AI Readiness in Organisations: A Systematic Literature Review and the TOP-L Framework Development

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Abstract: The growing importance of artificial intelligence (AI), particularly Generative AI (GenAI), is opening up significant potential for corporate knowledge management (KM) and knowledge-intensive work. To remain competitive, organisations must effectively implement these technologies. AI readiness, understood as preparedness and capacity to successfully implement and use AI in a value-creating way (Ali & Khan, 2025; Alsheibani et al., 2018), has therefore become a critical concept. However, the underlying factors remain contested, and existing research is fragmented, with a strong focus on technical and environmental aspects, while human factors and organisational learning (OL) are underrepresented. In addition, practical assessment tools are still limited, particularly for small and medium-sized enterprises (SMEs). To address this gap, this paper presents a systematic literature review of AI readiness. A total of 34 frameworks and assessment instruments were analysed to identify key factors and evaluate existing approaches. Building on the socio-technical TOP framework (Kretschmer & Orth, 2025), the Technology-Organisation-People-Learning (TOP-L) framework is developed, integrating OL as a dynamic capability for continuous adaptation. The study identifies 372 AI readiness factors and synthesises them into the TOP-L framework consisting of four dimensions and 20 factor clusters, thereby laying the foundation for a practical assessment approach, particularly suited for SMEs.

Keywords: Artificial intelligence (AI), AI readiness, Corporate knowledge management (KM), SME, Socio-technical framework

1. Introduction

Knowledge is widely acknowledged as a key strategic resource and a core enabler of organisational performance, innovation, and resilience (Nonaka & Takeuchi, 1995; Kohl et al., 2016; Duchek, 2020). Against this backdrop, the growing importance of artificial intelligence (AI), particularly Generative AI (GenAI), is fundamentally changing how knowledge is created, structured, and governed within organisations (Kretschmer & Orth, 2025). As AI technologies increasingly permeate knowledge-intensive work, they influence organisational processes, decision-making, and collaboration. In this context, knowledge management (KM) is gradually shifting from a primarily repository-based function towards a more dynamic, AI-supported capability that enables continuous knowledge creation and use.

For organisations, using AI and GenAI is becoming a necessity to remain competitive and drive future growth. This is reflected in current investment priorities, with 74% of business leaders ranking AI among their top three technology investments for 2025 (Capgemini Research Institute, 2025). However, despite this strong commitment, many organisations struggle to translate AI potential into tangible value. Only 26% report having the capabilities required to move beyond pilot projects (de Bellefonds et al., 2024), while scaling and governance remain persistent challenges (Capgemini Research Institute, 2024; World Economic Forum, 2025).

These developments indicate that AI adoption is not merely a technological issue but requires broader organisational capabilities. In particular, organisational and human factors such as unclear roles, limited resources, insufficient competencies, and low user acceptance continue to hinder the integration of AI into knowledge processes (Märkel & Lundborg, 2020; BMWi, 2021; Bughin et al., 2018). This is especially evident in SMEs, which often lack structured approaches and formalised KM systems.

In this context, the concept of AI readiness has gained increasing importance. It refers to the preparedness and capability of an organisation to implement and use AI in a value-creating way (Ali & Khan, 2025; AlSheibani et al., 2018). However, existing approaches remain fragmented and tend to focus on technological and environmental aspects, while human and organisational dimensions are less developed (Kretschmer & Orth, 2025). In addition, the role of organisational learning (OL) as a mechanism for building capabilities over time has received limited attention. Moreover, practical approaches for assessing and developing AI readiness remain limited, particularly for SMEs.

Against this background, this paper addresses the following research question: *Which factors determine organisational AI readiness for KM, and how can they be structured within a socio-technical framework to support AI readiness assessment?*

A systematic literature review was conducted to identify existing AI readiness assessment instruments and relevant AI readiness factors. Based on these findings, the paper develops an extended socio-technical framework, the Technology-Organisation-People-Learning (TOP-L) framework, which integrates technological, organisational, and human dimensions while explicitly incorporating OL as a cross-cutting capability. The framework also serves as a foundation for a practical AI readiness assessment approach. The paper contributes in three ways. First, it identifies and synthesises 372 AI readiness factors from the literature and classifies them into a structured set of dimensions and factor clusters from a KM perspective. Second, it extends socio-technical perspectives by integrating organisational learning. Third, it provides the basis for a practical AI readiness check, particularly suited for SMEs.

