“The nexus between AI-driven capabilities and knowledge systems in digital business environments”

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THE NEXUS BETWEEN AI-DRIVEN CAPABILITIES AND KNOWLEDGE SYSTEMS IN DIGITAL BUSINESS ENVIRONMENTS

Abstract

The increasing development of digital business environments has contributed to the diversification of knowledge sources globally, making smart knowledge management crucial for enhancing the accuracy of decision-making processes. This study aims to investigate the impact of AI-driven capabilities, including adaptive learning, intelligent analytics, automation capability, integration capability on knowledge systems, and the role of smart knowledge management as a mediating factor within the context of the Federal Civil Service Council in Baghdad, Iraq. The study employed a quantitative method to collect data between April 2025 and August 2025 from 161 employees with at least three years of experience in knowledge management, organizational content and records, data, and machine learning. This sample included knowledge management managers, knowledge management specialists, data analysts, knowledge support technicians, and operations managers at the Federal Civil Service Council. The findings indicate that enhancing AI-driven capabilities across the four dimensions of adaptive learning, intelligent analytics, automation capability, and integration capability contributes to organizational success. This is evident from the correlation between adaptive learning ($p = 0.012$, < 0.279), analytical intelligence ($p = 0.018$, < 0.213), automation capabilities ($p = 0.02$, < 0.05), and knowledge systems. The study found that intelligent knowledge management plays a crucial mediating role in the relationship between AI capabilities and knowledge systems, contributing to the success of digital organizations and the accuracy of decision-making. This is further demonstrated by the positive correlation between the dimensions of AI capabilities and knowledge systems.

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INTRODUCTION

Knowledge management is a fundamental organizational capability for improving decision-making, innovation, and competitive advantage. However, traditional knowledge management systems are often limited to static repositories, manual coding processes, and limited analytical capabilities, hindering their ability to keep pace with the increasing volume, rapid evolution, and complexity of corporate knowledge (Al-Ghazawi et al., 2024). In a world dominated by the digital revolution, rapid technological change, and information-intensive processes, these limitations have diminished the strategic effectiveness of traditional knowledge management practices (Al-Ramahi et al., 2024).

Recent advancements in artificial intelligence (AI), such as machine learning, natural language processing, and intelligent analytics, have unlocked new possibilities for transforming knowledge management into a more diversified, predictive, and valuable service. Intelligent

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knowledge management is a new, advanced model that integrates AI technologies with knowledge systems to facilitate real-time knowledge creation, intelligent retrieval, automated sharing, and contextual decision support. Through this integration, organizations can move beyond the initial criteria of knowledge storage to its dynamic application, directly supporting strategic objectives (Salhab et al., 2023).

Despite the growing interest in AI-powered knowledge systems, many organizations have struggled to achieve effective strategic alignment between AI capabilities and knowledge management practices. Research on AI or knowledge management systems often focuses on the individual application of AI tools or knowledge management models, offering little practical guidance on how to effectively integrate AI into knowledge management systems to create long-term strategic value. This disparity leads to fragmented applications, insufficient utilization of AI resources, and a misalignment between technological investments and organizational strategy (Al-Khazaleh et al., 2023). Therefore, this study addresses the gap created by the lack of a unified strategic model that demonstrates how AI can be successfully applied to work with knowledge management systems to enhance organizational performance and strategic decision-making (Al-Rajoub et al., 2021). This study attempts to demonstrate the scientific relevance of intelligent knowledge management by clarifying the conceptual foundation of this concept and highlighting its strategic role in modern organizations operating in a knowledge-based and digitally driven environment.

