AI adoption addressed the first core investigative research question that is *'How can a diagnostic-prescriptive approach be designed to identify critical resource gaps and provide actionable, context-specific guidance for effective AI adoption?'*. Drawing on empirically derived significance weightings and capability gap analysis, this phase represents the primary building block of the framework. It addresses the frequent misestimation of SMEs preparedness and establishes the essential foundation directing the subsequent phases of the adoption process. The study reconceptualises AI readiness as a weighted multidimensional construct extending the standard view of digital readiness from a mere static prerequisite and infrastructural perspective. By operationalizing readiness through empirically weighted granular AI readiness construct (comprising of dimensions, elements, and attributes), it advances a more comprehensive and structured understanding of the organisational capabilities. Whilst prior assessment models have treated readiness dimensions as homogeneous blocks, the the proposed model evaluates their relative importance through assigned significance ratings. Along with enabling a diagnostic and systematic AI readiness calculation scheme structured around four predefined readiness states, it offers a prescriptive roadmap for logical progression helping SMEs to systematically prioritise areas for improvement. It serves as an operationalizable and diagnostic tool of the AI-adoption framework that evaluates organisational feasibility conditions rather than prescribing technological choices. It therefore answers the question: '*Are we capable?*' rather than '*What should we implement?*'.

Building on this foundation, firms must subsequently calibrate implementation efforts, allocate scarce resources effectively, and reduce risks associated with misaligned transformation objectives. Therefore, Phase 2 investigated the second research question: *'How can a structured approach be developed to align transformational plans with clearly defined sustainable performance enhancement goals?'*

Although AI readiness factors (Phase 1) and AI implementation enablers (Phase 2) are conceptually distinct constructs, they operate at complementary levels within the adoption architecture. Readiness factors capture structural and contextual capacity for adoption, whereas implementation enablers represent the facilitating factors that influence performance outcomes. Therefore, Phase 2 does not modify the readiness constructs or their empirical weights established in Phase 1. Instead, it introduces a performance-oriented prioritisation logic operating within the capability boundaries through readiness assessment. The readiness assessment defines the feasible transformation space; Phase 2 examines which enabling conditions, if strengthened, are most strongly associated with targeted performance dimensions.

This analysis addresses the 'Why AI is to be pursued?' aspect of AI adoption lifecycle. Empirical findings indicate associative relationships rather than causal effects, demonstrating that AI enablers exert dimension-dependent influence across performance outcomes. It identified high-impact AI implementation enablers for each performance dimension within the concerned AI adoption context suggesting moving beyond generic adoption models. Within the broader framework, this phase functions as a strategic alignment checkpoint. It ensures that the transformational initiatives remain coherently linked with the organisation's intended performance objectives.

Once the capability awareness (phase 1) and performance-oriented prioritisation (Phase 2) are clarified, SMEs are better positioned to address the third core research question that is '*How can task-level AI adoption opportunities be identified and prioritised to guide effective decision-making in SMEs?*'. It extends the adoption logic by translating strategic intent to operational execution. Rather than refining earlier constructs, it operationalises their implications through task-level deployment analysis. Using the TTF framework, Phase 3 evaluates the suitability of specific AI applications across organisational tasks, providing structured guidance on where AI solutions may be most effectively deployed. Therefore addressing the *'What and where to deploy?'* aspect of the AI adoption lifecycle. By conceptualising AI not as a monolithic technology but as a portfolio of differentiated functional role, it proposes a layered conceptualization of fit, encompassing primary, shared, supporting, and peripheral alignments. These classifications represent expert-derived suitability assessments rather than validated performance outcomes, offering evaluative guidance for informed decision-making. The suitability model enables organisations to align technological capabilities with task characteristics, supporting progressive and resource-constrained adoption pathways.

Collectively, the three phases represent a structured progression from capability diagnosis, to strategic alignment, and ultimately operational configuration. The final artefact therefore emerges through analytical deepening across levels of decision-making, rather than empirical iteration of constructs. Each phase relied on distinct datasets, methods, and participant groups; therefore, relationships between phases should be interpreted as conceptually complementary rather than statistically dependent. This layered architecture integrates organisational preparedness, performance-oriented prioritisation, and task-level deployment into a coherent adoption roadmap for SMEs. Furthermore, expert participants primarily consisted of academics, IT managers, and consultants rather than SME operational decision-makers. Consequently, the proposed roadmap represents structured decision guidance grounded in expert judgement and analytical reasoning. Its applicability may vary depending on sectoral context, organisational maturity, data governance conditions, and implementation environments.

7.2. Overall perspective of the framework

The proposed framework presents an analytically integrated approach that combines diagnostic assessment with prescriptive guidance across multiple levels of AI adoption. AI adoption in SMEs is conceptualised not as a linear but a multi-layered decision process determined by interdependent set of multidimensional factors. Rather than assuming that success at one level automatically ensures success at another, the framework emphasises the importance of conditional coherence across stages of adoption. In this sense, it does not propose a strict causal dependency between phases. Instead, it offers a structured decision architecture that connects awareness of organisational capabilities, strategic alignment, and operational deployment. Through this structure, organisational preparedness, performance-oriented alignment, and task-level opportunity identification are brought together within a coherent roadmap for AI adoption.

