Generative AI in Knowledge Management: A Comparative Mixed-methods Study of Jordan and Europe

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Abstract: Generative artificial intelligence (GenAI) is rapidly transforming organisational knowledge management (KM) processes. Yet limited research has examined how cultural and institutional contexts shape GenAI-enabled KM adoption across developed and developing economies. This study investigates the organisational, cultural, and institutional factors influencing GenAI-enabled KM practices in Jordan and Europe through a mixed-methods approach. Quantitative data were collected from 456 respondents across higher education institutions, SMEs, public-sector organisations and large enterprises. Qualitative data was collected through 36 semi-structured interviews. The findings reveal notable variations in the extent of GenAI adoption, readiness of organisational structures, maturity governance and trust in AI systems across cultures. Structural model analysis showed that technological infrastructure, AI literacy, leadership support, financial resources, and data governance positively affected GenAI adoption. Power distance and uncertainty avoidance negatively moderated adoption effectiveness. Qualitative results revealed that GenAI has high potential for supporting explicit knowledge processes, including externalisation and combination. Tacit knowledge processes such as socialisation remain dependent on people, trust and collaborative organisational culture. The study advances knowledge management theory by extending the SECI model through a GenAI-enhanced perspective that differentiates AI effects across tacit and explicit knowledge conversion processes. The study advances knowledge management theory by: (1) extending the SECI model through a GenAI-enhanced perspective that differentiates AI effects across tacit and explicit knowledge conversion processes—demonstrating process-contingency not previously specified; (2) reconceptualising GenAI capabilities as context-sensitive dynamic capabilities within the Knowledge-Based View, requiring complementary organisational resources; and (3) integrating cultural moderators into AI adoption theory, showing that cultural dimensions function as effectiveness moderators rather than just direct predictors. The study makes a novel contribution to cross-cultural AI adoption literature through a context-based model combining organisational readiness, cultural dimensions, and institutional maturity.

Keywords: Knowledge management, Cross cultural comparison, Organisational readiness, AI adoption, Jordan, Europe

1. Introduction

Organisational knowledge management (KM) is transforming rapidly with generative artificial intelligence (GenAI), but current research focuses largely on developed economies (Kudryavtsev et al., 2024). Empirical studies often assume Western findings transfer universally, overlooking how cultural and institutional conditions shape GenAI-enabled KM adoption—a critical gap for developing economies where digital infrastructure and organisational culture differ significantly from Europe.

While the SECI model (Nonaka & Takeuchi, 1995) frames tacit-explicit knowledge conversion, it lacks clarity on how GenAI interacts with cultural dimensions like power distance and uncertainty avoidance. Prior studies show GenAI enhances externalisation and combination (Sumbal et al., 2024), yet comparative evidence across divergent institutional environments remains limited. Without cross-cultural research, policymakers risk one-size-fits-all strategies.

This study addresses these gaps using a comparative mixed-methods design, exploring relationships between organisational readiness, cultural dimensions, institutional maturity, and GenAI-enabled KM practices in Jordan and Europe. Our theoretical lens integrates the SECI model, Knowledge-Based View, and cross-cultural technology adoption theory. We surveyed 456 respondents across higher education, SMEs, public sector, and large corporations, supplemented by 36 semi-structured interviews and 12 case studies. This study addresses three research questions:

RQ1: How do organisational readiness factors influence GenAI adoption intensity across Jordanian and European contexts?

RQ2: To what extent do cultural dimensions (power distance, uncertainty avoidance) and regulatory maturity moderate the readiness-adoption relationship?

RQ3: How does GenAI adoption differentially affect SECI knowledge conversion processes (socialisation, externalisation, combination, internalisation)?