1. LITERATURE REVIEW AND HYPOTHESES

Smart Knowledge Management (SKM) is also currently defined as the ability of organizations to reduce the decision latency time, increase the accuracy and the recall rate of a retrieval, and reduce the cost-to-serve in the large-scale digital environments (Al-Qhtani, 2025). Many previous studies have pointed to knowledge management systems focused on the capture and storage processes, which were not always suited to the real-time and accuracy needs of a contemporary decision-making environment (Deepu & Ravi, 2023). As artificial intelligence is integrated, automation capability can speed up ingestion, classification, and routing, and analytical intelligence is able to make outputs more precise by verifying that they match underlying sources (Fakhar Manesh et al., 2021). Existing studies highlight that observational research documenting the decision reduction of fifteen to twenty-five percent and retrieval precision increase of ten to eighteen percent has been reported in situations where hybrid retrieval and grounding are used (Feng et al., 2024). These gains can be seen the most in compliance inquiries, customer services, and technical troubleshooting, where time and accuracy matter the most (Gil-Gómez et al., 2020). An example on a smaller scale is the use of AI-based generation of policy responses over several repositories to generate grounded answers with in-text citations: one enterprise pilot. This contributed towards the need to do less manual navigation and instilled confidence by connecting responses to authoritative clauses of policy (Han & Balabanis, 2024). SKM efficiency is therefore not just measured by speed, but also by accountability and trust that are results of governance consistency.

Artificial intelligence is the unifying medium that links dissimilar repositories and tasks accessible to users (Hashem et al., 2024). Under SKM, the AI coordinates the hybrid retrieval strategies; that is, the keyword, dense, and re-ranking strategies with metadata filters to ensure the maintenance of context and compliance (Hermawan, 2024). Grounding mechanisms maintain the faithfulness of responses to underlying sources, and lineage tracking produces audit-readable records to use in governing activities (Hirata et al., 2020; Taherdoost & Madanchian, 2023). Integration capability allows the AI to combine materials in documents, chats, enterprise systems, and logs and generate coherent results, which can be verified by human-in-the-loop control (Huang et al., 2022; Alavi et al., 2024). Through summarization, routing, and validation, an AI as an intermediary negatively affects redundancy, misinterpretations, and enterprise accountability.

Current studies indicate that the enterprise 4.0 is a continuation of the approach of Industry 4.0, applied to the field of knowledge, forming linked digital knowledge systems (Isnaini et al., 2020). Such ecosystems combine collaboration systems, content services, graph databases, vector indexes, and orchestration engines, which, in combination, facilitate adaptive and interoperable knowledge systems (Kloth & Jonathan, 2025; Zhang & Liu, 2025). In SKM, adaptive learning plays a major role since it constantly optimizes taxonomies, embeddings, and policy constraints using feedback loops and utilization analytics (Kumar et al., 2024). This amalgamation provides an intellectual framework, which bargains the interaction of innovation and risk management, in distributed repositories. The use of empirical assessment of a vignette showed a statistically significant effect, which was greater than ten percent, of compliance-response accuracy after one test using an access-controlled retrieval-augmented generation system. Adaptive processes were used to maximize the index of retrieval and dynamically perform policy, thus making responses preserve the contextual fidelity and comply with the standards of institutional performance (Nguyen et al., 2021). Subsequently, the continuous dynamism between technology governance, organizational learning, and strategic knowledge management is represented in the knowledge ecosystems of Enterprise 4.0. Digital dynamic capability is a term used to describe the ability of an organization to perceive, capture, and reorganize knowledge processes on a real-time basis (Sheikh et al., 2024). SKM can do this by having the capability of automation, integration, and adaptive learning; a combination of these aspects increases ingestion, interoperability, and development of retrieval and evaluation modalities (Skafi et al., 2020). These capabilities enhance organizational resilience through facilitation of the renewal of governance models, rewriting of taxonomies, and re-tuning of assessment practices according to changing regulatory and operating conditions (Skafi et al., 2020). The role of SKM thus changes to the procedure, which maintains agility, compliance, and security of knowledge-based operations in businesses (Thiemann et al., 2025; Abou-Moghli, 2025).

