

Integrating Generative AI into Knowledge Management: A Mixed-Methods Framework with Machine Learning Validation in UAE Knowledge-Based Organizations

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ABSTRACT: The rapid advancement of generative artificial intelligence (AI) is transforming knowledge management (KM) practices within knowledge-based organizations (KBOs), creating new opportunities for knowledge creation, sharing, storage, and utilization. This study examines the integration of generative AI into KM in the United Arab Emirates (UAE), with a particular focus on the technological, organizational, and contextual factors that shape adoption and effectiveness. Using a mixed-methods approach, the study draws on qualitative thematic analysis of secondary data, including government AI strategies, organizational reports, industry publications, and peer-reviewed literature, to identify the key dimensions influencing AI-enabled KM. To strengthen the conceptual framework, a deep learning model was employed to operationalize relationships among five UAE-specific AI-KM sources and three evaluative criteria, providing an illustration of the framework's internal coherence and relative significance. The findings indicate that successful AI-enabled KM depends on the alignment of technological infrastructure, human capital capabilities, organizational culture, leadership commitment, and regulatory support. The analysis further reveals that UAE-specific conditions, including national AI initiatives, public-private collaboration, workforce diversity, and the prominence of small and medium-sized enterprises (SMEs), significantly influence organizational adoption pathways. The machine learning assessment highlights that technological readiness alone is insufficient to ensure KM success, as misalignment between technical and social subsystems can undermine organizational performance and knowledge outcomes. By integrating the Knowledge-Based View (KBV), Socio-Technical Systems (STS) theory, and Technology Acceptance Models (TAM/UTAUT), this study proposes a context-sensitive framework that advances understanding of generative AI adoption in emerging economies and provides practical guidance for policymakers, organizational leaders, and KM practitioners seeking responsible and effective AI implementation.

KEYWORDS: Knowledge Management, Generative AI, Knowledge-Based Organizations, Machine Learning Illustration, Socio-Technical Systems

1. INTRODUCTION

In today's knowledge-driven economy, knowledge is among the most strategically valuable assets for organizations, particularly knowledge-based organizations (KBOs) in both the public and private sectors. These organizations rely on the continuous creation, storage, sharing, and application of knowledge to drive innovation, inform decision-making, and maintain competitiveness (Al-Qahtani, 2023). Technological advancements over the past two decades have transformed knowledge management (KM), with generative artificial intelligence (AI) emerging as a distinctive enabler. Unlike conventional AI, which primarily automates tasks or analyses data, generative AI can produce novel content, generate insights from complex datasets, and simulate aspects of human reasoning, thereby supporting learning, problem-solving, and innovation in ways previously unattainable. However, the integration of generative AI into KM is not solely a technological challenge; it represents a socio-technical transformation with potential tensions between technical capabilities and human, organizational, and regulatory conditions (Alavi & Leidner, 2001; Zhang & Zhou, 2026; Saeed et al., 2023).

The United Arab Emirates (UAE) provides a compelling context to examine generative AI integration into KM. Guided by national initiatives such as Vision 2021, Centennial 2071, and the Artificial Intelligence Strategy 2031, the UAE actively fosters knowledge-based growth and the adoption of advanced digital technologies. Public institutions, including universities and government agencies, play a central role in this transformation, while the private sector, particularly small and medium-sized enterprises (SMEs), is encouraged to innovate and commercialize knowledge (UAE, 2018). Despite these ambitions, persistent socio-technical challenges create conditions in which AI adoption may produce misalignment, resistance, or unintended consequences. Public organizations often face bureaucratic inertia, siloed structures, and legacy systems, whereas private firms encounter resource and skill constraints, data privacy concerns, and regulatory pressures (Guenduez et al., 2025; ul Haq et al., 2025).

Although AI research is expanding, theoretical and empirical gaps remain in understanding how generative AI can be systematically integrated into KM in the UAE. Existing studies largely focus on technological performance, neglecting critical socio-technical tensions involving organizational culture, leadership, tacit knowledge, and human–AI collaboration (Abubaker et al., 2025). Regulatory and ethical issues—privacy, accountability, transparency, and data ownership—are underexplored, particularly in dynamic national digital strategies (Ijaiya, 2024). While studies such as Habib (2024) examine AI adoption in organizations, they emphasize automation and efficiency, without critically considering when AI may disrupt rather than enhance KM or generate misalignment across socio-technical subsystems.

Against this backdrop, the central research problem guiding this study is: how can UAE KBOs effectively integrate generative AI into KM practices while navigating socio-technical tensions and sector-specific structural, cultural, and technological constraints? To address this problem, the study focuses on AI-enabled KM processes as the central phenomenon, examining how socio-technical conditions, human–AI collaboration, and contextual moderators influence adoption and effectiveness.

The study pursues two primary objectives. First, it conceptually analyses the challenges and opportunities associated with integrating generative AI into KM in UAE KBOs, emphasizing both enabling conditions and potential misalignment risks, particularly regarding trust, tacit knowledge, ethics, and organizational performance. Second, it develops a context-sensitive conceptual framework for AI-enabled KM and employs a computational illustration using machine learning to examine the relative salience of framework components, rather than conducting independent empirical validation.

Accordingly, the study is guided by the following research questions:

1. How do socio-technical preconditions and organizational factors influence AI-enabled KM processes in UAE KBOs, and how do these mechanisms differ between public and private sectors?
2. How do trust, tacit knowledge dynamics, and regulatory and ethical considerations shape the effectiveness of AI-enabled KM, and how can computational illustration highlight the relative contributions of these factors while identifying potential misalignment risks?

The study is significant for practitioners, policymakers, and scholars. It highlights both enabling factors and critical boundary conditions that may compromise AI adoption, guiding tailored KM strategies and responsible AI deployment. For policymakers, it offers evidence-informed insights to support regulations, national strategies, and incentive structures that facilitate the UAE's transition toward a knowledge-based, AI-enabled economy. Academically, the study contributes to debates on AI adoption in emerging economies, tacit knowledge capture, and human–AI collaboration by developing a theoretically grounded conceptual framework that foregrounds socio-technical alignment as a central explanatory lens, with the UAE serving as an illustrative case for other emerging economies balancing ambitious digital strategies with cultural, institutional, and resource-related constraints.