Findings reveal significant cross-cultural differences, with GenAI most strongly enhancing explicit SECI processes (combination and externalisation) but weakly affecting tacit socialisation. Theoretically, we extend the SECI model by demonstrating differential AI effects, reconceptualise GenAI capabilities as context-sensitive dynamic capabilities within the Knowledge-Based View, and integrate cultural moderators into AI adoption theory. Practically, we provide guidance for policymakers to invest in infrastructure and governance, and for KM practitioners to implement GenAI as an augmentative tool supported by training and trust-building (Kumorovitzová, 2025).

2. Literature Review

2.1 Knowledge Management and Generative AI

The SECI model (Nonaka & Takeuchi, 1995) remains foundational for understanding tacit-explicit knowledge interaction (Bolisani et al., 2024). Systematic reviews confirm AI assists these conversions (Palm et al., 2025). Generative AI (GenAI) advances this further by moving beyond retrieval to active generation and contextualisation, a shift that fundamentally challenges conventional KM assumptions and requires a systematic reframing of the SECI model (Zhang Y et al., 2025). Empirical studies show that GenAI-augmented KM processes directly enhance decision-making and organisational performance by enabling firms to synthesise large knowledge repositories, codify tacit expertise, and deliver personalised learning experiences (Panizzon et al., 2024; Sumbal et al., 2024). Consequently, GenAI should be understood as a socio-technical capability embedded within broader governance and literacy structures, not merely a technological tool (Kretschmer et al., 2025; Turner, 2025; Taherdoost et al., 2023).

2.2 Cross-cultural and Institutional Influences

KM practices are consistently shaped by national and organisational culture. Hofstede's cultural dimensions are particularly relevant for technology adoption: high power distance centralises AI-related decisions and limits bottom-up experimentation, while high uncertainty avoidance fosters caution toward emerging technologies (Wang et al., 2024; Alamri, 2025). These cultural effects are amplified in AI-enabled KM because GenAI requires collaborative input and iterative refinement. The study shows that high power distance contexts show low AI readiness because of a hierarchy that stifles communication and sharing of information that is necessary for successful AI deployment (Frontiers, 2026). Institutional conditions further differentiate adoption outcomes: mature regulatory frameworks (e.g., GDPR, EU AI Act) provide governance clarity and institutional legitimacy, whereas developing economies face infrastructure and expertise constraints (AlKalbani, 2025). Middle Eastern KM adoption shows inconsistent organisational readiness. Research to date has been limited to developed economies, with comparative evidence on the role of cultural & institutional factors on the relationships between GenAI KM being minimal.

2.3 Digital Transformation and Organisational Readiness

GenAI integration into KM occurs within broader digital transformation (DT) efforts. A recent EJKM article notes that decentralised KM designs and digital transformation are closely intertwined, with DT acting as both a driver and a contextual boundary for KM innovation (Turner, 2025). Technological infrastructure, leadership commitment, digital literacy, financial resources and data governance are strongly associated with organisational readiness, and all of these factors have been a consistent predictor of successful GenAI adoption. Survey data from 778 decision-makers across multiple industries indicate that perceived benefits and readiness are the strongest enablers of GenAI adoption, while complexity represents a persistent barrier (Pokar, 2025). Leadership support and strategic alignment emerge as critical for translating technical opportunities into business value, and adoption patterns are broadly consistent across firm sizes (Pokar, 2025). GenAI is not a substitute for human skills, but rather an augmentative skill that complements human judgement and creativity (Jarrahi et al., 2025). However, significant gaps persist: empirical evidence from developing economies is scarce; existing frameworks rarely integrate organisational, cultural and institutional factors; and there is limited comparative analysis of how GenAI differentially affects SECI knowledge conversion processes. This study aims to answer these questions by conducting a comparative mixed methods research of GenAI empowered KM in Jordan and Europe.