2. Theoretical Background: AI Readiness in Knowledge Management

2.1 AI in Knowledge Management: Towards an AI Readiness Perspective

AI as a cross-cutting technology has increasingly become a key enabler of KM extending the capabilities of traditional KM technologies. While earlier KM systems primarily focused on storing, retrieving, and sharing explicit knowledge through repositories and collaboration platforms, recent advances in AI are fundamentally reshaping these functions (Liu et al., 2023; Kretschmer & Orth, 2025). In particular, GenAI technologies based on large language models (LLMs) and related technologies as Retrieval-Augmented Generation (RAG) and Knowledge Graphs, enable new forms of knowledge interaction, including contextual search, automated summarisation, and the generation of knowledge artefacts.

These capabilities open up new possibilities for addressing persistent challenges in KM such as knowledge silos, difficulties in reusing existing knowledge, and the loss of critical expertise (Kretschmer & Orth, 2025). AI-based systems can support the integration and reuse of distributed knowledge, facilitate onboarding processes, and help make tacit knowledge more accessible (Davenport & Mittal, 2022; Sumbal et al., 2024; Kretschmer & Orth, 2025). As a result, KM is increasingly shifting from static knowledge repositories towards more dynamic, interactive knowledge ecosystems.

At the same time, the integration of AI into KM is not without challenges. Beyond technical aspects, organisational and human factors play a crucial role. The effective use of AI in KM depends on user acceptance, trust, competencies, and the alignment of AI systems with organisational processes and workflows (Märkel & Lundborg, 2020; Grüneke et al., 2024), highlighting the socio-technical nature of AI-supported KM.

In response to these challenges, the concept of AI readiness has emerged as a central lens for understanding how organisations can systematically develop the capabilities required to successfully adopt and utilise AI technologies. Previous research postulates that successful implementation of such technological innovations depends on contextual factors, such as the organisational strategy and available resources (Jöhnk et al., 2021). These factors ultimately comprise an organisations AI readiness, defined here as preparedness and capacity of an organisation to effectively implement and use AI technologies in a value-creating way (see Ali & Khan, 2025; Alsheibani et al., 2018). However, there is no clear consensus in the literature on the factors that constitute AI readiness. However, several frameworks emerge consistently in the context of AI readiness, such as the Technology-Organisation-Environment (TOE) framework (Alsheibani et al., 2018; Pumplun et al., 2019), and the Technology Acceptance Model (TAM) (Shonhe, 2025; Tarasenko et al., 2024; Urbani et al., 2024), both are frequently applied to explain the adoption of technological innovations.

2.2 Socio-technical Perspective/Socio-technical Systems

The idea that work systems consist of interacting social and technical components dates back to research in the 1950s and forms the basis of socio-technical systems theory (Dander et al., 2021). The central assumption is that organisational performance depends on how well technical (technology) and social subsystems (organisation & people) are aligned. Instead of treating technical and social aspects separately, both need to be considered together and designed in relation to one another. In this sense, socio-technical system design emphasises the joint optimisation of technology use and organisational structures (Dander et al., 2021).

In the context of ongoing digitalisation and the increasing use of AI, this perspective has become more relevant. Introducing AI into organisations is not simply a matter of implementing new technologies (Kretschmer & Orth, 2025). It affects how work is organised, how decisions are made, and how people interact with knowledge. AI tools are not used in isolation but become part of everyday routines and workflows. Their effectiveness therefore depends not only on technical performance but also on how they are integrated into organisational practices and supported by users (Märkel & Lundborg, 2020; Grüneke et al., 2024).

From an AI readiness perspective, the implementation and sustained use of AI technologies require the consideration of different socio-technical dimensions. While frameworks such as TOE emphasise technological conditions, including data quality and IT infrastructure (Lee et al., 2024), models such as TAM highlight the role of perceptions, attitudes, and behavioural intentions in shaping AI adoption (Shonhe 2025, Tarasenko et al. 2024, Urbani et al. 2024). Together, these perspectives underline the need to consider both technological and social factors when assessing AI readiness.