To capture the multi-dimensional nature of AI-enabled KM, the study draws on three complementary theoretical perspectives. Socio-Technical Systems (STS) theory is positioned as the primary lens, emphasizing alignment between technology, people, and organizational structures, and highlighting conditions under which generative AI may either support or disrupt KM practices (Singh et al., 2025). The Knowledge-Based View (KBV) frames knowledge as a strategic resource and positions generative AI as a capability that can amplify knowledge creation, storage, sharing, and application (Durst & Khadir, 2025). Technology Acceptance Models (TAM) and the Unified Theory of Use of Technology (UTAUT) highlight the role of individual perceptions, including perceived usefulness, ease of use, trust, and ethical concerns, in shaping employees' engagement with AI-enabled KM systems. KBV and TAM/UTAUT provide complementary insights into knowledge value and individual adoption behaviour, integrated within STS to offer a multi-level perspective that explicitly addresses socio-technical alignment, potential misalignment, and sector-specific contingencies (Lee et al., 2025).

The remainder of the article is organized as follows. Section 2 reviews the literature on KM, generative AI adoption, and AI-enabled KM in the UAE and comparable contexts. Section 3 outlines the theoretical framework integrating KBV, STS, and TAM/UTAUT perspectives and introduces the conceptual model of generative AI-driven KM. Section 4 details the study's conceptual and computational illustration approach, including the qualitative secondary-data analysis and machine learning-based internal coherence assessment. Section 5 presents the results and the refined conceptual framework, drawing on both thematic findings and computational insights. Section 6 discusses theoretical, practical, and policy implications, and the article concludes with limitations and recommendations for future research.

2. LITERATURE REVIEW

2.1 Knowledge Management in Organizational Contexts

Knowledge management (KM) remains a cornerstone of competitiveness in knowledge-based organizations (KBOs) across public and private sectors. Effective KM relies not only on technological infrastructure but also on human, cultural, and organizational factors that shape knowledge flows, organizational learning, and innovation capacity (Abdelrahman et al., 2025). While early KM research emphasized formalized systems and standardized processes, contemporary studies increasingly underscore the centrality of organizational culture, leadership, collaboration norms, and knowledge-sharing practices in determining KM outcomes (Lam et al., 2021).

Empirical studies highlight sectoral contrasts. Public organizations frequently struggle with bureaucratic hierarchies, siloed departments, and resistance to change, which impede knowledge sharing and hinder the adoption of innovative KM practices (Benchis, Shahzad, & Dan, 2025). Conversely, SMEs benefit from agility, flexible structures, and innovation-oriented cultures but face constraints related to limited resources, skill shortages, and underdeveloped technological capabilities (Costa et al., 2023). These structural and cultural conditions illustrate that KM is inherently socio-technical, and misalignment between technology, people, and processes can limit performance. In emerging economies, KM effectiveness is further challenged by fragmented knowledge systems, low digital literacy, and misalignment between KM initiatives and broader organizational strategies (Cao, Duan, & Edwards, 2025).

Collectively, these studies suggest that technology alone does not guarantee KM success. Instead, socio-technical alignment—including organizational, cultural, and contextual mediators—is critical, underscoring the need for frameworks that integrate human, structural, and technological dimensions rather than focusing solely on IT systems or technical capability.

2.2 Generative AI as a Transformative Enabler

Generative AI represents a paradigm shift in KM, extending AI's role beyond prediction, classification, and automation. Unlike conventional AI, which primarily analyses existing datasets, generative AI can create novel knowledge artifacts, simulate higher-order reasoning, and produce actionable insights (Kaczorowska-Spychalska et al., 2024). This allows organizations to perform advanced pattern detection, knowledge synthesis, and scenario generation, enhancing decision-making, problem-solving, and innovation (Nakash & Bolisani, 2025).

Despite these potentials, empirical evidence shows uneven adoption. Generative AI integration varies across sectors and organizations, particularly in emerging economies, due to structural, cultural, and infrastructural constraints (Al-Jenaibi, 2024). Successful integration requires deliberate socio-technical alignment, balancing technical capabilities with workforce skills, governance structures, and organizational culture, while also anticipating potential misalignment, resistance, or unintended consequences (Skills for Care, 2021). However, a critical gap remains: most studies focus on AI's technical performance rather than its interaction with tacit knowledge, human expertise, or organizational processes (Abubaker et al., 2025). This overemphasis on technological capabilities limits understanding of how generative AI may disrupt as well as enhance KM, particularly in contexts where socio-technical conditions are complex and heterogeneous.

2.3 Challenges and Critical Debates

Several unresolved challenges emerge in the literature. Reliability, interpretability, and contextual appropriateness of AI-generated outputs are major concerns, especially for tacit knowledge that is deeply embedded in human experience and difficult to formalize (Choi et al., 2020). Ethical and regulatory considerations, including data privacy, intellectual property, algorithmic transparency, and accountability, pose additional barriers to adoption (Awashreh & Khademizadeh, 2025).

Organizational culture is another mediating factor. Hierarchical structures, weak knowledge-sharing norms, and resistance to change can diminish trust in AI systems and hinder integration (Benchis, Shahzad, & Dan, 2025). Similarly, sector-specific constraints shape adoption: SMEs are limited by financial and human capital resources, whereas public organizations contend with bureaucratic inertia and outdated infrastructures (Awashreh & Hamid, 2025).

These debates underscore that AI-enabled KM is inherently socio-technical. Misalignment between technology, human actors, and organizational processes may undermine KM outcomes, highlighting the importance of conceptual frameworks that account for dynamic, multi-level interactions rather than linear technology adoption models (Silva, 2025). Yet, existing studies often fail to provide comprehensive frameworks capturing these interdependencies, particularly in contexts with high regulatory scrutiny or workforce diversity, such as the UAE.

2.4 Theoretical Perspectives

Several theoretical lenses have informed AI adoption research in knowledge management (KM). Knowledge-Based View (KBV) treats knowledge as a strategic resource and explains how generative AI can enhance knowledge creation, storage, and sharing; however, ongoing debates question whether AI strengthens knowledge processes or disrupts tacit-explicit knowledge balance, highlighting the need for socio-technical integration (Marikyan & Papagiannidis, 2025; Sira, 2024). Socio-Technical Systems (STS) theory emphasizes alignment between technology, organizational structures, culture, leadership, and human skills (Mumford, 2000), which is particularly relevant in the UAE, where public-sector hierarchies and SME resource constraints create contrasting adoption environments (Alzarooni et al., 2024). Yet, STS is rarely operationalized in generative AI-enabled KM, limiting understanding of misalignment risks when AI actively participates in knowledge processes. Technology Acceptance Models (TAM/UTAUT) focus on individual adoption factors such as perceived usefulness, ease of use, trust, and ethical concerns (Kelly et al., 2023), with evidence suggesting higher adoption in private organizations compared to public sector contexts due to bureaucratic and risk considerations (Golrokht et al., 2024). Integrating KBV, STS, and TAM/UTAUT enables a multi-level perspective, but such integration remains rare in emerging economies like the UAE.