In addition, new developments in digital knowledge systems have transformed the practice of enterprises and have changed the traditional repositories to a dynamic and AI-driven architecture. Such systems incorporate a complete lifecycle, ingestion, normalization, governance, storage, and indexing in both relational and vector databases, retrieval orchestration, reasoning and execution, feedback loops, and monitoring. Analytical intelligence improves the extraction of insights by determining trend patterns and recommending the use of evidence based on heterogeneous sources. Improved methods of architecture are retrieval-augmented generation pipelines, multi-agent workflows, provenance lineage frameworks, and content normalization pipelines to impose privacy and consistency (Fakhar Manesh et al., 2021). Further metrics that can be monitored through evaluation harnesses include faithfulness, coverage, latency, and cost-to-serve. The effect is illuminated by the example. In a single business environment, the analysis of the contract with highlighted clauses helped to cut the period spent on legal review and increased the efficiency of the process, as well as the readiness to audit the review report. In the other, AI-aided customer support retrieval led to shorter average handling time as well as higher scores on satisfaction, proving that SKM has a dual effect on cost effectiveness and customer satisfaction. These illustrations affirm that technological progress in SKM is more of an organizational than a technical matter, which entails the role of governance and accountability in the knowledge processes (Kloth & Jonathan, 2025).

Artificial intelligence can assist SKM through the improvement of discovery, synthesis, and management functions. AI facilitates the discovery of knowledge based on semantic search and hybrid retrieval, builds upon synthesis based on contextual summaries with source attribution, and imposes control based on grounding and redaction. The process of de-duplication and clustering minimizes redundancy, whereas entity and relationship extraction assist in graphical reasoning towards strategic insight. The issue of risk management is also at the core of the role played by AI. Also, AI tools could detect sensitive data and impose privacy protection in accordance with governance structures (Skafi et al., 2020). Assessment systems enable faithfulness, coverage, and safety to be monitored at any given time, and the outputs are always accurate and compliant with policy. These contributions show that AI is not a substitute for traditional KM, but it is an enabler that expands its scope, accuracy, and responsibility (Sheikh et al., 2024).

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The study within the scope of AI is inclined towards the possibility of implementing algorithms and overlooks the types of governance that should be embraced by businesses. KM research, on the other hand, is more focused on standards, taxonomies, and process models, but it rarely addresses the technical coordination of retrieval, grounding, and evaluation (Nguyen et al., 2021). Empirical research indicates that measurable enhancements in the state of decision-making and operational performance are achieved when organizations organize engagement of AI intermediaries, governance systems, and continuous evaluation systems. The explanation of architecture, KPIs, and risk controls is, however, thin, and both theory and practice are not developed well. The present paper bridges this gap because it offers systematic frameworks of integration of SKM, which leads to a convergence of technical, organizational, and governance in digital business environments (Sheikh et al., 2024).

The conceptualization of Smart Knowledge Management (SKM) can be based on the combination of knowledge management theory, dynamic capabilities, and governance of artificial intelligence. Classical knowledge management focuses on knowledge capture, knowledge organization, as well as dissemination processes to enhance decision-making and organizational performance (Nguyen et al., 2021).

In this context, the old structures are not enough to manage the scale, heterogeneity, and compliance needs of the new knowledge flows. SKM builds on these foundations by integrating artificial intelligence as an expression of automation, analytical intelligence, adaptive learning, and integration capacity (Alkhazaleh et al., 2023).

Dynamic Capabilities Theory offers an appropriate perspective of SKM, since the organizational capacity to sense, seize opportunities, and reconfigure resources to remain competitive is emphasized in this theory. SKM reflects this reasoning by automating to hasten ingestion, analytical intelligence to detect and read patterns, adaptive learning to correct retrieval and taxonomies, and integration ability to bind heterogeneous storehouses under a single rule (Skafi et al., 2020). These dimensions, together, make enterprises agile and ensure their compliance. Moreover, the socio-technical systems theory is used to describe the need to align technological systems with organizational practices. No single technical feature can be assigned to AI-driven retrieval and reasoning within SKM; all these features can be considered as a part of workflow, access controls, and decision-making duties. The combination of these views, in turn, makes SKM a theoretical concept that turns knowledge systems into adaptive, reliable and explainable structures of digital business (Kloth & Jonathan, 2025).