Integrative frameworks that capture the interplay between technological, organisational, and human dimensions remain scarce, particularly in practice-oriented forms (Grüneke et al., 2024). The theoretical foundation for the framework developed in this paper builds on the socio-technical TOM model (german: Technologie-Organisation-Mensch), originally introduced by Bullinger et al. (1998). The model emphasises that successful KM initiatives depend on the balanced consideration of technological infrastructures, organisational structures, and human factors. Subsequent work further shows that sustainable KM cannot be achieved through IT solutions alone but requires organisational alignment and a clear focus on human factors (Heisig & Orth, 2005; Orth et al., 2011). With the increasing use of AI technologies this becomes even more apparent: while they can enhance knowledge creation and access, their value depends on how effectively they are embedded into organisational processes, supported by user competencies, and governed through appropriate structures (Kretschmer & Orth, 2025). This perspective provides the conceptual basis for structuring AI readiness along the dimensions of technology, organisation, and people, which is further extended in this paper.

2.3 Organisational Learning

While the socio-technical perspective provides a useful foundation for understanding the interplay between technological, organisational, and human factors, it does not fully capture how organisations actually develop and sustain capabilities over time, particularly how they learn to adapt, integrate new knowledge, and improve their use of technologies such as AI.

OL can be understood as a continuous process through which organisations enhance their ability to respond to internal and external challenges by acquiring, sharing, and applying knowledge (Will et al., 2026, Ludwig, 2024; Geißler & Heidsiek, 2010). Its main objective is to improve problem-solving capacity and support adaptation to changing conditions. Learning occurs across multiple levels and becomes organisationally relevant when individual knowledge is shared and embedded in collective practices and structures (Mynarek et al., 2021). Social interaction and knowledge sharing are central to this process (Mynarek et al., 2021). OL therefore depends not only on individual competencies, but also on collaboration, communication, and some degree of alignment with shared organisational objectives. It can also differ in depth, ranging from incremental improvements within existing assumptions (single-loop learning) to more fundamental changes that question and reshape underlying norms and practices (double-loop learning) (Will et al., 2026).

In the context of AI and KM, these dynamics become particularly visible. The effective use of AI requires organisations not only to introduce new technologies, but also to develop competencies, adjust processes, and integrate new forms of knowledge into existing structures over time. Increasingly, this involves forms of human-AI teaming, in which AI systems are embedded in collaborative processes where humans and AI jointly contribute to shared goals (Chen et al., 2025). This includes learning how to use AI tools appropriately, critically interpret and validate AI-generated outputs, and embed them into everyday work and knowledge practices, while fostering shared understandings and supporting continuous learning through knowledge sharing, capability development, monitoring mechanisms and feedback loops mechanisms (Chen et al., 2025). This points to a limitation of many existing socio-technical approaches to KM and AI readiness. While they describe how technology, organisation, and people (TOM); or for AI readiness, environment (TOE) are related, they often say less about how capabilities actually develop over time. OL as dimension for AI readiness therefore adds an important perspective. It helps to explain how AI readiness emerges, changes, and can be sustained in practice. In this sense, it provides the basis for extending the socio-technical view and for including learning as a distinct dimension in the framework developed in this paper.

3. Systematic Literature Review: Procedure and Findings

3.1 Review Procedure

The search was conducted in Scopus. The interdisciplinarity of the database allows for the inclusion of sources across computer science, social sciences, management, and other fields relevant to the research area of AI readiness and KM. To ensure relevance and parsimony, English and German articles, book chapters, (conference) reviews, and conference papers were included. Sources from subject areas not directly related to the research question were excluded (e.g. astronomy, nursing, dentistry, etc.).

Relevant keywords and corresponding synonyms were organised into seven overarching terms (AI, GenAI, readiness, organisation, Human-AI interaction, sociotechnical, and measurement). Individual keywords and overarching terms were then combined to answer the research question presented above, resulting in a total of 24 search strings. The search strings resulted in 623 publications, including 138 duplicates. The 485 non-duplicate publications were retained for subsequent title and abstract screening.