2.4 Research gap and Theoretical Positioning

Prior literature treats GenAI primarily as a technological efficiency driver, rarely differentiating effects across SECI processes or examining cross-cultural moderators. This study addresses these gaps by proposing that GenAI-enabled KM effectiveness emerges from interactions between organisational readiness, cultural context, and institutional maturity. We integrate three theoretical perspectives to explain this phenomenon. First, the SECI model provides the foundational mechanism for knowledge conversion, distinguishing between tacit and explicit processes. Second, the Knowledge-Based View explains why organisations differ in their capability to leverage GenAI as a dynamic capability—where AI tools represent combinative capabilities that reconfigure knowledge resources. Third, cross-cultural technology adoption theory (drawing on Hofstede's dimensions and institutional theory) explains how national and organisational cultural contexts moderate the translation of readiness into effective adoption. The integration occurs as follows: organisational readiness represents the KBV-based resource base; SECI processes are the conversion mechanisms through which GenAI creates value; and cultural/institutional factors moderate the effectiveness of both readiness→adoption and adoption→SECI pathways. This integrated perspective addresses the limitations of prior research that treated these as separate domains.

3. Conceptual Framework and Hypotheses

3.1 Conceptual Framework

The proposed framework integrates the SECI model, the Knowledge-Based View and cross-cultural technology adoption research. Organisational readiness is the most important precursor to GenAI adoption intensity, with technological infrastructure, AI literacy, leadership support, financial resources, and data governance being the primary factors. Cultural dimensions—power distance and uncertainty avoidance—together with institutional regulatory maturity moderate the readiness–adoption relationship. GenAI adoption intensity then differentially influences the four SECI processes: stronger effects are expected on explicit processes (combination and externalisation) than on tacit processes (socialisation). Enhanced SECI processes ultimately improve overall KM effectiveness (knowledge accessibility, learning, innovation capability, decision quality).

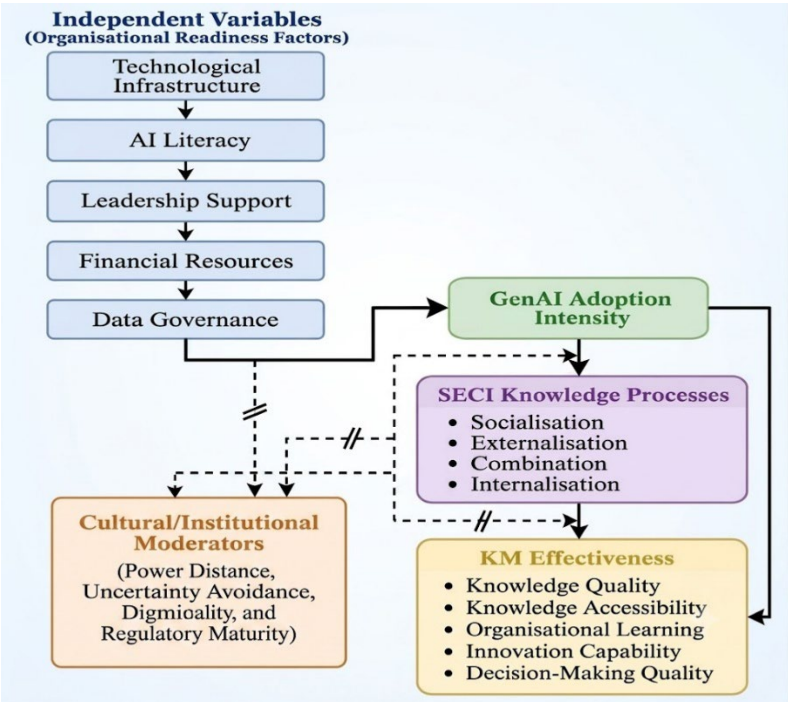

Figure 1: Conceptual Framework for GenAI-Enabled Knowledge Management Adoption

3.2 Hypotheses Development

Organisational readiness and GenAI adoption

Organisational readiness—technological infrastructure, AI literacy, leadership support, financial resources, and data governance—determines GenAI integration effectiveness. A survey of 778 decision-makers found readiness is the strongest enabler of GenAI adoption (Pokar, 2025). Hence:

> *H1: Organisational readiness (comprising technological infrastructure, AI literacy, leadership support, financial resources, and data governance) positively influences GenAI adoption intensity, with this relationship being stronger in European organisations compared to Jordanian organisations.*

3.2.1 Cultural and institutional moderators

In high power distance cultures, centralised decision-making limits bottom-up experimentation and cross-functional collaboration (Hofstede, 1983), negatively affecting AI readiness (Frontiers, 2026). Hence:

> *H2: Power distance negatively moderates the relationship between organisational readiness and GenAI adoption intensity.*

High uncertainty avoidance cultures favour predictable processes, yet GenAI's probabilistic outputs create ambiguity. This conflicts with established rules, making workers apprehensive about reliability and accountability (Alamri, 2025; Li et al., 2025). Thus:

> *H3: Uncertainty avoidance negatively moderates the relationship between the organisational readiness and the intensity of GenAI adoption.*

Regulatory maturity is the clarity, stability and enforceability of regulations and guidelines about the use of AI. Mature regulatory frameworks—such as the EU AI Act, which classifies AI systems by risk level and imposes transparency obligations—reduce legal ambiguity and build organisational confidence in adopting GenAI (AlKalbani, 2025). Clear and consistent regulations allow firms to better gauge compliance expenses, budget for compliance, and educate staff without worrying about a new set of regulations coming into effect. Lack of clarity or fluidity in regulations, on the other hand, fosters uncertainty, which inhibits investment and slows adoption. A global survey of business leaders found that nearly 80% report that unclear and evolving regulations impact the time, money and people investments they are making in AI (KPMG, 2025). Accordingly:

> *H4: Regulatory maturity positively moderates the relationship between organisational readiness and GenAI adoption intensity.*

3.2.2 GenAI Adoption and SECI knowledge processes

According to the SECI model, GenAI's capabilities map onto the four knowledge conversion processes with varying intensity (Palm et al., 2025; Zhang W et al., 2025). Accordingly, H5: GenAI adoption intensity has differential effects on SECI knowledge conversion processes—specifically, stronger positive effects on explicit processes (Externalisation and Combination) than on tacit processes (Socialisation and Internalisation). Combination is GenAI's most natural application, synthesising multiple explicit sources. Internalisation is moderately supported but requires human engagement. Socialisation remains least affected, as tacit transfer relies on trust and non-verbal cues that AI cannot replicate (Atraqchi et al., 2026; He, W. et al., 2024).

3.2.3 SECI processes and KM effectiveness

Improved knowledge conversion processes are ultimately expected to strengthen overall organisational KM effectiveness. Organisations that excel at socialisation build richer relational capital and trust networks, facilitating tacit knowledge flow across teams. Effective externalisation preserves critical expertise that would otherwise remain locked in employees' minds, reducing knowledge loss from turnover. By leveraging existing explicit knowledge, robust combination can lead to the creation of new insights, fostering innovation and strategic agility (Al-kfairy, 2025).

Lastly, employees are able to continuously learn inform the repositories and enhance their decision quality and problem solving capability by using strong internalisation. In combination, these enhanced SECI processes contribute directly to measurable KM outcomes, including faster knowledge accessibility, higher organisational learning rates, greater innovation output and improved decision-making quality (Panizzon et al., 2024; Sumbal et al., 2024). Thus:

> *H6: Enhanced SECI knowledge conversion processes positively influence overall KM effectiveness, and these SECI processes mediate the relationship between GenAI adoption intensity and KM effectiveness.*

4. Research Methodology

A sequential explanatory mixed-methods design was selected for three reasons. First, the research questions require both breadth (to establish generalisable patterns across contexts) and depth (to understand contextual mechanisms). Second, the comparative nature of the study demands quantitative comparisons of adoption rates and effects, while qualitative data is necessary to explain *why* these differences occur (Anim et al., 2025). Third, given limited prior cross-cultural research in this domain, an explanatory design allows quantitative findings to identify patterns that qualitative inquiry can then investigate in depth. Integration occurred at the interpretation stage through joint displays and narrative synthesis (Nguyen et al., 2025).