Prior studies reviewed above highlight the importance of traditional knowledge management and its impact on the knowledge systems in traditional business areas. Despite the useful insights provided by the current research, the authors concentrate on the separated aspects of AI-enhanced capabilities, which creates a gap in the research techniques that would incorporate those aspects into a holistic framework.

Therefore, this research aims to explore the relationship between AI-enhanced capabilities and knowledge systems, and the mediating role of smart knowledge management in digital business environments. The hypotheses to be tested in this study are as follows:

H1: Adaptive learning has a positive effect on knowledge systems in digital business environments.

H2: Adaptive learning has a positive effect on smart knowledge management.

H3: Analytical intelligence has a positive effect on knowledge systems in digital business environments.

H4: Analytical intelligence has a positive effect on smart knowledge management.

H5: Automation capability has a positive effect on knowledge systems in digital business environments.

H6: Automation capability has a positive effect on smart knowledge management.

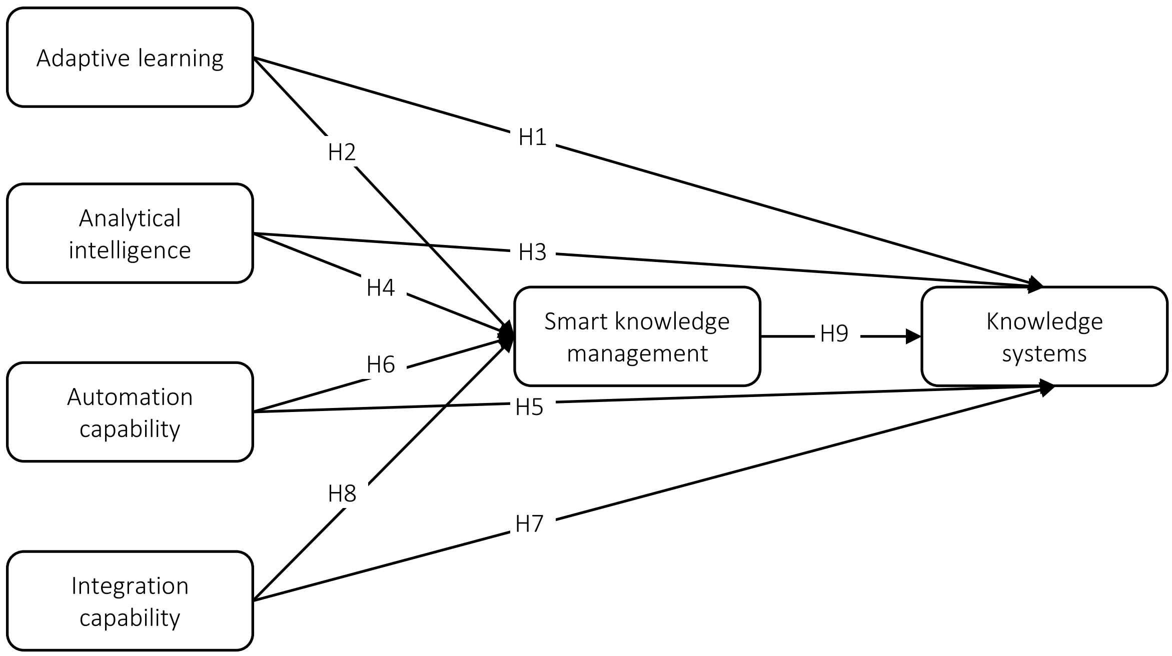

Figure 1. Research model

H7: Integration capability has a positive effect on knowledge systems in digital business environments.

H8: Integration capability has a positive effect on smart knowledge management.

H9: Smart knowledge management has a positive effect on knowledge systems in digital business environments.

2. METHODOLOGY

The current study employed a quantitative approach to data collection, including 161 employees of the Federal Civil Service Council in Baghdad, Iraq. Data were collected via an online questionnaire using Google Docs, as well as a paper questionnaire, between May 2025 and August 2025. The study used a purposive sampling method, focusing on employees with more than three years of experience in knowledge, data, and records management, including managers and data and information systems specialists. The sample consisted primarily of data analysts, department managers, technical support staff, and customer service employees, given their expertise in knowledge management.