In first-stage screening, publications were included if they (1) discussed AI readiness, (2) presented factors relevant for organisational AI readiness, (3) integrated AI readiness factors in a sociotechnical framework, or (4) proposed metrics for AI readiness in organisations.

Second-stage screening refined these criteria to focus on organisational AI readiness. Publications addressing AI readiness without organisational relevance, socio-technical framing, or measurement tools were excluded. Additionally, publications discussing AI readiness in domain-specific applications (e.g. education, medicine, defence etc.) were likewise excluded, unless they discussed organisational considerations or provided highly transferable AI readiness factors. Consequently, 82 publications were identified as relevant, of which 42 were selected for full-text analysis based on their direct relevance or inclusion of an AI readiness assessment tool. The systematic literature review was complemented by an online search and backward snowballing procedure, resulting in seven additional relevant AI readiness assessments and publications. Relevantly, the online search captured assessment tools developed by technology-focused enterprises such as Microsoft (n.d.) and TDWI (n.d.), not published in academic databases.

In the final stage of screening and evaluation, frameworks and assessments were scored from 1 (not relevant) to 4 (highly relevant) based on the following evaluation criteria: (1) conceptual alignment with the definition of AI readiness, (2) coverage of socio-technical dimensions, (3) structured conceptualisation, (4) compatibility with other AI readiness frameworks and models (5) transferability to organisational contexts.

3.2 Identified conceptual Frameworks and Assessment Tools

The evaluation stage resulted in 34 relevant frameworks and assessment tools with a score of 3 (relevant) or 4 (highly relevant). This final selection of publications was grouped into 17 conceptual frameworks (see Table 1) and 17 fully operationalised AI readiness assessments tools (see Table 2), both of which inform the subsequent development of a new AI readiness assessment framework. This differentiation allows for targeted use of the literature in that operationalised assessments reflect the practical application methods of the abstract construct of AI readiness and AI readiness factors, while the conceptual frameworks likewise contribute to an empirical understanding of which factors are relevant to consider for later operationalisation.

Table 1: Conceptually relevant publications included in analysis

Author(s) (Year)	Publication title
Akbarighatar (2022)	Maturity and readiness models for responsible artificial intelligence (RAI): A systematic literature review
Ali & Khan (2025)	Factors influencing readiness for artificial intelligence: a systematic literature review
AlSheibani et al. (2018)	Artificial intelligence adoption: AI-readiness at firm-level
Felemban et al. (2024)	Exploring the Readiness of Organisations to Adopt Artificial Intelligence
Frangos (2022)	An Integrative Literature Review on Leadership and Organizational Readiness for AI
Horvat & Heimberger (2023)	AI Readiness: An Integrated Socio-technical Framework
Huzooree et al. (2025)	Reskilling for the AI Age: Project management approaches and organisational strategies for workforce readiness
Kalleparambil & Akoum (2025)	AI Organisational Readiness for SMEs: A Tailored Model for AI Adoption Success
Kulkarni et al. (2024)	Artificial intelligence technology readiness for social sustainability and business ethics: Evidence from MSMEs in developing nations
Naheed et al. (2025)	A Preliminary multidimensional AI readiness assessment model for SME's
Nortje & Grobbelaar (2020)	A Framework for the Implementation of Artificial Intelligence in Business Enterprises: A Readiness Model
Pathak & Bansal (2024)	Factors Influencing the Readiness for Artificial Intelligence Adoption in Indian Insurance Organizations
Pumplun et al. (2019)	A new organizational chassis for artificial intelligence – Exploring organizational readiness factors
Roszelan & Shahrom (2023)	Readiness for Artificial Intelligence Adoption in Malaysian Manufacturing Companies
Shonhe (2025)	Conceptual framework to explore artificial intelligence technology (AIT) readiness and adoption intention in records and information management (RIM) practices: a proposal
Tehrani et al. (2024)	Decoding AI readiness: An in-depth analysis of key dimensions in multinational corporations
Yuniarto & Subiyakto (2025)	Artificial intelligence of things: society readiness