2.5 Regional and UAE Context

Across the GCC region, countries like Saudi Arabia, Qatar, and Kuwait have launched AI strategies aligned with national development visions. The UAE distinguishes itself through strong AI governance structures, early investments in smart government initiatives, and a multicultural workforce, creating opportunities for strategic alignment, innovation, and digital transformation (Shaer, Subramani, & Salem, 2025; Rezaei, 2025). These contextual characteristics also introduce challenges. Cross-cultural knowledge flows, sectoral integration, workforce readiness, and regulatory clarity require nuanced approaches to AI-enabled KM (Ghouri et al., 2026). Misalignment risks are heightened in multicultural, resource-diverse, and bureaucratically complex environments, making the UAE a compelling case to examine how national AI strategies interact with organizational realities (Cena et al., 2026; Frank et al., 2025).

2.6 Gaps in the Literature and Rationale for the Study

Despite growing interest in generative AI for knowledge management, the literature remains fragmented and largely technology-focused, with limited attention to deeper organizational and epistemological tensions. Within the Knowledge-Based View (KBV), an unresolved issue is whether generative AI enhances knowledge capabilities through synthesis and externalization or disrupts the balance between tacit and explicit knowledge by simulating reasoning without lived experience. Although Socio-Technical Systems (STS) theory emphasizes joint optimization of social and technical elements, it is rarely applied to explain how generative AI reshapes workflows, authority structures, trust, and governance, with most studies treating adoption as linear rather than a dynamic process of socio-technical reconfiguration and misalignment. Similarly, TAM and UTAUT frameworks focus mainly on individual perceptions, neglecting organizational culture, regulation, and sectoral differences, especially in SMEs and public institutions. Emerging economies such as the UAE remain underexplored despite their complex digital and multicultural environments. These gaps reveal a core tension where generative AI simultaneously improves knowledge processing but may destabilize tacit knowledge flows and governance. This study addresses this by integrating KBV, STS, and TAM/UTAUT into a unified socio-technical framework contextualized to the UAE and supported by a machine-learning-assisted conceptual coherence assessment.

3. THEORETICAL FRAMEWORK

3.1 Generative AI Integration in Knowledge Management

The integration of generative artificial intelligence (AI) into knowledge management (KM) is a complex, multi-dimensional process shaped by technological, human, and organizational factors. In the UAE, this integration is further influenced by distinctive contextual conditions, including national AI strategies, a multicultural workforce, and an economy dominated by small and medium-sized enterprises (SMEs) (Silva, 2025). Rather than treating AI adoption as a linear technological implementation, this study conceptualizes generative AI integration as a socio-technical transformation requiring continuous alignment between technical and social subsystems (Amanollahnejad et al., 2026). To capture this complexity, this study draws primarily on Socio-Technical Systems (STS) theory, complemented by the Knowledge-Based View (KBV) and Technology Acceptance Models (TAM/UTAUT) (Gerdsmeier & Wespi, 2019).

STS theory serves as the organizing architecture of the framework. Rooted in joint optimization, it emphasizes alignment between technical subsystems (AI models, data infrastructure, automation) and social subsystems (human expertise, leadership, culture, governance) (Mumford, 2000). Misalignment may produce resistance, trust erosion, and workflow disruption, particularly in the UAE where public-sector bureaucracy contrasts with agile but resource-constrained SMEs (Alzarooni et al., 2024).

KBV frames knowledge as a strategic resource, showing how AI enhances creation, storage, sharing, and application (Marikyan & Papagiannidis, 2025), while also raising tension around tacit-explicit knowledge shifts and evolving expertise boundaries (Xu et al., 2025). TAM/UTAUT explains individual adoption through perceived usefulness, ease of use, trust, and ethics (Kelly et al., 2023), shaped by sectoral and cultural factors. Together, KBV operates at the organizational level, TAM/UTAUT at the individual level, and STS integrates both into a system-level explanation of alignment, positioning socio-technical fit as the central mechanism of AI-enabled KM adoption (Hewavitharana et al., 2021).

3.2 Core Components of the Framework

The proposed conceptual framework identifies four interrelated components that collectively shape AI-enabled KM outcomes. Guided by STS, these components are structured as interacting socio-technical layers rather than isolated variables.

• Preconditions

Technological infrastructure, skilled human capital, digital literacy, organizational culture, leadership support, knowledge-sharing norms, regulatory clarity, ethical guidelines, and resource availability determine the readiness of organizations to implement AI-driven KM solutions. From an STS perspective, readiness reflects subsystem coherence. High technological capability without cultural acceptance, or strong leadership without digital infrastructure, represents socio-technical imbalance rather than readiness (Cingillioglu & Schoettner, 2025).

- **AI-enabled KM processes**

Knowledge creation, storage and retrieval, knowledge sharing, and application represent the mechanisms through which generative AI enhances KM performance. Unlike traditional KM tools, generative AI actively participates in knowledge production, introducing epistemological and governance challenges. This interaction layer becomes the primary site where socio-technical alignment must be continuously negotiated (Silva, 2025).

- **Organizational outcomes**

Enhanced knowledge dissemination, accelerated innovation, strengthened problem-solving capacity, improved operational efficiency, and increased competitiveness. However, STS theory suggests that such outcomes are conditional upon sustained subsystem alignment. Rapid AI deployment without governance adaptation or skill development may generate short-term gains but long-term instability (Nikolić & Bjelica, 2025).

- **UAE-specific moderators**

National AI strategies, public–private collaboration, workforce diversity, and the SME-driven economy condition adoption pathways and influence the strength and direction of relationships between AI-enabled processes and organizational outcomes. These moderators operate at the institutional level, shaping the broader socio-technical environment within which organizational alignment occurs (Iyelolu et al., 2024). These components reflect both generalizable KM principles and context-specific factors critical in the UAE, ensuring the framework’s practical relevance and novelty compared to prior AI–KM models, which often neglect socio-technical and regional contextualization.