At its foundation, the framework begins by examining and refining a firm's understanding of its technological, environmental, organisational, and human capabilities through a structured readiness assessment. Readiness is not treated as a static checklist of prerequisites, but rather as an evolving capability profile that reflects the organisation's preparedness at a particular moment in its adoption journey. The capability structure follows the TOE framework, extended with an explicitly defined human dimension. This addition responds to limitations observed in earlier readiness models, where human-related factors were typically embedded within broader organisational constructs, often obscuring their distinct influence on AI adoption outcomes. By separating the human dimension analytically, the framework allows for the independent examination of factors such as employee expertise, perceptions, behavioural responses, cognitive readiness, and the capacity for effective human-AI interaction. Recognising how employees understand, engage with, and adapt to AI systems highlights that technological success depends not only on infrastructure and strategic direction but also on human competence, acceptance, and active participation. This distinction serves primarily to enhance analytical clarity rather than to imply that human factors exist independently of organisational structures, thereby improving conceptual transparency within the readiness evaluation.

In addition, the framework decomposes readiness into more granular attributes, allowing capability gaps to be identified with greater precision. Rather than treating readiness dimensions as uniform categories, the model differentiates the relative importance of their micro-level components through empirically derived significance weightings. These weightings are intended to guide prioritisation rather than to predict adoption outcomes. In doing so, the readiness assessment moves beyond a purely descriptive exercise and becomes a structured diagnostic tool that can inform capability development efforts. As a result, the readiness phase offers organisations targeted guidance for strengthening capabilities in line with the relative influence of different readiness components.

Building on this diagnostic foundation, the second phase examines how existing capabilities can be aligned with intended performance improvements. While readiness establishes the boundaries of what is realistically feasible, this phase introduces a performance-contingent prioritisation logic within those limits. Through cross-context analysis, the relationship between AI implementation enablers and multiple performance dimensions is explored, revealing both consistent patterns and context-specific variations. This perspective enhances the practical relevance of the framework by helping SMEs identify which enabling conditions are most strongly associated with particular performance outcomes.

Rather than promoting uniform investment strategies, the analysis demonstrates that the influence of AI enablers varies across performance dimensions and organisational contexts. This insight shifts the focus of transformation planning away from technology-driven adoption and toward a more performance-oriented form of strategic calibration. By aligning transformation initiatives with clearly defined objectives, the framework helps reduce the risks associated with misaligned priorities and inefficient resource allocation. In doing so, it encourages SMEs to move beyond viewing AI adoption as an abstract technological ambition and instead approach it as a strategically grounded instrument for performance improvement.

The third analytical layer extends this perspective further by translating strategic priorities into operational deployment considerations through the principles of Task–Technology Fit (TTF). Applying this logic within the complex setting of Sales and Operations Planning (S&OP) illustrates the framework's applicability in interdependent organisational environments. By focusing on functional-level planning and decision-making tasks, this phase enhances both the relevance of the analysis and its practical interpretability. Within this layer, AI is conceptualised not as a single, uniform technology but as a portfolio of differentiated yet complementary capabilities. The framework's layered interpretation of fit offers a more nuanced understanding of how value may be generated, categorising AI–task relationships into primary alignment, shared fit, supporting contribution, and peripheral relevance. These categories represent expert-informed assessments of technological suitability rather than empirically verified performance outcomes. As such, they provide structured guidance while avoiding deterministic claims about implementation success. This differentiation supports more efficient allocation of resources and encourages progressive, capability-building adoption pathways that reflect the constraints typically faced by SMEs.

The progression implied by the framework encourages reflection and recalibration rather than mechanical iteration. Although SMEs may revisit earlier assessments as organisational capabilities evolve, the framework does not assume automatic feedback loops or continuous iterative cycles between phases. Instead, it offers a coherent analytical structure that allows decision-makers to move from capability awareness to strategic prioritisation and ultimately toward operational execution. Within this architecture, each phase operates at a different level of decision-making abstraction. Limitations identified at earlier analytical stages may inform subsequent decisions, but they do not rigidly determine them. For instance, limited readiness may reduce the range of strategically viable initiatives, while poorly aligned enabler prioritisation may diminish the potential benefits of otherwise appropriate task-level deployments. Consequently, the proposed roadmap framework (illustrated in Figure 7.1) should be understood as a system of analytically interconnected layers rather than as a linear causal sequence, where readiness informs strategic prioritisation and prioritisation, in turn, guides reasoning about operational deployment.

Through this structure, SMEs are supported in reducing adoption uncertainty, allocating resources more effectively, and aligning AI initiatives with long-term performance objectives. The framework therefore contributes a decision-oriented architecture that integrates diagnostic understanding, strategic reasoning, and operational guidance into a unified yet analytically modular AI adoption pathway.