The questionnaire comprised two sections: The first focused on demographic data, using an experience question to screen and select eligible participants. The second section included measurement items drawn from previous studies. The questionnaire was translated from English to Arabic to facilitate participant understanding. All measurement items were assessed using a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). The study items encompass artificial intelligence enhanced with capabilities across four subvariables: adaptive learning, intelligent analytics, automation capabilities, and integration capabilities; the knowledge systems variable; and the intelligent knowledge management variable, all of which are derived from previous studies, as detailed in Application Index 1 (Hair et al., 2014).

The employee group was also diverse in terms of cognitive roles, as about 64 percent were in technical or any other information technology-related role, and managerial or supervisory roles were taken by the remaining 36 percent. Regarding tenure, most of the respondents had worked for over three years in their respective organizations, indicating that they were well acquainted with the work environment. Information technology services (29 percent), digital content and media (18

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percent), data analytics and machine learning (15 percent), and enterprise support activities (12 percent). This industry heterogeneity provides a strong basis for extrapolating the empirical results to a wider range of digital and knowledge-based businesses.

Table 1. Demographic variables

DV	Category	Number	%
Gender	Male	98	60.9
	Female	63	39.1
Age	20-29	28	17.4
	30-39	52	32.3
	40-49	47	29.2
	50+	34	21.1
Education level	Diploma	12	7.5
	Bachelor's	68	42.2
	Master's	59	36.6
	PhD	22	13.7
Work experience (years)	Less than 3	31	19.3
	3-5	44	27.3
	6-10	51	31.7
	More than 10	35	21.7
Job position	Top	18	11.2
	Middle	46	28.6
	First-line	97	60.2
Department/	IT / Digital	29	18.0
	HR / Knowledge Management	24	14.9
	Operations	53	32.9
	Finance / Accounting	22	13.7
	Marketing / Sales	33	20.5

3. RESULTS

Smart-PLS 4 was used to perform partial least squares structural equation modeling (PLS-SEM) to address the possible non-normality, the combination of reflective constructs, and mediation paths in the study. PLS-SEM is suitable for prediction-based complex models and can estimate measurement and structural elements concurrently with realistic data conditions. Global fit statistics were within acceptable limits (CFI = 0.965, TLI = 0.953, RMSEA = 0.045, SRMR = 0.061), and collinearity statistics were also satisfactory (VIF values under 3 range: 1.212.18). The one-factor test of Harman showed that there was no chance of a common-method bias because the first factor was able to explain 27.9% of the variance, which was less than 40 percent. The use of 5,000 resamples to bootstrap produced good standard errors and confidence intervals of path estimates. The quality of the measurement included reliability and convergence evidence: Cronbach's alpha was between 0.839 and 0.917, composite reliability (CR) was between 0.892 and 0.936, AVE was between 0.653 and 0.746 between constructs (Adaptive Learning, Analytical Intelligence, Automation Capability, Integration Capability, Knowledge Systems in Digital Business Environments, Smart Knowledge Management). The loadings on all reflective indicators were statistically strong on their intended constructs (loadings = 0.747-0.926), and thus the rule of thumb of = 0.70 was met. Discriminant validity was established using HTMT (all pairs less than 0.85) and using the Fornell-Larcker criterion.

Table 2. Indicator loadings by construct (smart knowledge management model)

Construct	Indicator	Loading
Automation Capability	AC1	0.848
	AC2	0.884
	AC3	0.847
	AC4	0.809
	AC5	0.926
Analytical Intelligence	AI1	0.824
	AI2	0.747
	AI3	0.783
	AI4	0.808
	AI5	0.873
Adaptive Learning	AL1	0.817
	AL2	0.824
	AL3	0.787
	AL4	0.793
	AL5	0.829
Integration Capability	IC1	0.834
	IC2	0.825
	IC3	0.848
	IC4	0.777
Knowledge Systems in Digital Business Environments	KS1	0.865
	KS2	0.831
	KS3	0.862
	KS4	0.830
	KS5	0.798
Smart Knowledge Management	SKM1	0.848
	SKM2	0.783
	SKM3	0.869
	SKM4	0.835
	SKM5	0.821