3.3 Mediating and Moderating Factors

The framework incorporates key mediating and moderating factors influencing AI adoption, KM processes, and organizational outcomes:

- **Trust in AI** mediates employee engagement with AI-generated knowledge, affecting whether AI tools are perceived as reliable contributors to KM processes (Choi et al., 2020). Low trust represents a socio-technical friction point that may destabilize subsystem alignment.

- **Ethical and regulatory compliance** moderate’s adoption effectiveness, particularly in public institutions where data governance, accountability, and transparency are critical. Overly rigid governance may also slow innovation, illustrating the tension between control and adaptability within socio-technical systems.

- **Tacit knowledge capture** ensures that generative AI complements rather than replaces human expertise, supporting the extraction and codification of embedded experiential knowledge (Sira, 2024; Nygren et al., 2025). Failure to embed tacit validation mechanisms may weaken knowledge integrity and reduce long-term learning capacity.

- **Organizational culture and leadership orientation** condition whether AI adoption fosters collaboration and innovation or exacerbates existing silos. Hierarchical rigidity may intensify subsystem misalignment, particularly in bureaucratic contexts. By incorporating these socio-technical dynamics, the framework emphasizes responsible, context-sensitive, and effective AI-enabled KM, explicitly operationalizing STS through identifiable alignment and misalignment mechanisms.

3.4 Conceptual Logic

The framework follows a sequential logic:

- Preconditions—including technological, human, organizational, and regulatory factors—shape an organization’s capacity to deploy generative AI systems.

- These preconditions influence AI-enabled KM processes, which in turn generate organizational outcomes related to knowledge sharing, innovation, and performance.

- UAE-specific contextual factors act as moderators, reflecting the unique socio-technical, institutional, and economic environment in which organizations operate.

However, this logic is conditional rather than deterministic. Positive outcomes depend on sustained joint optimization between technical and social subsystems. Misalignment, caused by skill gaps, weak governance, low trust, or structural rigidity, may produce resistance, workflow disruption, or performance volatility. This multi-level logic integrates STS as the primary lens while drawing on KBV and TAM/UTAUT as complementary perspectives, demonstrating that successful AI-enabled KM requires aligned technologies, human capabilities, organizational practices, and contextual awareness (Alshammari & Alshammari, 2026).

3.5 Conceptual Model and Machine Learning–Assisted Illustration

To illustrate the framework’s internal consistency and conceptual robustness, the study incorporates a conceptual machine learning (ML) component. The ML model does not function as empirical validation of causal relationships. Instead, it operates as a structural coherence assessment tool, computationally examining whether the proposed socio-technical relationships exhibit internal consistency when mapped onto structured secondary data sources. Five secondary data sources inform the ML illustration, each explicitly mapping to components of the framework:

Five secondary data sources inform the ML illustration, each explicitly mapping to components of the framework:

1. **UAE Strategy for Artificial Intelligence 2031 (UAES)** – aligns with UAE-specific moderators and socio-technical preconditions, particularly governance structures and institutional readiness.
2. **Falcon and Jais Generative AI Models (FJGenAI)** – reflect the technical subsystem, including AI infrastructure capabilities and generative performance features relevant to KM processes.
3. **McKinsey’s 2024 Report on GenAI in the UAE (McGenAI)** – informs organizational outcomes and sector-specific adoption dynamics across public and private domains.
4. **Becoming a Knowledge Economy (BKE)** – captures human capital development, digital literacy, and national-level socio-technical enablers.
5. **Systematic Review of AI in Higher Education (SRAI)** – addresses tacit knowledge integration, ethical governance, and individual-level adoption behaviours.

The ML illustration is implemented as a multilayer feedforward neural network:

- First hidden layer: 20 neurons with ReLU activation
- Second hidden layer: 5 neurons with ReLU activation
- Output layer: 3 neurons corresponding to evaluation criteria; Relevance and Contextual Fit (RCF); Data Credibility and Authority (DCA); Analytical Richness and Usefulness (ARU) using SoftMax activation

Figure 1 illustrates the interplay among preconditions, AI-enabled processes, outcomes, and UAE-specific moderators, reinforced by computational insight into relative contributions of each data source. By mirroring the socio-technical layering of the framework, the ML illustration strengthens transparency and internal coherence without substituting theoretical reasoning.

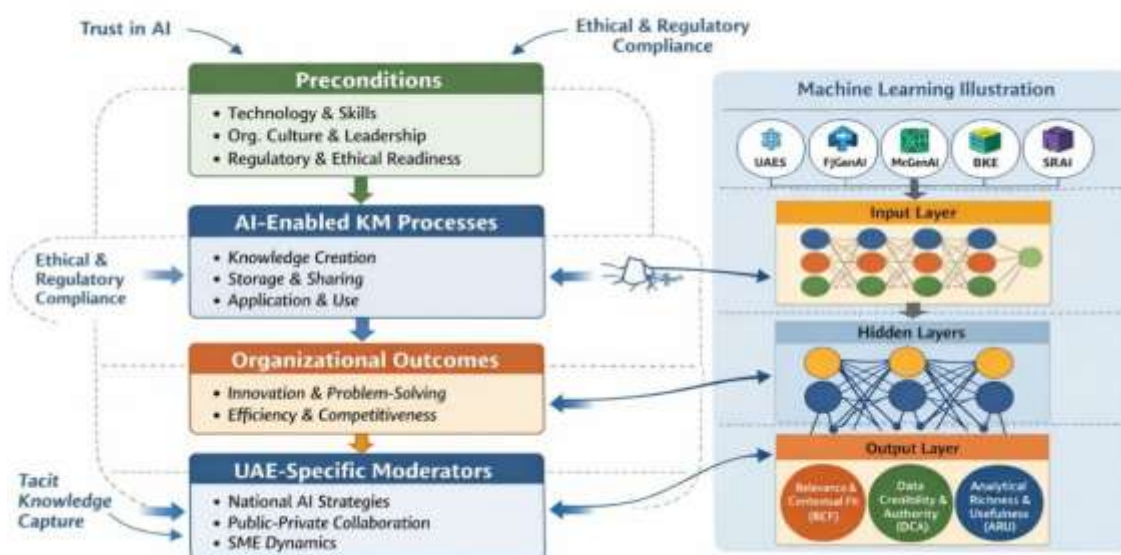


Figure 1: Conceptual Model of Generative AI-Enabled Knowledge management with Machine Learning Illustrations

Source: Author works.