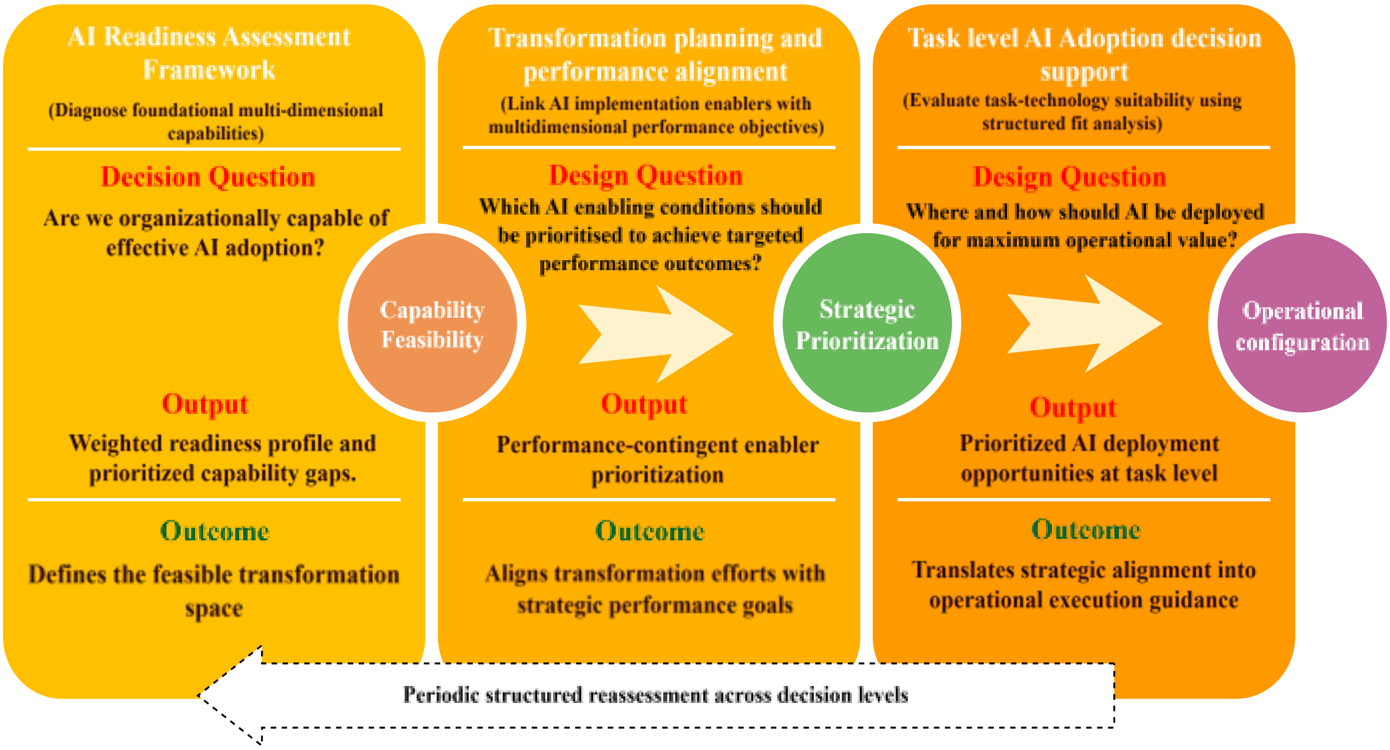


Figure 7.1: An integrated adoption roadmap for SMEs

7.3. The role of the industrial partner

As explained above, the industrial partner's operational environment played a central role in shaping the relevance, scope and foundation of the research. It provided the detailed insights into its structure, processes, resource constraints, and performance objectives. Its resource constrained environment, operational variability and evolving strategic priorities offered a practical operational context for aligning the conceptual developments with the realities of SME industry. The continuous engagement functioned both as a source for gaining contextual insights and for empirical validation of proposed ideas. This real-world setting helped with the interpretive investigation of the results with regard to readiness conditions along with contextual alignment and relevance.

An initial evaluation of organisational processes and infrastructure established a grounded understanding of its existing state and requirements. This defined the research starting point and subsequently guided in addressing its requirements. For instance, DT context for analysing the impact of AI enablers on performance dimensions was shaped by the company's ongoing transformation strategy. Also, the choice of S&OP for AI-task suitability analysis was primarily determined by organisational access and industrial collaboration conditions. Accordingly, the case study should be interpreted as a demonstrative application designed to evaluate the operational applicability of the framework rather than as a framework-prescribed identification of a priority adoption domain.

Throughout the research, managerial insights and other useful operational data from the company also contributed towards the development of conceptual foundation. It further provided a crucial setting for empirical testing of the theoretical assumptions and framework's application. For instance, it was one of the exploratory use cases through which the readiness model's diagnostic capability and practical relevance were evaluated. This way, its capability to distinguish between the different levels of preparedness, highlight capability gaps, and generate actionable insights was critically evaluated. Thus, by situating the theoretical contributions within organisational realities and validating it through applied testing, the partnership ensured theoretical robustness and empirical reliability of the coherent model.

7.4. Theoretical and practical contributions

The three phases of the study collectively reconceptualizes the concept of AI adoption from a discrete managerial decision to a multi-layered sequential process involving multiple inter dependant phases. These phases both independently and collectively advance the theoretical knowledge, addressing the existing fragmented, impractical and contextually insensitive perspective found in AI adoption scholarship.

C1: Dynamic and process-oriented approach for AI adoption

The existing models conceptualize AI adoption as a static decision, reducing it to a linear cause and effect relationship. They offer a fragmented approach for assessing distinct facets of AI adoption like the identification of factors impacting AI adoption, exploration of organisational readiness for AI adoption, the advantages of AI adoption etc. Although, some have proposed holistic frameworks for effective AI adoption, these remain conceptual and lack empirical grounding (as detailed in section 2.3.3). Consequently, they provide limited guidance for understanding AI adoption as a dynamic, multi-layered capability-building process.

In response, the proposed three-layered, cross-level capability transformation roadmap advances a sequential and interdependent developmental trajectory rather than a single adoption decision. It offers a more holistic, theoretical account of how SMEs progress from foundational preparedness, to capability alignment and effective task-level deployment. In contrast to existing AI adoption studies that predominantly emphasise antecedent identification, this framework shifts the analytical focus toward structured capability progression and transformation sequencing. Rather than treating AI adoption as a static decision event, it reconceptualizes into a staged, progressively conditioning capability-building phases linking readiness formation, goal-aligned orchestration, and task-level deployment. Each empirically examined phase is embedded within a coherent developmental trajectory, collectively constituting a conceptual refinement that integrates cross-level capability formation into a staged transformation logic.