4.1 Phase 1: Quantitative Phase

A structured online questionnaire measured GenAI adoption, organisational readiness, SECI process impacts, and cultural dimensions (power distance, uncertainty avoidance). All constructs used 7-point Likert scales adapted from validated instruments (Ribeiro, 2025).

4.1.1 Pilot testing

A first test of the survey was conducted with 36 participants, 18 from Jordan and 18 from Europe, to check clarity, cultural appropriateness and translations (Arabic and European languages). Items were revised, based on feedback. All Multi Item scales had Cronbach's alpha > 0.80 on the Reliability Testing.

4.1.2 Sampling strategy for quantitative phase

Stratified random sampling ensured representation across sector (higher education, SMEs, large corporations, public sector, non-profit), organisation size (small, medium, large), and region (Jordan: Amman, Irbid, Zarqa, Aqaba; Europe: Western, Northern, Southern, Eastern). The final sample presented in Table 1 comprised 456 respondents (Jordan n=232, Europe n=224), exceeding the minimum 200 cases required for structural equation modelling (Nguyen et al., 2025). Stratified random sampling was used to ensure representation across higher education, SMEs, large corporations, public sector, and non-profit organisations, with random selection from Jordanian and European databases. A target sample of 450 was set based on power analysis for structural equation modelling, exceeding the minimum requirement of 360 cases (10 cases per 36 parameters) with oversampling for incomplete responses.

Table 1: Sample Demographic and Organisational Characteristics

Variable	Category	Jordan (n=232)	Europe (n=224)	Total (N=456)
Gender	Male	136 (58.6%)	121 (54.0%)	257 (56.4%)
	Female	96 (41.4%)	103 (46.0%)	199 (43.6%)
Age Group	21–30	54 (23.3%)	49 (21.9%)	103 (22.6%)
	31–40	88 (37.9%)	82 (36.6%)	170 (37.3%)
	41–50	63 (27.2%)	71 (31.7%)	134 (29.4%)
	51+	27 (11.6%)	22 (9.8%)	49 (10.7%)
Sector	Higher Education	64 (27.6%)	58 (25.9%)	122 (26.8%)
	SMEs	71 (30.6%)	63 (28.1%)	134 (29.4%)
	Large Corporations	48 (20.7%)	59 (26.3%)	107 (23.5%)
	Public Sector	35 (15.1%)	28 (12.5%)	63 (13.8%)
	Non-Profit	14 (6.0%)	16 (7.2%)	30 (6.5%)
Organisation Size	Small (10–50)	76 (32.8%)	54 (24.1%)	130 (28.5%)
	Medium (51–250)	89 (38.4%)	82 (36.6%)	171 (37.5%)
	Large (>250)	67 (28.8%)	88 (39.3%)	155 (34.0%)
Current GenAI Use	Active Adoption	90 (38.8%)	152 (67.9%)	242 (53.1%)

Note: Percentages may not total 100 due to rounding.

4.1.3 Data collection procedure

Data were collected (September–December 2025) via professional networks, university partnerships, LinkedIn, and snowball sampling. Survey was translated into English, Arabic, German, French and Spanish using back translation. Multiple reminders were sent to non respondents.

4.2 Phase 2: Qualitative Phase

Semi-structured interviews (60–90 minutes each) were conducted with 36 participants (18 Jordan, 18 Europe), including KM managers, IT directors, and knowledge workers. The interviews were conducted, transcribed word for word and structured around six thematic areas: organisational context, adoption journey with GenAI, cultural and institutional influences, human AI collaboration, benefits/challenges, and future directions.