Another significant finding is the dominance of established theoretical foundations. Most saliently, several publications draw upon the Technology-Organisation-Environment (TOE) model, for further AI readiness framework development (Alsheibani et al. 2018, Felemban et al. 2024, Frangos 2022, Horvat and Heimberger 2023, Jöhnk et al 2021, Kulkarni et al. 2024, Naheed et al. 2025, Pathak and Bansal 2024, Pumplun et al. 2019, Roszelan and Shahrom 2023, Shonhe 2025). A further significant theory is the Technology Acceptance Model (TAM), which is widely applied in AI readiness research (Frangos 2022, Kalleparambil and Akoum 2025, Shonhe 2025, Urbani et al. 2024). Further influential, but less cited models are the Unified Theory of Acceptance and Use of Technology (UTAUT; e.g. Kalleparambil and Akoum 2025, Shonhe 2025), the Diffusion of Innovation theory (DOI; e.g. Alsheibani 2018), and the Theory of Planned Behavior (TPB; e.g. Felemban et al. 2024).

Table 2: Operationalised AI readiness assessment tools included in analysis

Author(s) (Year)	Assessment tool/publication title
Berretta et al. (2023)	The Job Perception Inventory
Cisco (n.d.)	Cisco Global AI Readiness Index
Cooper (2025)	AI Readiness Index
Detecon (n.d.)	Detecon AI Readiness Assessment
Holmström (2022)	From AI to Digital Transformation: The AI Readiness Framework
Jöhnk et al. (2021)	Ready or Not, AI Comes – An Interview Study of Organizational AI Readiness Factors
Lee et al. (2024)	Enhancing citizen service management through AI-enabled systems – a proposed AI readiness framework for the public sector
Lee & Park (2023)	AI as "Another I": Journey map of working with artificial intelligence from AI-phobia to AI-preparedness
Li et al. (2023)	An Assessment of Human-AI Interaction Capability in the Generative AI Era: The Influence of Critical Thinking
Microsoft (n.d.)	Microsoft AI Readiness Assessment
Rübel & Hussung (2024)	Wie fit ist Ihr Unternehmen für KI? Der KI-Readiness Check zum Entdecken Ihres KI-Potenzials.
Saari et al. (2019)	VTT's AI Maturity Tool
SAP LeanIX (n.d.)	SAP AI readiness checklist
Tarasenko et al. (2024)	Awareness and readiness to use artificial intelligence by the adult population of Ukraine: Survey results
TDWI (n.d.)	TDWI AI Readiness Assessment and Guide
Urbani et al. (2024)	Managerial framework for evaluating AI chatbot integration: Bridging organizational readiness and technological challenges
Viskovich & Mohan (2025)	Ethical Dilemmas and Human Factors in the Application of AI in Cybersecurity

3.3 Collection and Analysis of AI Readiness Factors

The extraction of AI readiness factors from the 34 relevant publications resulted in an initial set of 372 factors, which was reduced to 301 distinct terms and phrases following deduplication. For efficiency and accuracy in consideration of the volume of the factor list, a new application within the PartyRock platform was constructed to conduct a semantic analysis, with the objective to identify relevant clusters (dimensions) and sub-clusters (factor clusters) of AI readiness factors emerging from the literature. The application was instructed to enable semantic analysis of a large set of keywords. It accepts optional user-defined clusters and a required input of terms treated as individual semantic units, producing clusters (dimensions) with assigned terms based on semantic similarity. If pre-defined clusters are provided, the system assigns all terms accordingly and generates an alternative model that retains these clusters while proposing additional ones. If not, it derives an optimal clustering structure, analogous to factor analysis. In both cases, the model can create sub-clusters (factor clusters) where appropriate to improve clarity, parsimony, and interpretability. While the use of such AI-supported analysis enables efficient handling of large datasets, the results depend on the underlying model and parameter settings. To mitigate this limitation, the clustering results were iteratively reviewed and interpreted in light of the theoretical framework and the literature.