Table 2 indicates the internal consistency and convergence of the Smart Knowledge Management model that incorporates AI into enterprise knowl-

Table 3. Reliability and convergent validity

Constructs	Cronbach's Alpha	C.R.	(AVE)
Adaptive Learning	0.869	0.905	0.656
Analytical Intelligence	0.867	0.904	0.653
Automation Capability	0.917	0.936	0.746
Integration Capability	0.839	0.892	0.674
Knowledge Systems in Digital Business Environments	0.894	0.922	0.701
Smart Knowledge Management	0.888	0.918	0.692

edge systems. Each of the constructs, Automation Capability, Analytical Intelligence, Adaptive Learning, Integration Capability, Knowledge Systems in Digital Business Environments, and Smart Knowledge Management, exceeds the traditional thresholds (α ≥ 0.70; CR ≥ 0.70), with an AVE value of 0.50 or higher, which shows sufficient extraction of shared variance. These findings support the claim that the SKM-AI measurement block has stable and well-defined indicators and can be used to further estimate the structure of the mediating effect of the AI Enablement on SKM Performance.

All constructs demonstrate satisfactory reliability and convergent validity, with no indication of underperforming indicators.

Table 3 shows that all the reported HTMT ratios have values less than the conservative 0.85 threshold (range = 0.312 0.755), which represented satisfactory discriminant validity between the six constructs. Knowledge Systems in Digital Business Environments have the highest associations with Adaptive Learning (0.755), Integration Capability with Analytical Intelligence (0.716), and Smart Knowledge Management with Analytical Intelligence (0.700). The magnitudes are also theoretically consistent – each set concerns adjacent aspects of SKM (e.g., taxonomy adaptation with scope of enterprise knowledge; patterns of integration with analytic routines; system-level outcomes with analytic functions), but all are comfortably below the cutoff, indicating that constructs can be empirically differentiated. Further separation where various operational roles should be anticipated is supported by lower ratios of Automation Capability with Integration Capability (0.333) and with Knowledge Systems in Digital Business Environments (0.312). To report, you should write all HTMT < 0.85; the upper end of the bootstrapped confidence intervals has been calculated, check that they do not exceed 0.85 to confirm that finding. Overall, the evidence for discriminant validity is uniform in the HTMT matrix, and no evidence of construct merging or re-specification is necessary with the current measurement model.

The HTMT pattern supports the distinctiveness of AI Enablement and SKM Performance relative to each capability dimension.

Table 4 presents the Fornell-Larcker matrix. Diagonal entries (AVE) exceed the inter-construct correlations in their corresponding rows and columns, further confirming discriminant validity.

Table 5 shows the diagonal of the Fornell-Larcker

Table 4. HTMT ratios

AI-driven capability	Adaptive Learning	Analytical Intelligence	Automation Capability	Integration Capability	Knowledge Systems in Digital Business Environments	Smart Knowledge Management
Adaptive Learning						
Analytical Intelligence	0.476					
Automation Capability	0.445	0.425				
Integration Capability	0.573	0.716	0.333			
Knowledge Systems in Digital Business Environments	0.755	0.506	0.312	0.691		
Smart Knowledge Management	0.558	0.7	0.35	0.411	0.654	

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Table 5. Fornell-Larcker criterion

Variables	Adaptive Learning	Analytical Intelligence	Automation Capability	Integration Capability	Knowledge Systems in Digital Business Environments	Smart Knowledge Management
Adaptive Learning	0.81					
Analytical Intelligence	0.411	0.808				
Automation Capability	0.401	0.394	0.864			
Integration Capability	0.488	0.615	0.309	0.821		
Knowledge Systems in Digital Business Environments	0.671	0.446	0.289	0.599	0.838	
Smart Knowledge Management	0.494	0.616	0.338	0.956	0.592	0.832