Furthermore, it establishes a conceptual link between strategic alignment and operational feasibility to address the persisting gap in the adoption research. It frames AI adoption as a dynamic process in which readiness develops organisation's capacity to identify, assimilate, transform, and use the capabilities. The understanding of AI enablers impact on performance outcomes function as an alignment mechanism, and AI-Task suitability provides help in operationalizing intended performance outcomes. This linkage addresses the stativity of existing adoption models and introduces dynamic and process-oriented approach for AI adoption.

C2: Micro-level decomposition and Weighted AI readiness architecture

As presented in table 2.7 and explained in section 2.3.3, prior readiness frameworks have treated readiness dimensions as homogeneous blocks. They lack explanatory depth regarding the influence and contribution of the different elements and their attributes to overall readiness. They further remain descriptive, lacking an operationalizable assessment scheme. Consequently, the proposed readiness assessment (Phase 1) while aligning with the existing scholarship on AI readiness and its multidimensional nature, extends the construct by proposing an additional level of granularity. It introduces explanatory depth and advances a structured understanding of the key organisational capabilities by defining them to their micro-level attributes.

The framework further advances computational assessment capability by explicitly accounting for the differentiated impact of individual elements in shaping organisational readiness states. It introduces a systematic AI readiness calculation scheme grounded in empirically estimated low-level attributes and elements weights within each dimension. Beyond providing ordinal classification of firms across readiness stages (like the maturity models), the proposed architecture enhances diagnostic precision by analytically differentiating between the relative contribution of individual attributes. Thereby, it along with enabling a more granular and actionable assessment, can help organisations with formulation of a clear roadmap for progression toward higher levels of AI readiness.

C3: Goal-aligned and Context-sensitive AI adoption logic

The existing literature linking AI adoption with business performance outcomes remain generic in discussing the impact of AI adoption on organisational performance. They assume that the AI enablers exert generalized effects on performance dimensions, whereas this study challenges the traditional 'AI improves performance' assumption. The phase 2 of the study empirically analysed the impact of diverse AI enabler influence across economic, operational, governance, social, and innovation performance dimensions. It demonstrated that AI enablers do not exert uniform influence. Instead, it displays dimension-dependent variability. Whilst contingency theory highlights the key role of contextual alignment for performance enhancement, this study advances the discourse by empirically specifying differentiated enabler–performance mappings. It supports a goal-aligned adoption logic grounded in empirical heterogeneity rather than theoretical possibility alone. In this way, the study advances adoption theory by showing that sustainable performance improvement requires differentiated pathways, aligned with the specific intended outcomes. Building on a systematic assessment of organisational capabilities, this phase argues that capability enhancement should be selectively configured to match specific strategic goals. Thereby reframing AI adoption as a strategic and context-sensitive capability orchestration process rather than a homogeneous progression.

C4: Task-level decision support framework

Following the strategic enhancement of organisational capabilities aligned with differentiated performance objectives, the third layer of the proposed roadmap introduces task-level decision support for AI adoption within complex organisational processes. Existing technology suitability frameworks primarily conceptualize relevant task dimensions for assessing technological fit. However, they remain largely static, focusing on one-to-one task–technology relationships and under-operationalised, offering limited guidance for practical implementation. Moreover, these frameworks do not account for the simultaneous deployment of multiple AI applications embedded within complex decision-support environments.

Accounting for that, phase 3 advances the dyadic task-technology alignment discourse by empirically demonstrating coordinated AI capability configuration within a broader decision-support ecosystem. In doing so, it reconceptualizes technological deployment as a coordinated configuration of complementary and enabling AI functionalities that collectively support planning performance. The core contribution lies in reconceptualizing 'fit' as a multidimensional construct encompassing functional alignment, contextual compatibility, and inter-technology complementarity. Thereby shifting TTF from one-to-one alignment towards an ecosystem-level configuration logic. Beyond primary task-technology alignment, it highlights the critical role of collaborative and enabling functions, emphasizing that effective AI adoption in complex processes depends not only on direct task substitution but also on supportive and integrative technological roles. Ultimately, it advances the adoption theory by shifting the analytical lens from 'Which technology would be the best fit for the task?' to ' What AI configuration would best support the complex organisational work?'.

Practical contribution

From a practical standpoint, this staged perspective underscores that AI adoption in SMEs should not be regarded as a discrete or isolated investment in technology. Instead, it must be approached as a staged transformation journey, progressing through interdependent phases. Each of these phases contributes specific tools and insights to reduce risks, align resources with organisational needs, and enhance the likelihood of sustainable impact. For instance, the empirically assigned significance ratings to the identified comprehensive set of capabilities enable organisations to more accurately recognize their roles and systematically prioritise areas for improvement. For industry professionals, the proposed AI readiness model provides an operationalizable and diagnostic tool to assess existing AI capabilities in depth and to identify adoption-related challenges with greater precision. Beyond diagnosis, the framework also introduces an iterative mechanism. It mitigates uncertainty and supports a well-monitored, continuous, and structured improvement process. By embedding this iterative orientation, the model equips SMEs with an adaptable, informed, and strategically aligned pathway to prepare for and advance along the AI adoption journey. On the other hand, the findings from the phase 2 provide SME leaders with a structured and actionable framework for strategically navigating their AI transformation journeys. By identifying the influential enablers for each of the performance dimensions, the model allows managers to calibrate their implementation efforts. It can help allocate scarce resources more effectively, and avoid risks associated with misaligned goal-setting or blanket adoption strategies. This iterative and dimension-sensitive approach equips practitioners to maximize performance gains along with maintaining flexibility to adjust to evolving business contexts. Lastly, AI-task suitability offers an actionable guidance for prioritizing specific technologies and designing hybrid AI configurations for maximum performance impact. Importantly, this task-level, requirement-driven logic also allows the approach to be extended to other domains, provided that context-specific adaptations, such as redefining task structures and recalibrating evaluation parameters are undertaken.