Multiple analyses were conducted to a arrive parsimonious and interpretable clustering solution. Analyses without pre-defined clusters tended to result in large numbers of main clusters deemed impractical for further operationalisation and application outside of theoretical development. Further analyses were conducted using the dimensions (1) *technology*, (2) *organisation*, and (3) *people* from Kretschmer & Orth (2025) as pre-defined clusters with the addition of (4) *organisational learning*. This additional dimension is grounded in the theoretical considerations outlined in Section 2.4, which highlight OL as a critical, yet underrepresented, dimension for understanding the development and adaptation of AI-related capabilities over time. Results showed that all AI readiness factors were matched onto the four pre-defined dimensions, indicating a good fit between the pre-defined model and the data. The synthesis and validation of multiple analyses resulted in a classification of all 301 distinct AI readiness factors into four dimensions and 20 factor clusters detailed in section 4.1: the *technology* dimension comprised five factor clusters with 80 overall AI readiness factors; the *organisation* dimension comprised five factor clusters with 110 factors; the *people* dimension contained five factor clusters with 85 factors and lastly, the *learning* dimension encompassed five factor clusters with 26 factors. Due to the scope limitations of a conference paper, the individual factors are not reported separately but are represented through their aggregation into factor clusters.

4. Towards a Socio-Technical Framework for AI Readiness in KM: The TOP-L Framework

4.1 Development and Structure of the TOP-L Framework

Based on the factors identified in the literature review, a socio-technical framework for AI readiness in KM was developed. The framework structures organisational AI readiness across the dimensions of (1) technology, (2) organisation, and (3) people, while integrating (4) learning as a cross-cutting organisational capability (see Figure 1). The review revealed a large number of heterogeneous factors, described at different levels of abstraction. While existing conceptual frameworks and fully operationalised AI readiness assessments offer insights into specific aspects of AI readiness, they often lack an integrative structure that captures the interplay between technological, organisational, and human factors. To address this, the identified factors were consolidated and clustered based on semantic similarity. Drawing on the socio-technical perspective outlined in Section 2.3, the dimensions of technology, organisation, and people served as an initial structuring logic. The analysis showed that the factors could be consistently assigned to these dimensions, confirming their suitability as a foundation.

At the same time, both the literature review and the theoretical discussion pointed to a limitation of existing approaches. While socio-technical models capture structural aspects, they do not sufficiently explain how capabilities develop over time. In particular, OL emerged as a critical but underrepresented aspect. The framework was therefore extended by integrating learning as a cross-cutting organisational dimension. The resulting Technology-Organisation-People-Learning (TOP-L) framework conceptualises AI readiness not as a static state, but as a set of (over time) evolving capabilities. While the dimensions of technology, organisation, and people capture distinct sets of capabilities required for AI readiness, the learning dimension reflects the processes through which these capabilities are developed, adapted, and sustained over time, thereby extending existing socio-technical models with a dynamic, capability-oriented perspective to AI Readiness.

Figure 1: TOP-L Framework – Socio-Technical Framework for AI Readiness in KM

Technology

The technology dimension captures the technical foundations required for the implementation and use of AI in KM. This includes *IT infrastructure and technical architecture*, *data and information foundations and management*, and the *AI system functionality and performance*. Furthermore, *integration, compatibility, and interoperability* are critical for ensuring that AI applications can be effectively embedded into existing knowledge environments. In addition, *security, privacy, and risk management* influence whether AI systems can be deployed reliably. This dimension therefore reflects the extent to which technical resources enable meaningful and sustainable use of AI.

Organisation

The organisational dimension refers to the structural and strategic conditions shaping AI adoption. This includes *AI orientation, including strategy, vision, and technology*, such as the alignment of AI initiatives with KM and business objectives. *Governance, ethical alignment, and regulatory accountability* guide the responsible use of AI. *Organisational structures, processes, and operational management*, along with *financial, resource, and portfolio management*, influence how AI is embedded in KM operations. In addition, the *external environment, stakeholders, and market context* shape how organisations position and adapt their AI initiatives. Organisational readiness thus reflects how AI is integrated into both internal structures and broader organisational contexts

People

The people dimension addresses individual and collective capabilities, attitudes, and behaviours. This includes *individual skills, AI competencies, and digital literacy*, such as the ability to critically engage with AI-generated outputs. Furthermore, *attitudes, perceptions, behavioural intentions, and psychological readiness* influence whether AI is adopted in practice. *Leadership and managerial support* shape direction and foster engagement, while *AI-specific roles, human-AI interaction, human-AI teaming, and decision-making* influence decision-making and collaboration in knowledge processes. In addition, *collaboration, workforce dynamics, and social embeddedness* affect how individuals and teams work with AI in organisational contexts. AI readiness therefore depends not only on competencies, but also on social dynamics and engagement.