4.2.1 Case study selection

Purposive sampling selected 12 case study organisations (6 Jordan, 6 Europe) based on variation in GenAI adoption levels (early experimentation, pilot, full deployment), sector, readiness profiles (high/medium/low), and willingness to participate.

4.2.2 Data saturation

Thematic saturation was achieved after approximately 30 interviews, with the final 6 interviews confirming no new themes emerged.

4.3 Data Analysis

4.3.1 Quantitative data analysis

IBM SPSS Statistics 29 and SmartPLS 4 for structural equation modelling were used for quantitative data analysis. The analysis sequence comprised: (1) descriptive statistics and data screening (normality, multicollinearity); (2) PLS-SEM: measurement model assessment (reliability, convergent/discriminant validity) and structural model testing (path coefficients, R^2, f^2, Q^2); (3) multi-group analysis comparing Jordan and Europe, plus t-tests and ANOVA with effect sizes (Cohen’s d, eta-squared).

4.3.2 Qualitative data analysis

Thematic analysis was carried out using the steps developed by Braun and Clarke, with the assistance of NVivo 14. This coding was deductive (based on SECI constructs) and inductive. Cross-case synthesis identified patterns across the 12 case organisations.

4.3.3 Integration and mixing point

Integration occurred via: (1) quantitative results guiding purposive case selection and interview protocol refinement; (2) joint displays for interpretive synthesis and meta-inferences (Anim et al., 2025; Khan et al., 2024).

4.4 Validity and Reliability

Cronbach's alpha was used to test the reliability of the constructs and was found to be more than 0.70 for all constructs. Convergent validity was achieved when the AVE exceeded 0.50, while discriminant validity was achieved when HTMT ratios were < 0.85. Inter-coder reliability (Cohen's $\kappa = 0.84$) was used to ensure dependability of qualitative data.

5. Results

5.1 Hypotheses Testing Summary

All six hypotheses were supported. Table 2 presents measurement quality and structural model results. The quantitative results of each hypothesis are summarised below, qualitative evidence is presented in 4.3.4.

Table 2: Measurement Quality, Structural Model Results, and Hypothesis Testing Summary

Construct / Hypothesis	CR	AVE	Path Coefficient (β)	t-value	p-value	Result
Technological Infrastructure → GenAI Adoption	0.89	0.67	0.38	5.84	<0.001	Supported
AI Literacy → GenAI Adoption	0.91	0.71	0.41	6.27	<0.001	Supported
Leadership Support → GenAI Adoption	0.87	0.63	0.29	4.92	<0.001	Supported
Financial Resources → GenAI Adoption	0.86	0.61	0.33	5.11	<0.001	Supported
Data Governance → GenAI Adoption	0.90	0.69	0.36	5.66	<0.001	Supported
Power Distance × GenAI Adoption	—	—	-0.24	3.74	<0.01	Supported
Uncertainty Avoidance × GenAI Adoption	—	—	-0.19	3.18	<0.01	Supported
Regulatory Maturity × GenAI Adoption	—	—	0.31	4.83	<0.001	Supported
GenAI Adoption → Socialisation	0.84	0.58	0.19	2.41	<0.05	Supported

Construct / Hypothesis	CR	AVE	Path Coefficient (β)	t-value	p-value	Result
GenAI Adoption → Externalisation	0.91	0.72	0.46	6.82	<0.001	Supported
GenAI Adoption → Combination	0.93	0.75	0.57	8.11	<0.001	Supported
GenAI Adoption → Internalisation	0.88	0.65	0.34	4.96	<0.01	Supported
SECI Processes → KM Effectiveness	0.92	0.73	0.61	8.44	<0.001	Supported

Notes: CR = Composite Reliability; AVE = Average Variance Extracted. All CR values were above the recommended value of 0.70, and all AVE values were above the recommended value of 0.50, which indicated construct reliability and convergent validity.