Taken together, this contribution offers a decision-making utility for practitioners, reinforcing the value of adopting a performance-aligned and context-aware approach to AI adoption in SMEs. This phase-specific support for the adoption journey holds relevance beyond firm level implications, for the policymakers and SME support institutions. They can develop more targeted interventions by recognising that AI adoption unfolds through distinct stages. For example, during the diagnostic phase, resources may be directed towards supporting readiness assessments. This can be followed by initiatives aimed at strengthening skills and organisational capabilities, alongside incentives that encourage collaboration within broader innovation ecosystems to facilitate implementation. Viewed in this way, the framework provides guidance not only for managerial decision-making but also for policy design. It highlights the importance of support mechanisms that are tailored to the evolving needs of SMEs, rather than relying on generic measures, thereby enabling a more strategic and context-sensitive approach to AI adoption.

Chapter 8. Conclusion, limitation and future work

This chapter concludes the thesis by situating the findings within the broader discourse on AI adoption in SMEs. It presents a synthesizes of the insights generated across the three empirical studies, and clarifies the boundaries within which the results should be interpreted. It also outlines limitations arising from methodological and contextual constraints and identifies directions for future research that may further advance understanding of structured AI adoption pathways for SMEs.

8.1. Conclusion

This work investigates how SMEs can effectively prepare for and navigate the complex process of AI adoption. SMEs, constituting almost 99% of the European market, are considered the backbone of their economy. Yet, their progression towards digital transformation remains comparatively slow, typically constrained by limited resources, strategic uncertainty and insufficient decision support mechanisms for technology adoption. The current body of research on AI adoption among SMEs remains somewhat dispersed. Much of the literature is conceptual and provides limited guidance for organisations seeking to make practical adoption decisions. Addressing this gap, the present thesis develops and empirically examines an integrated framework for AI adoption structured around three analytically connected phases: the assessment of AI readiness, the prioritisation of context-specific enablers, and the evaluation of task–technology fit. The central premise of the study is that successful AI adoption in SMEs is not determined solely by isolated technological choices. Rather, it emerges from the alignment between organisational preparedness, strategic priorities, and the operational suitability of technological applications.

The first empirical phase applied a readiness model grounded in the TOEH framework, incorporating empirically derived weightings across dimensions, elements, and micro-level attributes. The analysis revealed notable differences in the relative importance of individual readiness components and allowed SMEs to be distinguished according to varying levels of adoption maturity. These results suggest that organisational preparedness should be viewed as a heterogeneous configuration of capabilities rather than as a single uniform prerequisite for adoption. By assigning relative weights to the underlying attributes, the model enhances diagnostic clarity, enabling firms to identify capability gaps and prioritise capability development in a more structured manner. At the same time, the model assesses relative preparedness rather than predicting the likelihood of successful adoption or prescribing particular AI investments.

To connect organisational capabilities with broader transformation objectives, the second phase examined how AI implementation enablers relate to multiple performance dimensions. The survey-based analysis identified associative relationships between particular enablers and different performance outcomes, although it did not establish direct causal links. These findings challenge the often-implicit assumption that the introduction of AI automatically leads to improved organisational performance. Instead, they underline the importance of a context-sensitive approach in which AI investments are deliberately aligned with clearly defined performance objectives.

In the third phase, this strategic alignment was explored further from an operational perspective through the application of the TTF framework. The analysis evaluated the suitability of various AI technologies for supporting planning activities within a S&OP environment. The findings indicated that AI applications can assume different functional roles within organisational processes, which may be described as primary, shared, supporting, or peripheral fits. This perspective moves beyond viewing AI as a single, uniform technology and instead frames it as a configurable set of complementary capabilities. In complex planning settings, hybrid combinations of technologies appear particularly valuable, as multiple tools may jointly support decision-making processes. Nevertheless, these classifications reflect expert-informed assessments of suitability rather than empirically validated implementation outcomes.

Taken together, the three phases form a layered adoption roadmap that moves from capability diagnosis to strategic prioritisation and, ultimately, to operational deployment considerations. The framework suggests that meaningful and sustainable AI adoption in SMEs depends on three interrelated conditions: a sufficient level of organisational readiness, alignment between adoption initiatives and performance objectives, and coherent implementation at the operational level. Within this study, integration occurs analytically across different levels of decision-making rather than through iterative empirical testing of the phases themselves. In this sense, the framework contributes a structured decision architecture that links these perspectives into a coherent multi-level logic for AI adoption.

From a practical standpoint, the framework offers SMEs and policymakers a systematic way of reducing uncertainty and supporting staged planning for AI-driven transformation. Its primary purpose is to inform decision-making before implementation takes place, rather than to provide empirically verified evidence of realised performance improvements. Accordingly, the framework should be understood as an advisory tool that helps organisations structure their reasoning and planning around AI adoption. Its main contribution lies in organising the decision process in a coherent and transparent manner, rather than in guaranteeing successful adoption outcomes.