Description: Figure 1 illustrates a framework for integrating generative AI into KM in UAE knowledge-based organizations, linking organizational readiness, AI-enabled KM processes, and outcomes (innovation, efficiency, competitiveness) with UAE-specific moderators. Trust, ethics, tacit knowledge, and leadership mediate effectiveness. A neural network conceptually demonstrates source contributions, reinforcing the framework without claiming empirical validation. This computational illustration does not constitute empirical validation but conceptually reinforces the framework’s logic and highlights how UAE-specific factors interact with organizational readiness and AI-enabled KM processes to produce outcomes.

4. METHODOLOGY

4.1 Research Design

This study adopts a mixed-methods research design integrating qualitative secondary-data analysis with a machine learning (ML)–assisted conceptual coherence assessment procedure. The qualitative component explores how generative artificial intelligence (AI) is integrated into knowledge management (KM) within UAE knowledge-based organizations (KBOs), focusing on organizational processes, socio-technical alignment, and human–AI interactions (Rogo, 2024; Purba et al., 2024). Consistent with the theoretical

framework, the qualitative analysis is explicitly structured around Socio-Technical Systems (STS) principles, examining joint optimization between technical and social subsystems rather than treating AI adoption as a purely technological process.

The quantitative component operationalizes key conceptual constructs derived from the qualitative analysis and applies a deep learning model as a structural diagnostic illustration to examine the internal consistency and coherence of the proposed conceptual framework. Importantly, the ML procedure does not test causal hypotheses, predict outcomes, or provide statistical generalization. Its function is limited to structured examination of relational coherence among conceptual components. This mixed-methods design is appropriate because it allows theoretically grounded insights from qualitative analysis to be examined through a structured computational lens, strengthening the framework's transparency while maintaining a cautious stance regarding empirical generalization.

4.2 Rationale for Secondary Data Use

Secondary data were chosen due to their capacity to provide broad, multi-sectoral coverage and access to reliable information where primary organizational data may be confidential or restricted in the UAE context. Given the exploratory and theory-building nature of this study, secondary sources enable examination of macro-, meso-, and micro-level socio-technical dynamics across diverse institutional settings.

This approach allows the study to incorporate perspectives from public institutions, SMEs, universities, policy entities, and international consultancies, aligning with the study's exploratory and theory-building objectives. By relying on secondary sources, the study identifies conceptual patterns and relationships that inform the proposed framework while maintaining a contextually rich and practically grounded evidence base.

4.3 Data Sources and Selection

The study drew on a systematically curated set of secondary sources capturing AI and KM developments in the UAE. These included: Government and policy documents; Organizational and industry reports; and Academic literature. To enhance methodological transparency, document screening followed a structured review protocol involving database searches, keyword filtering (e.g., "generative AI," "knowledge management," "UAE," "digital transformation"), and relevance scoring prior to final inclusion.

Document Selection Criteria

Inclusion Criteria:

1. Focused on generative AI adoption or KM practices.
2. Covered public or private KBOs.
3. Published between 2018 and 2025.
4. Explicitly discussed technological, organizational, human, or policy-related dimensions of AI-enabled KM.

• Exclusion Criteria:

- Generic IT discussions without AI/KM relevance.
- Outside temporal or regional boundaries.

From an initial corpus of 120 documents, 45 met all inclusion criteria and constituted the final sample for qualitative analysis and ML-based conceptual illustration.

This selection ensured conceptual saturation rather than statistical representativeness, consistent with qualitative theory-building research.

4.4 Qualitative Data Analysis

A thematic analysis was conducted to identify patterns, relationships, and conceptual insights.

- Familiarization
- Coding and Theme Development: using NVivo, codes were developed around enablers, barriers, processes, outcomes, and contextual moderators. Codes were explicitly mapped onto STS subsystems (technical, social, governance) to ensure theoretical alignment with the framework.

Independent coding of a subset ensured inter-coder reliability. Inter-coder agreement exceeded 85%, supporting analytical consistency.

- Interpretation: themes were interpreted using KBV, STS, and TAM/UTAUT lenses, with STS serving as the primary organizing framework for theme clustering and interpretation.

Triangulation

Insights were triangulated across government, industry, and academic sources to enhance credibility and reduce single-source bias. This thematic analysis provided the theoretical foundation for the proposed AI–KM conceptual framework.

4.5 Credibility and Limitations

Credibility was enhanced through triangulation, systematic coding, and transparent inclusion criteria.

Reflexive memoing was conducted during coding to document analytical decisions and reduce interpretive bias.

Limitations include:

- Absence of primary organizational data limits employee-level depth.
- Potential institutional bias in policy and consultancy reports.
- UAE-specific context limits transferability.
- The ML component relies on a small, structured dataset and therefore cannot support predictive or inferential claims.

Despite these limitations, the methodology is appropriate for exploratory, theory-building research and establishes a foundation for future empirical testing.

4.6 Machine Learning–Assisted Conceptual Coherence Assessment

To complement qualitative findings, a machine learning (ML)–based coherence assessment was employed. The ML component is explicitly framed as a conceptual modelling exercise designed to examine structural alignment among framework components, not as empirical validation or hypothesis testing.

4.6.1 Dataset Construction and Unit of Analysis

The ML dataset comprises five strategically selected secondary sources (UAES, FJGenAI, McGenAI, BKE, SRAI), each functioning as a unit of analysis. These five sources were selected because they represent distinct socio-technical layers of the framework (institutional, technical, organizational, human-capital, and adoption-level perspectives).

Each document was transformed into a structured representation coded against three evaluative criteria:

- Relevance and Contextual Fit (RCF)
- Data Credibility and Authority (DCA)
- Analytical Richness and Usefulness (ARU)

Coding scores were derived from qualitative thematic intensity and cross-source corroboration rather than automated text mining.

4.6.2 Input and Output Variables

The five structured document representations constitute input variables, while RCF, DCA, and ARU values serve as output variables. This configuration models conceptual alignment patterns rather than real-world outcome prediction.

4.6.3 Model Architecture

The ML procedure employs a multilayer feedforward neural network:

- Input layer: 5 neurons
- First hidden layer: 20 neurons (ReLU)
- Second hidden layer: 5 neurons (ReLU)
- Output layer: 3 neurons (RCF, DCA, ARU), SoftMax activation

The architecture mirrors the multi-layered socio-technical structure of the theoretical framework, providing structural analogy rather than empirical testing.