Learning (cross-cutting dimension)

The learning dimension cuts across the other dimensions and captures how organisations develop and adapt capabilities over time. This includes *organisational culture, knowledge sharing, and learning climate* as well as *capability building and readiness development* through experience. It also involves fostering *AI awareness, responsible AI learning, and reflexive practices* in working with AI. Learning further enables *innovation, strategic learning, and adaptive capacity* by supporting iterative adjustment through *assessment, monitoring, and feedback loops*. In this sense, it provides a dynamic layer that connects structural conditions with ongoing capability development and represents a key extension of existing socio-technical approaches.

4.2 Implications for AI Readiness Assessment

The TOP-L framework provides a structured foundation for assessing AI readiness in KM contexts. By integrating technological, organisational, human, and learning-related dimensions, it enables a comprehensive evaluation of organisational preparedness. Each dimension is further differentiated into clusters that capture specific capability areas, within which the 301 distinct AI readiness factors identified in the literature are systematically organised. For example, within the people dimension, the cluster *leadership and managerial support* comprises a set of 12 related factors that can serve as a basis for the development of concrete assessment items of the planned *AI Readiness Check*. In this way, the framework provides not only a conceptual structure but also a foundation for subsequent operationalisation.

In contrast to maturity-oriented approaches, AI readiness is not conceptualised as a fixed stage, but as a set of context-dependent capabilities that evolve over time. The framework supports the identification of strengths and weaknesses across dimensions by capturing AI readiness as a differentiated capability profile. This allows organisations to identify targeted development needs rather than positioning themselves within predefined maturity levels. This is particularly relevant for SMEs, where development paths are often highly context-specific.

The framework is grounded in a socio-technical perspective and builds on the TOM model, extended through the inclusion of OL. In doing so, it connects KM and OL by linking knowledge processes, organisational memory, and capability development with adaptive learning mechanisms. It also aligns with capability-oriented research by incorporating implementation processes, resource configurations, governance structures, and feedback loops.

In relation to existing models, the framework shows both alignment and differentiation. While it is compatible with the TOE framework in capturing technological and organisational aspects, it focuses on the interaction of socio-technical subsystems. Environmental factors are treated as contextual conditions that can be considered in a preceding stage of the AI readiness assessment (*AI Readiness Check*), for instance to inform context-specific weighting of the framework dimensions. Elements of TAM are reflected in the people dimension, particularly in relation to attitudes and interaction patterns.

5. Conclusion and Outlook

This paper addressed the research question of which factors determine organisational AI readiness in KM and how these can be structured within a socio-technical framework. Based on a systematic literature review, a large number of heterogeneous factors were identified and consolidated into the Technology-Organisation-People-Learning (TOP-L) framework. By extending established socio-technical approaches with a learning dimension, the framework captures both structural conditions and the dynamic processes through which AI-related capabilities are developed over time, thereby adding a dynamic, capability-oriented perspective to existing AI readiness conceptualisations.

For research, the framework contributes to KM by integrating socio-technical perspectives with OL and capability-oriented approaches, thereby offering a more comprehensive conceptualisation of AI readiness. For practice, it provides a structured basis for assessing AI readiness as a differentiated capability profile, supporting organisations in identifying targeted development needs.

Future research will focus on the further development and validation of the framework, including the design of an AI readiness assessment, the integration of AI- and GenAI-specific sub-scores, and the incorporation of context-sensitive weighting mechanisms. In particular, empirical applications across different organisational contexts will be required to validate and refine the framework. In addition, alignment with relevant standards and norms will be explored to enhance applicability and comparability.

Ethics Declaration: This research did not require ethical clearance.

AI Declaration: AI tools were used in the preparation of this paper, in particular for language refinement and stylistic assistance, as well as for data analysis and concept clustering as elaborated upon in the main text (PartyRock by Amazon Web Services, ChatGPT by OpenAI, NotebookLM by Google and DeepL). All content was carefully reviewed, revised, and validated by the authors. No AI tool was used to generate original scientific content, results, or interpretations. The authors take full responsibility for the content of the final paper.

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