Within the thesis, validation is understood as a multidimensional evaluation rather than outcome verification following full-scale implementation. The framework demonstrates validity as a structured decision-support approach for AI adoption in SMEs. Validation evidence emerges collectively across the three studies. For instance, analytical validity is supported in phase 1, where the weighted readiness model demonstrated the ability to differentiate SMEs according to adoption maturity. The observed association between readiness profiles and adoption progression indicates that the framework captures meaningful variations in organisational preparedness. Whereas, contextual validity is established in phase 2 through the identification of dimension-specific relationships between AI implementation enablers and performance outcomes. The findings indicate that the prominence of key enablers differs between operational and customer-oriented transformation contexts. This variation supports the framework’s central assumption that decisions regarding AI adoption should be shaped by the specific organisational context rather than guided by a universal set of prescriptions. Operational feasibility is further explored in Phase 3 through the application of the TTF model within a S&OP environment. By systematically linking organisational tasks with appropriate AI application types, the analysis demonstrates how broader strategic considerations surrounding adoption can be translated into more practical guidance for implementation. Collectively, these findings indicate that the proposed framework demonstrates validation in terms of analytical coherence, contextual sensitivity, and practical applicability. However, validation should be understood as demonstrating decision-support effectiveness rather than causal performance optimisation, which would require longitudinal implementation studies beyond the scope of this research.

8.2. Limitations and Future works

Whilst this research offers an organised and analytically integrated framework for AI adoption in SMEs, its limitations should also be recognized to inform the directions for future research. Recognizing these boundary conditions helps clarify which conclusions are firmly supported by the empirical evidence and where interpretations should remain more tentative.

Across the different empirical phases of the study, data collection was based on relatively small yet carefully selected samples, a situation that frequently arises in research involving SMEs due to practical access constraints. As a result, certain limitations emerge, particularly regarding the broader generalizability and scalability of the findings. For example, in Phase 1 the proposed model was applied within real industrial contexts in order to evaluate its practical relevance and applicability. But the results cannot be generalized as the sample size of sixteen SMEs was relatively small. Its broader application across a larger group of SMEs, varying organisational settings and across diverse industry contexts is necessary to evaluate its generalizability. Similarly, phase 2 relied on the survey data that was collected from Italian SMEs that had initiated AI-related initiatives in operations and customer experience management. Engaging SMEs in research proved challenging as their participation constrained by issues such as limited willingness to disclose sensitive organisational information and low response rate from the industry experts.

A more pronounced limitation was the temporal restriction inherent to the study design. Since, the research were conducted within a defined period, the insights for the three phases that are AI readiness, enabler prioritisation, and task suitability were captured within a specified time. The findings reflect the conditions surrounding AI adoption during a specific period of investigation, thereby providing a cross-sectional perspective rather than tracing developments over time. As a result, the study captures a snapshot of organisational readiness and adoption factors within the defined research window rather than documenting a longitudinal process of transformation. Future research could build on these insights by conducting longitudinal analysis to examine how the relative importance of these factors evolves as organisations gain greater experience with AI technologies. Evaluating the model across successive stages of adoption would also offer stronger evidence regarding its robustness and its capacity for iterative application. While such limitations are typical in empirical studies involving SMEs, they may nevertheless constrain the scope of insights that can be drawn. The application of advanced analytical methods, including the Random Forest algorithm, helped strengthen the reliability of the findings despite the data constraints. Nonetheless, the relatively small sample size limits the extent to which the results can be generalised statistically. Consequently, while the findings provide meaningful patterns and predictive insights, they are somewhat indicative. Future research using larger, more diverse, and cross-sectoral datasets can further enhance the model's predictive validity and scalability across different organisational contexts.

Further, the empirical grounding of the research was partially shaped by the industrial collaboration context, introducing sectoral specificity. To mitigate this limitation, phase 1 applied the proposed readiness model across SMEs from manufacturing and services sectors at three different stages of AI adoption (that are exploration, exploration to implementation and initiated implementation). However, multiple sectors like construction, agriculture and logistics etc. can also be analysed in future to determine the universality and scalability of the model. Phase 2 also analysed the AI enablers impact on performance dimensions across two transformation contexts (processes & operations enhancements and customer service improvements). However, future studies can broaden the scope to multiple contexts (such as product development and business model optimization etc.) for more generalized findings. Similarly, phase 3 also addressed this challenge by synthesizing the S&OP tasks from multiple production environments (such as MTO, CTO, MTS and ETO etc.). This helped analysing the capabilities of AI application for a generalized production environment rather than a specific one.

A key boundary condition concerns the nature of empirical inputs. Several analytical stages relied on expert judgement obtained primarily from academics, IT managers, and consultants rather than SME employees or manufacturing practitioners directly implementing AI systems. Consequently, the results reflect informed expert evaluation of technological suitability rather than direct organisational adoption behaviour. Future research should incorporate practitioner-based validation and implementation case studies to examine real-world deployment outcomes.

With regard to the validation of the framework, the empirical studies relied upon the surveys reflecting managerial perceptions. The validation presented in this thesis reflects evaluation of framework usability, analytical robustness, and operational applicability rather than measurement of objective performance outcomes. Because empirical investigations were conducted within bounded temporal and organisational settings, the findings represent evidence of decision-support capability rather than longitudinal performance causality. Finally, following full organisational implementation. Future research employing extended implementation studies and objective performance metrics could further strengthen outcome-based validation.

Though these highlighted limitations suggest the delimitation of the generalization and temporal scope of the study, these do not undermine the overall contribution of the study. These underscore the complexity of the research area and context (AI adoption in SMEs) along with highlighting the opportunities for further exploration within this area. It points out that the effectiveness of the proposed framework can be enhanced through a broader, cross industry and cross context deployment and through objective validation mechanisms.

Furthermore, the study captures AI adoption conditions within a defined research period, representing a cross-sectional snapshot rather than a longitudinal transformation trajectory. Assessing the model's performance across multiple adoption cycles would provi de stronger evidence of its robustness and iterative applicability. Though these constraints are common in empirical studies of SMEs, but may limit the breadth of insights obtained. The use of advanced analytical techniques such as the Random Forest algorithm enhanced the robustness of results under constrained data conditions. However, the modest sample size restricts the statistical generalizability. Consequently, while the findings provide meaningful patterns and predictive insights, they are somewhat indicative. Future research using larger, more diverse, and cross-sectoral datasets can further enhance the model's predictive validity and scalability across different organisational contexts.