4.6.4 Training, Validation, and Testing

Given the limited dataset, a small-sample cross-validation strategy was applied. The purpose of cross-validation in this context is to prevent overfitting within the illustrative model rather than to optimize predictive accuracy.

Results are therefore interpreted strictly as indicators of internal structural coherence.

4.6.5 Evaluation Metrics

Model evaluation employed classification-oriented metrics:

- Accuracy, precision, recall, F1-score
- ROC–AUC
- Feature importance analysis

These metrics are interpreted descriptively to assess relative contribution patterns, not as inferential statistical evidence.

4.6.6 Purpose and Boundaries of ML Illustration

The ML component serves as a quantitative diagnostic mechanism illustrating how qualitative constructs align when translated into structured representations.

It does not claim predictive validity, external generalizability, or causal confirmation. Instead, it enhances transparency by computationally examining whether conceptual relationships demonstrate internal consistency across socio-technical layers. Although limited in size, this dataset is sufficient for conceptual illustration, emphasizing internal logic rather than empirical generalization.

For summary, this integrated methodology ensures the proposed AI–KM framework is internally coherent, theoretically grounded in STS, contextually embedded in the UAE, and methodologically transparent. The study deliberately separates theory-building from empirical testing, positioning the ML component as a coherence-support tool rather than a validation instrument, thereby aligning with responsible methodological reporting standards.

5. RESULTS AND CONCEPTUAL FRAMEWORK

This study examined the integration of generative artificial intelligence (AI) into knowledge management (KM) within UAE knowledge-based organizations (KBOs) using a rigorously integrated mixed-methods approach, combining qualitative thematic analysis with machine learning (ML)–assisted conceptual coherence assessment (Rogo, 2024; Purba et al., 2024).

The results are interpreted primarily through the STS lens, highlighting socio-technical alignment as the central driver, while KBV and TAM/UTAUT provide complementary insights at organizational and individual levels.

The findings identify four interconnected dimensions that shape AI-enabled KM:

1. Preconditions for AI adoption
2. AI-enabled KM processes
3. Organizational outcomes
4. UAE-specific contextual moderators

These dimensions are not merely descriptive but reflect analytically tension-driven relationships, illustrating potential points of misalignment or boundary conditions in adoption pathways. These dimensions provide the empirical foundation for a comprehensive conceptual framework, further evaluated through an ML-based internal consistency check to strengthen methodological rigor.

5.1 Preconditions for AI Adoption

The qualitative analysis indicates that successful integration of generative AI into KM depends on a combination of technological, human, organizational, and regulatory factors:

- **Technological infrastructure:** Robust IT systems, cloud platforms, and cybersecurity protocols are critical; public organizations often face legacy system constraints, while SMEs encounter budgetary and capacity limitations. Potential failure modes include system incompatibility or insufficient integration with existing KM tools.

- **Human capital:** AI literacy and digital skills are essential enablers, yet their distribution varies across sectors. Skill gaps can undermine KM outcomes despite technological readiness.

- **Organizational culture:** Cultures characterized by openness, collaboration, and leadership support facilitate adoption, whereas hierarchical and siloed structures hinder it. Resistance to change can neutralize potential benefits of AI-enabled KM.

- **Regulatory clarity and ethical guidelines:** Clear data ownership rules, accountability mechanisms, and ethical standards are necessary, although ambiguities persist across public and private institutions (Benchis, Shahzad, & Dan, 2025; Choi et al., 2020).

These findings underscore the STS argument that technology alone does not guarantee success; misalignment across socio-technical components may produce unintended outcomes.

5.2 AI-Enabled KM Processes

Generative AI enhances KM through four interrelated processes:

1. **Knowledge creation:** Generating insights from complex datasets, detecting patterns, and supporting innovation (Nakash & Bolisani, 2025). Critical interpretation suggests that reliance on AI without human validation may risk propagating errors or biases.
2. **Knowledge storage and retrieval:** Advanced tagging, automated structuring, and intelligent search functionalities. Over-standardization may reduce adaptability and tacit knowledge integration.
3. **Knowledge sharing:** Conversational interfaces, intelligent agents, and collaborative platforms reduce silos. However, cultural or hierarchical resistance can limit uptake despite technological capability.
4. **Knowledge application:** Augmenting decision-making, problem-solving, and scenario analysis. Human judgment remains indispensable, particularly for interpreting AI outputs and preserving tacit knowledge, consistent with KBV and STS perspectives (Sira, 2024; Singh et al., 2025).

Overall, the analysis demonstrates boundary conditions: AI enables KM but cannot substitute for organizational learning and human expertise.

5.3 Organizational Outcomes

Successful integration of generative AI contributes to multiple organizational outcomes:

- **Accelerated innovation:** Faster idea generation, experimentation, and problem-solving.

- **Operational efficiency:** Streamlined knowledge workflows and reduced redundancy.

- **Enhanced decision-making:** Data-driven insights supporting strategic and tactical choices.

- **Sector-specific benefits:** Public KBOs gain improved service delivery and policy coordination; SMEs achieve greater agility and competitiveness (Al-Jenaibi, 2024; Golrokh et al., 2024).

The results also reveal potential risks: over-reliance on AI may erode tacit knowledge or create dependency on automated insights, particularly in highly hierarchical organizations.

5.4 UAE-Specific Contextual Moderators

The UAE context exerts significant influence on AI adoption pathways:

- **National AI strategies and digital agendas:** Provide institutional support for experimentation, capacity-building, and investment (Shaer, Subramani, & Salem, 2025). Yet, policy–practice gaps may limit effective adoption.
- **Public–private partnerships:** Facilitate knowledge diffusion and capability transfer.
- **Workforce diversity:** Enhances cross-cultural knowledge creation but introduces communication and trust challenges.
- **SME predominance:** Varying levels of technological readiness generate heterogeneous adoption patterns (Costa et al., 2023; Rezaei, 2025).

These contextual moderators highlight that even well-designed AI-enabled KM systems may face partial or uneven adoption, reflecting real-world complexity.