5.2 Quantitative Findings

5.2.1 GenAI adoption rates (H1, H2)

H1 (higher adoption in Europe): Supported. European organisations showed 68% adoption (152/224) vs. 39% in Jordan (90/232); t(454)=7.82, p<0.001, Cohen's d=0.74 (large effect).

H2 (size/sector differences): Supported. ANOVA: F(3,452)=12.34, p<0.001. Higher education (mean=5.82/7) and large corporations (5.67/7) led adoption; SMEs (3.91/7) and public sector (4.02/7) lagged.

5.2.2 Organisational readiness differences (H3, H4)

H3 (readiness gaps): Supported. Multi group SEM: Europe scored higher on technological infrastructure (mean diff=1.82, p<0.001), digital literacy (1.31, p<0.001), financial resources (2.14, p<0.001), leadership support (0.63, p<0.05), and data governance (2.43, p<0.001).

H4 (financial resources stronger in Jordan): Supported. PLS-SEM: β=0.44 (Jordan) vs. 0.21 (Europe), p<0.001 for difference.

5.2.3 KM Process improvements: Impact on SECI model (H5, H6)

H5 (differential SECI effects): Supported. Path coefficients: Combination β=0.57 (p<0.001), Externalisation β=0.46 (p<0.001), Internalisation β=0.34 (p<0.01), Socialisation β=0.19 (p<0.05).

H6 (stronger Combination/Externalisation in Europe): Supported. Multi-group analysis: Combination Δβ=0.18 (p<0.01), Externalisation Δβ=0.12 (p<0.05) favouring Europe.

5.3 Qualitative Findings

Three dominant themes emerged from thematic analysis of 36 semi-structured interviews. First, organisational readiness emerged from first-order concepts including poor AI integration capability and weak internal datasets. Second, AI literacy and adaptation was reflected in employee fear of AI and lack of prompt engineering skills. Third, leadership and governance encompassed executive AI advocacy and unclear AI accountability. Cultural and institutional constraints appeared through fear of AI errors and hierarchical decision approval. Finally, human-AI collaboration was characterised by AI-assisted report writing and human oversight mechanisms.

5.3.1 Theme 1: Organisational readiness

Organisational readiness – infrastructure, leadership, AI literacy, governance – was the most frequently discussed factor. European participants described GenAI adoption as an extension of existing digital transformation strategies with mature IT ecosystems (Alarefi, M.A. et al., 2025). Jordanian respondents framed adoption as an emerging experiment constrained by resource limitations and uneven digital maturity.

"We already had mature digital knowledge systems before introducing generative AI tools. The transition was less about technological disruption and more about integrating AI into workflows that employees already trusted." (Senior innovation manager, German technology company)

5.3.2 Theme 2: Cultural and institutional influences

Power distance, uncertainty avoidance, and regulatory maturity significantly shaped adoption. European organisations benefited from clear governance (e.g., GDPR), providing employee confidence. In Jordanian organisations, higher power distance centralised AI decisions, while uncertainty avoidance amplified concerns about AI hallucinations and legal accountability.

> *"Employees are more comfortable using AI tools when there are clear governance rules about accountability, data handling, and human oversight." (Compliance officer, Sweden)*

5.3.3 Theme 3: Human–AI collaboration

GenAI was viewed as augmentative rather than replacement. Employees used GenAI for synthesis, drafting, and retrieval while retaining human validation. AI literacy, trust and organisational policies were crucial for effectiveness.