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Appendix

Appendix 1: Questionnaire for assessing Firm's capabilities related to AI adoption

Table 10.1: Questionnaire for assessing Firm's capabilities related to AI adoption

Capability	Organisational state (Lowest state 1 to 5 Highest state)				
Organisational ability to analyse and choose the right AI technology	No capability at all	Minimal capability	Moderate capability	High capability	Expert
Organisational knowledge about the impact of AI systems on business processes	No knowledge at all	Limited knowledge	Moderate knowledge	Considerable knowledge	Extensive knowledge
Ability to formulate clear technology management strategies for the implementation of AI	No capability at all	Minimal capability	Moderate capability	High capability	Expert
Ability to analyse the concerned technology in terms of compatibility	No capability at all	Minimal capability	Moderate capability	High capability	Expert
Ability to analyse the concerned technology in terms of technological maturity	No capability at all	Minimal capability	Moderate capability	High capability	Expert
Ability to analyse the concerned technology in terms of impact on organisation's daily business	No capability at all	Minimal capability	Moderate capability	High capability	Expert
Ability to analyse the concerned technology in terms of ROI	No capability at all	Minimal capability	Moderate capability	High capability	Expert
Ability to develop performing plans to control organisation's records and information	No capability at all	Minimal capability	Moderate capability	High capability	Expert
Data available across different operational layers	Not available	Minimal availability	Moderate availability	Readily available	Extensively available
Flow, smoothness and reliability of data across operational layers	Significant disruptions	Noticeable inefficiencies	Adequate but could be improved	Good with few noticeable issues	Consistently excellent
Employees access to the relevant and quality data	No access at all	Limited access	Moderate access	Good access	Excellent access
Awareness about the cyber and data security	No awareness at all	Limited awareness	Moderate awareness	Considerable awareness	High/ extreme awareness
Organisation capabilities to deal with security concerns	Not capable at all	Minimal capability	Moderate capability	Highly capable	Extensive/ expert capability
Has the organisation identified or has the capability to identify requirements regarding required advanced communication models?	Not capable at all	Minimal capability	Moderate capability	High capability	Expertly identified
Do current IT infrastructure include or capable to support advanced computing models?	Not capable at all	Minimal support	Moderately supportive	Highly supportive	Completely/ Perfectly supportive

Have the organisation identified or exhibit required network connectivity within business for AI?	Not at all	Minimal support	Moderately supportive	Highly supportive	Completely/ Perfectly supportive
Has the organisation identified or has the capability to identify the services that will incorporate AI?	Not capable at all	Minimal capability	Moderate capability	Highly capable	Extensive/ expertly identified
Has the organisation identified or has the capability to identify the information networks involved with implementation, operation and management of AI?	Not capable at all	Minimal capability	Moderate capability	Highly capable	Extensive/ expertly identified
Has the organisation developed or has ability to develop the technology sustainability map for AI?	Not capable at all	Minimal capability	Moderate capability	Highly capable	Extensive/ expertly developed
Leadership commitment and support for AI adoption in terms of strategic assistance, funding and cooperation	Not convinced at all	Skeptical	Support initiative but still unclear	Commitment subjected to expert analysis	Highly committed and convinced
Senior management and leadership's understanding of AI technologies	No understanding at all	Layman understanding	Theoretical knowledge about AI technologies	Experienced	Expert
Senior management and leadership's clarity in AI vision and strategy	No strategy at all	Unclear strategy	Somewhat clear	Clear but not defined vision	Clear and strategic vision
How well aligned and streamlined are the current operating systems?	No alignment at all	Misaligned with frequent issues	Aligned with occasional issues	Aligned but still require refinement	Very well aligned
Has integration requirements of desired AI systems been evaluated?	No evaluation at all	Pre-evaluation phase	Evaluation phase	Evaluated with some unclarity	Completely evaluated
What is the integration capability of the current system with AI systems?	Not capable at all	Require drastic improvements	Moderate integration requiring refinements	High integration capability	Extensive and seamless capability
What is the level of commitment to monitoring, accepting change and continuous improvement?	Non- committed	Non committed but accepting	Committed but hesitant	Committed and receptive to improvement	Flexible, compliant and versatile
What is organisation's attitude towards new technologies including ability to exploit technologies?	Resistive attitude	Non resistive but non-AI friendly attitude	AI friendly attitude	AI friendly and exploratory attitude	Friendly and exploiting attitude
Is the organisation capable of taking initiative to develop an AI adoption strategy?	Inexpert and resistant	Inexpert and reluctant	Non-professional	Skilful but inexperienced	Adept and experienced
How ready and capable is the organisation to manage change?	Novice	Inexperienced but committed	Less experienced but exploratory	Experienced and able	Expert and exploiting
How well is the hierarchy of the organisation defined?	No structure at all	Ill-defined structure	Horizontal structure	Hierarchal but without clear definition	Well defined hierarchy
How clear are the roles and responsibilities defined across the hierarchy?	Not defined at all	Vaguely defined	Provisionally defined	Well defined but demand flexibility	Clear roles and responsibilities