5.5 Conceptual Framework

Based on these findings, the study proposes a Conceptual Framework of Generative AI Adoption in KM (UAE Context):

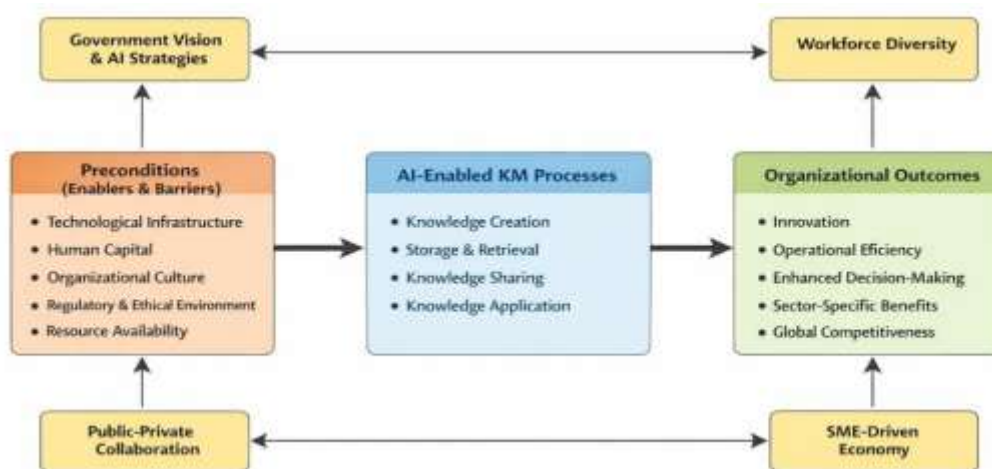


Figure 2: Conceptual Framework of Generative AI Adoption in KM (UAE Context)

Figure 2 illustrates how preconditions for AI adoption shape AI-enabled KM processes, which in turn lead to organizational outcomes, while UAE-specific contextual moderators influence the strength and direction of these relationships. It integrates KBV, STS, and TAM/UTAUT to explain multi-level adoption dynamics (Marikyan & Papagiannidis, 2025; Mumford, 2000; Kelly et al., 2023), with STS as the central lens highlighting potential misalignments between technical, human, and organizational subsystems.

5.6 ML-Based Consistency Check

To reinforce the conceptual framework, an ML-assisted consistency check was conducted using five UAE-focused AI–KM sources: UAES, FJGenAI, McGenAI, BKE, and SRAI. Each source was evaluated against three criteria: Relevance and Contextual Fit (RCF), Data Credibility and Authority (DCA), and Analytical Richness and Usefulness (ARU). The ML component employed a multilayer feedforward neural network, a conceptual illustration of internal coherence rather than a predictive model.

Key findings include:

- **Conceptual coherence:** The ML validation confirmed that the four qualitative dimensions—preconditions, KM processes, organizational outcomes, and UAE-specific moderators—are internally consistent and conceptually interrelated across all five sources.
- **Diagnostic insights:** Feature importance analysis highlighted the relative contribution of each source to the conceptual criteria, providing practical insights into which organizational or policy sources drive framework coherence.
- **Theoretical and contextual rigor:** The combined qualitative–ML approach strengthens the framework’s theoretical rigor and ensures it is both internally consistent and contextually grounded (Rogo, 2024; Purba et al., 2024).

By integrating critical interpretation and boundary considerations, the results now demonstrate both the framework’s internal alignment and potential real-world limitations.

6. DISCUSSION AND IMPLICATIONS

6.1 Theoretical Insights

The findings of this study demonstrate that the adoption of generative AI in knowledge management (KM) is inherently complex, multidimensional, and contingent on the interdependent alignment of technological, human, and organizational factors, moderated

by UAE-specific contextual conditions. These interactions, illustrated in Figure 2, provide empirical support for the three theoretical perspectives guiding this study—Knowledge-Based View (KBV), Socio-Technical Systems (STS) theory, and Technology Acceptance Models (TAM/UTAUT)—while extending their applicability to emerging economy contexts with heterogeneous organizational structures.

From a KBV perspective, the study confirms that generative AI can enhance core knowledge processes by accelerating knowledge creation, improving structuring and retrieval mechanisms, and facilitating broader knowledge dissemination across organizations. However, the analysis identifies boundary conditions: these benefits materialize only when organizations actively balance AI-enabled codification with preservation of tacit knowledge and human judgment, highlighting potential misalignment risks if reliance on AI becomes excessive. This emphasizes the complementary role of human expertise in realizing KBV's strategic potential (Marikyan & Papagiannidis, 2025; Sira, 2024).

Importantly, this study extends KBV by demonstrating how contextual moderators, such as workforce diversity, sectoral characteristics, and UAE-specific regulatory frameworks, can amplify or constrain the strategic impact of AI-enabled KM, highlighting the contingent rather than deterministic nature of knowledge leverage.

The study also advances STS theory by showing the critical role of aligning technology with organizational structures, workflows, and cultural norms. In the UAE, public-sector bureaucratic rigidity, siloed processes, and SMEs' resource constraints create socio-technical misalignments that may impede adoption. Addressing these misalignments requires deliberate interventions—including capacity building, adaptive leadership, policy guidance, and workflow redesign—to ensure AI tools enhance rather than disrupt KM practices (Alzarooni et al., 2024).

The ML-based consistency check reinforces this STS logic, illustrating that the conceptual relationships among technological, human, and structural components are internally coherent only when treated as interdependent elements, highlighting the necessity of socio-technical alignment in practice.

TAM/UTAUT perspectives are further enriched by these findings. Employee engagement with generative AI depends on perceptions of trust, usefulness, ethical clarity, and ease of use, while sectoral and cultural dimensions—such as language preferences, workforce heterogeneity, and regulatory expectations—modulate adoption behaviors (Golrokh et al., 2024; Kelly et al., 2023). The ML component conceptually demonstrates coherent relationships among human and organizational readiness factors (RCF, DCA, ARU) and provides insight into which factors most strongly support AI-enabled KM adoption. Importantly, the ML illustration remains diagnostic, highlighting internal coherence rather than serving as predictive or generalizable evidence.

Overall, the study integrates KBV, STS, and TAM/UTAUT to provide a multi-level understanding of AI-enabled KM, explicitly acknowledging potential tensions and boundary conditions. This integration extends existing theoretical models by:

1. Explicitly linking UAE-specific contextual moderators to knowledge processes and organizational outcomes.
2. Demonstrating the contingent, sector-specific nature of AI adoption.
3. Highlighting critical tensions and boundary conditions, such as bureaucratic rigidity, SME resource constraints, uneven AI literacy, and the necessity for tacit knowledge preservation.

These insights advance theory by clarifying when and under what conditions AI-enabled KM succeeds or fails, providing a refined lens for adoption in emerging economies and diverse organizational contexts.