> *"There is a danger that employees become passive consumers of AI-generated summaries without critically evaluating the underlying knowledge." (Policy advisor, Netherlands).*

6. Discussion

6.1 Theoretical Contributions

This study extends the SECI model in three specific ways. First, prior SECI research treats knowledge conversion as a unified process; we demonstrate process-contingency—that GenAI's effects vary significantly across conversion modes. This introduces a technology-specific boundary condition to the original model. Second, we show that SECI processes should be understood not merely as knowledge conversion mechanisms but as outcome variables that are differentially influenced by technological interventions—an extension that reframes SECI from a descriptive model to a predictive framework. Third, we identify that socialisation—typically considered the foundation of knowledge creation—may not be enhanced by GenAI, challenging the assumption that digital tools universally improve all knowledge processes. This suggests a revised SECI model where explicit processes (Combination, Externalisation) are technologically augmentable, but tacit processes (Socialisation, Internalisation) require complementary social and organisational interventions.

6.2 Practical Implications

For Jordanian policymakers, our findings suggest prioritising investment in foundational digital infrastructure—including cloud, data storage, and connectivity—as this represents a primary readiness gap (mean difference = 1.82, $p<0.001$), while simultaneously developing AI literacy programmes targeting SMEs where adoption lags significantly (mean=3.91/7 versus 5.82/7 in higher education), and establishing data governance frameworks to build trust, which our qualitative data indicates is a primary concern. For European policymakers, the emphasis should be on maintaining and refining existing governance frameworks such as GDPR and the EU AI Act, as these provide a competitive advantage ($\beta=0.31$ moderation effect), addressing the SME adoption gap through sector-specific guidance, and promoting human-AI collaboration models rather than replacement narratives to reduce uncertainty avoidance concerns. For multinational organisations, we recommend conducting cultural diagnostics before implementation, as our findings show cultural moderation effects ($\beta=-0.24$ and -0.19) that cannot be addressed through technology alone, and tailoring training approaches accordingly—with European contexts potentially emphasising compliance and governance, while Jordanian contexts may benefit more from demonstrating practical value and securing leadership advocacy.

6.3 Limitations and Future Research

The study's cross-sectional design, while appropriate for exploratory comparative analysis, prevents establishing causal direction—longitudinal research is needed to confirm that readiness precedes adoption and that adoption drives SECI enhancement. Self-reported perceptual data may introduce common method bias, although Harman's single-factor test (28% variance) suggests this is not a significant concern. The treatment of Europe as a monolithic entity masks considerable within-region heterogeneity, particularly between Northern and Southern European contexts; however, sub-regional sample sizes (n=45-90) were insufficient for meaningful disaggregation. Additionally, the sectoral focus excludes manufacturing and healthcare, where GenAI applications and knowledge management challenges differ markedly from the sectors examined. Finally, while we measured cultural dimensions at the individual/organisational level using adapted Hofstede items, these may not perfectly correspond to national-level cultural indices, suggesting value in future multi-level modelling to disentangle individual, organisational, and national cultural effects (Storey, 2025; Sun et al., 2025).

7. Conclusion

This comparative mixed-methods study reveals substantial adoption gaps (68% Europe vs. 39% Jordan), with GenAI more strongly enhancing explicit SECI processes (externalisation, combination) than tacit ones (socialisation, internalisation). Financial resources drove adoption more in Jordan, while data governance maturity gave Europe a clear edge. Theoretically, we refine the SECI model by demonstrating technology-process interaction effects—showing GenAI's differential impact on knowledge conversion modes—extend KBV through a dynamic capabilities lens, and identify cross-cultural moderators of AI adoption. Practically, findings urge infrastructure and governance investment, culturally adaptive strategies, and treating GenAI as augmentation backed by training and trust. Future research should adopt longitudinal designs, broaden regional scope, and address ethical implications.

Ethical Considerations: The research was approved by the lead researcher's Institute's Review Board. The informed consent was obtained for all the participants and anonymity was guaranteed by using pseudonyms and keeping encrypted and password-protected servers. The study adhered to GDPR in Europe and Jordanian data protection laws.

9AI Declaration: During the preparation of this work, the authors used DeepSeek for the purpose of language refinement and grammar checking. The authors reviewed and edited all content and took full responsibility for the publication.

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