How well defined are the cooperation & interaction points among organisation units?	Non digitized interaction mediums	Digitized but non recorded interaction	Recorded but difficult to trace interactions	Traceable and recorded interactions	Sophisticated and advanced interaction mediums
Has the organisation carried out financial feasibility analysis for AI adoption?	No feasibility analysis	Preliminary feasibility phase	Initial feasibility analysed	Final feasibility covering initial implementation	Final feasibility covers implementation, operation and management
How would you describe the financial capacity of organisation to cover all expenses associated with the implementation, operation and management of AI technology?	Lack initial financial capability	Acquiring financial capability	Acquired initial financial capability	Financially capable but constrained	No financial constraints
Do organisation possess capabilities to carry out or has conducted an efficient competitor analysis?	No capability at all	Informal and static analysis capabilities	Formal and dynamic analysis capabilities	Advanced analysis capabilities	Strategic analysis capabilities
Is organisation aware of the possible competitor threats with regard to leveraging AI?	No knowledge at all	Limited knowledge	Moderate knowledge	Considerable knowledge	Extensive knowledge
Will concerned AI technology be compatible with the existing values of the organisation?	No compatibility at all	Slightly compatible	Moderately compatible	Very compatible	Completely compatible
Will concerned AI technology be able to uphold the ethical and business values?	Not at all confident	Slightly confident	Moderately confident	Very confident	Completely confident
Will concerned AI technology abide by the industrial regulations?	Not at all confident	Slightly confident	Moderately confident	Very confident	Completely confident
Is Govt. supporting the initiative of AI adoption for SME's?	Not at all supportive	Slightly supportive	Moderately supportive	Very supportive	Completely supportive
Is Govt. providing financial or other incentives for AI adoption?	No incentives at all	Modest incentives	Moderate incentives	Sizeable incentives	Significant incentives
Do organisation possess capabilities to carry out customer analysis?	No capability at all	Informal and static analysis capabilities	Formal and dynamic analysis capabilities	Advanced analysis capabilities	Strategic analysis capabilities
Do organisation has a strategy to assess the customer satisfaction and AI acceptance.	No strategy at all	Minimal strategy	Moderate strategy	Well-developed strategy	Comprehensive strategy
Is there any mechanism or strategy to determine the impact of AI technologies on the customers?	No strategy at all	Minimal strategy	Moderate strategy	Well-developed strategy	Comprehensive strategy
Do organisation possess capabilities to carry out efficient market analysis?	No capability at all	Informal and static analysis capabilities	Formal and dynamic analysis capabilities	Advanced analysis capabilities	Strategic analysis capabilities
Is organisation able to determine potential market threats and opportunities with regard to leveraging AI for business growth?	No knowledge at all	Limited knowledge	Moderate knowledge	Considerable knowledge	Extensive knowledge
Are suppliers willing to collaborate and coordinate with regard to AI?	Not willing at all	Minimal willingness	Somewhat willing	Quite willing	Extremely willing

Are collaborators willing to collaborate and coordinate with regard to AI?	Not willing at all	Minimal willingness	Somewhat willing	Quite willing	Extremely willing
Do Supplier's systems have capability to integrate with AI systems?	No compatibility at all	Slightly compatible	Moderately compatible	Very compatible	Completely compatible
Do collaborator's systems have capability to integrate with AI systems?	No compatibility at all	Slightly compatible	Moderately compatible	Very compatible	Completely compatible
How aware are the employees of AI technologies?	Unconscious	Pre-consciousness	Conscious	Advanced knowledge	Expert knowledge
How involved are the employees in strategic planning?	Completely disengaged	Involvement for basic needs	Individual feedback and viewpoints	Inclusive engagement	Strategic engagement
Do the employees perceive AI useful for the business?	Negligible	Low usefulness	Moderate usefulness	High usefulness	Extremely useful
Do the employees perceive adoption of AI as a threat to their job (job insecurity)?	Negligible	Low insecurity	Moderate insecurity	High insecurity	Extreme insecurity
Is there any recruitment strategy to hire AI literate employees?	No strategy at all	Need based recruitment	Precision recruitment	Predictive recruitment	Strategic recruitment
Do organisation have skills and expertise to implement and manage AI?	Inadequate	Unaccomplished skills	Limited skills	Competent	Expert
Are there any training and other activities for skill development?	No training at all	Insufficient	Occasional specialized training	Regular specialized training	Strategic training
Is there any clear strategy to upskill employees with regard to AI?	No strategy at all	Classic planning	Sequential approach	Adaptive approach	Agile approach

Appendix 2: Questionnaire for assessing AI enablers impact on performance dimensions

Section A: General Information

1. Name of your organisation: ___________________________

2. Industry type:

- Manufacturing
- Services
- Retail

- Others ________

4. Position/Role:

- Owner
- Manager
- Technical Lead
- Other ________

5. Have you implemented AI in:

- Business Processes & Operations
- Customer Experience
- Both
- Other________

Section B: Impact Strength Mapping

Please rate how strongly you believe each factor influences the following performance dimensions for your AI adoption context. Use the scale below for each matrix: Same value can be assigned to more than one dimensions.

1 = No Impact   2 = Low   3 = Moderate   4 = High   5 = Very High

Following table presents detailed performance metrics relevant to the performance dimensions.

Sustainable Business Performance dimensions	Metrics
Economic	Return on investment
	Cost savings
Operational performance	Enhanced quality
	Operational efficiency
Governance	Enhanced and strategic decision-making

	Regulation and compliance
Social performance	Employee well-being
	Customer satisfaction
Innovation	Novel solutions
	Novel tech utilization

AI Enabler	Economic	Operational	Governance	Social	Innovation
Technology infrastructure					
Data management					
Interoperability					
Security					
Workflow alignment					
Cross-functional co-operation					
Change management strategy					
Sustained financial capability					
Compatibility with external system					
Customer & market conformation					
Employees' skill level					
Employees' experience					
Employees' in strategic planning					
Employees' perception about AI					