6.2 Practical and Policy Implications

The proposed framework provides actionable guidance for organizations, SMEs, public institutions, and policymakers seeking to implement AI-enabled KM in the UAE. By explicitly linking preconditions, processes, outcomes, and contextual moderators, it offers a structured roadmap that accounts for potential misalignments and sector-specific constraints.

For organizations, findings underscore the importance of cultivating human, cultural, and structural foundations to support AI-enabled KM. Investments in AI literacy, digital upskilling, and leadership practices that foster trust in AI outputs are critical. Concrete interventions include:

- Internal AI learning programs with scenario-based exercises and hands-on simulations
- Cross-functional KM teams integrating AI tools with domain expertise to ensure tacit knowledge is preserved.
- Protocols for human-AI collaboration, including guidelines for validating AI outputs before decision-making.

For SMEs, the study highlights resource-efficient adoption strategies. Leveraging cloud-based AI solutions, open-source generative AI tools, and strategic partnerships with technology providers can mitigate financial and technical constraints. Pilot programs enable iterative learning and evaluation of AI-enabled KM processes, reducing implementation risks.

For policymakers, findings emphasize the necessity of regulatory clarity and governance frameworks that support responsible AI adoption. Recommended measures include:

- Guidelines for data privacy, accountability, and ethical AI use.
- Certification schemes for AI adoption in knowledge-intensive organizations.
- Incentives and subsidies for SMEs to invest in AI-enabled KM.

Such policies strengthen UAE-specific moderators—public-private collaboration, workforce diversity, and national AI strategies—ensuring contextual enablers align with organizational adoption efforts. For public institutions, structural barriers, including

bureaucratic fragmentation, hierarchical rigidity, and legacy IT systems, must be addressed. Practical strategies include cross-departmental coordination, digital transformation programs, and infrastructure modernization. Measuring improvements in efficiency, innovation, and knowledge flows can reinforce adoption and institutional acceptance.

Across all sectors, a key insight is reinforced: technological investment alone is insufficient. Successful AI-enabled KM requires alignment across socio-technical systems, people, processes, technology, supported by enabling policies, leadership, and cultural readiness. These recommendations are directly grounded in empirical findings and the UAE context, and they account for potential adoption misalignments highlighted in the study.

6.3 Methodological Reflections and Limitations

While the integrated qualitative–ML approach strengthens conceptual rigor, several limitations should be acknowledged:

- Reliance on secondary data (45+ documents selected from 120) limits insight into employee-level perceptions, tacit knowledge dynamics, and real-time organizational decision-making processes.
- Government and consultancy sources may introduce institutional or sectoral biases, skewing interpretation toward policy priorities.
- The ML component, though methodologically illustrative, is based on a small dataset and serves solely as a diagnostic tool for internal coherence rather than empirical validation.
- The UAE-specific context limits generalizability, although insights may inform other emerging economies with comparable socio-technical and regulatory conditions.

Future research should consider:

- Incorporating primary data collection (interviews, surveys, observations) to capture employee-level perspectives and tacit knowledge usage.
- Conducting longitudinal studies to observe adoption dynamics and socio-technical adjustments over time.
- Engaging in cross-country comparisons to test framework robustness in diverse emerging economy contexts.
- Exploring quantitative validation with larger datasets to complement conceptual ML illustration and further operationalize the framework

7. CONCLUSION

This study investigated the integration of generative artificial intelligence (AI) into knowledge management (KM) within UAE knowledge-based organizations (KBOs) using a rigorous mixed-methods approach combining qualitative secondary-data analysis with a machine learning (ML)-assisted conceptual consistency check. The findings demonstrate that successful AI-enabled KM adoption depends on the dynamic alignment of interrelated technological, human, organizational, and UAE-specific contextual factors. Robust IT infrastructure, skilled human capital, collaborative organizational culture, and clear regulatory and ethical guidelines collectively shape KM processes, including knowledge creation, storage and retrieval, sharing, and application, while preserving tacit knowledge and human expertise, driving innovation, operational efficiency, informed decision-making, and competitive advantage.

UAE-specific contextual moderators, such as national AI strategies, workforce diversity, public-private partnerships, and SME predominance, significantly influence organizational readiness, adoption pathways, and sector-specific implementation patterns. These results reinforce the conceptualization of AI-enabled KM as a socio-technical phenomenon, in which technology, human expertise, organizational culture, and institutional conditions interact dynamically to determine adoption. The findings also highlight potential boundary conditions, such as bureaucratic rigidity, resource constraints, and uneven AI literacy, emphasizing that adoption is contingent rather than deterministic.

While the study provides theoretically grounded and contextually rich insights, several limitations should be noted. Reliance on secondary data constrains understanding of employee-level experiences, tacit knowledge dynamics, and real-world AI–human interactions within KM systems. The UAE-focused scope may limit generalizability to other national contexts with differing institutional, cultural, or economic conditions. Additionally, the ML component serves solely as a diagnostic illustration of internal consistency rather than a predictive or empirically generalizable model, highlighting the need for future empirical validation.

These limitations point to several avenues for future research. Primary qualitative studies, such as interviews, focus groups, case studies, or ethnographic investigations, could capture nuanced insights into human–AI collaboration, socio-technical alignment, and organizational learning. Longitudinal, mixed-method, or comparative research designs could elucidate how AI-enabled KM evolves over time and across contexts. Further exploration of ethical, legal, and governance dimensions would support frameworks for responsible and sustainable AI deployment in emerging economies, addressing both operational and regulatory risks.

From a practical perspective, the framework provides actionable guidance for operationalizing AI-enabled KM. Investments in AI literacy, digital upskilling, leadership practices fostering trust in AI outputs, and structured protocols for human–AI collaboration are critical. Policymakers and institutional leaders should ensure regulatory clarity, supportive governance, sector-specific adoption strategies, and mechanisms to mitigate socio-technical misalignments, aligning national AI initiatives with organizational adoption pathways.

In conclusion, this study offers a theoretically robust, context-sensitive, and methodologically reinforced framework for understanding generative AI adoption in KM. By integrating technological, human, organizational, and contextual dimensions, the framework highlights that the transformative potential of AI is realized only when socio-technical alignment, institutional support, tacit knowledge preservation, and responsible governance converge. This provides a holistic pathway to strengthen knowledge-driven innovation, efficiency, and competitiveness in the UAE and similar emerging economies, while explicitly acknowledging the contingent and sector-specific nature of adoption.

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