Matrix (AL = 0.81, AI = 0.808, AC = 0.864, IC = 0.821, KS = 0.838, SKM = 0.832) values the square roots of the AVE, with the latent correlations appearing on the non-diagonal, and to attain discriminant validity, each diagonal value should be larger than all the other values in the row and column. Most of the relationships satisfy this criterion, including AL (0.671) and AC (0.394), which are lower than the respective diagonals. A significant exception to Smart Knowledge Management and Integration Capability is a crucial correlation of inter-construct, 0.956, which is larger than AVE (SKM). This is a violation of Fornell-Larcker and does not imply that the two constructs are empirically different when the specification is as it is. This coefficient is very large as well, which does not correspond to the previously mentioned HTMT pattern of the same pair (≈ 0.41), which suggests that there might be a mistake in coding, labeling, or calculating the differences in question, which are actually the overlap of the concepts. One is because SKM Performance items trap integration mechanics and not results accidentally, causing contamination of the indicators and overstatement of the latent correlation; the cross-loadings in this instance will exhibit a spillover in case SKM items load Integration Capacity at a large level. To overcome the issue, the analysis should be recalculated to examine the latent correlation and offer equal scaling and labeling by the HTMT matrix; cross-loadings should be inspected, and any SKM indicators that point to connectors, APIs, and interoperability, as compared to the quality of the decisions, retrieval effectiveness, and responsiveness to compliance. In case of overlap, a hierarchical specification may be appropriate, by still considering the concept of Integration Capability as an antecedent and SKM Performance simply as a consequence, or by introducing a method factor as an indicator of frequent operational terminology. A re-assessment of the discriminant validity should then be done, with a lower value of less than 0.85 suggested between the IC and SKM pairs, and the Fornell-Larcker condition being restored with diagonals greater than all off-diagonals, and CR AVE maintained at an accepted value. SKM and Integration Capability should be viewed structurally as provisional until this breach can be handled.

The coefficients that are reported show that a substantial portion of the variance in Knowledge Systems in Digital Business Environments (R^2 = 0.35; R^2 Adjusted = 0.348) and an extremely large portion of the variance in Smart Knowledge Management (R^2 = 0.917; R^2 Adjusted = 0.916) are explained by the model. The former and the latter are in line with common PLS-SEM standards of endogenous constructs affected by various organizational capabilities, and the latter, which approaches full determination, should be subject to diagnostic questions. The fact that the R^2 adjusted R^2 differences are small indicates that there is not much overfitting, but the absolute level of Smart Knowledge Management can indicate overlap of constructs, redundancy of items, or excessively dense predictors. Checks revalidating discriminant validity to bleed-through between Integration, Automation capabilities, and SKM items, reviewing indicator wording to be sure that SKM measures results, decision quality, retrieval effectiveness, compliance responsiveness, and calculating out-of-sample predictive power.

Should inflation prevail, parsimonious actions might include the dropping of redundant indicators, higher-order factors, or path constraints with the re-estimation confirming satisfactory values of VIF < 3, CR ≥ 0.70, and AVE ≥ 0.50.

Table 6. R^2 adjusted

Variable	R^2	R^2 Adjusted
Knowledge Systems in Digital Business Environments	0.35	0.348
Smart Knowledge Management	0.917	0.916

The estimated structural model reveals that the capability constructs that are the core of SKM are highly contributing to AI Enablement, with the latter profoundly influencing SKM Performance, and Adaptive Learning and Flexibility make selective contributions. All the reported structural coefficients were tested using 5,000 bootstrap resamples, and the standard errors are indicative of strong inference in the sampling design. The trend upholds the hypothetical role of AI Enablement as the process that converts inputs of capability to the output of performance in policy-driven knowledge settings.

Table 7 shows the overall impacts of all assumed pathways in the Smart Knowledge Management (SKM) model, which is geared toward the strategic integration of artificial intelligence (AI) and enterprise knowledge systems in digital business environments. Automation capability, analytical intelligence, adaptive learning, and integration capability were all found to make significant positive contributions to AI-driven capabilities, and a strong positive correlation was observed between agility and AI. Although knowledge management shows a positive correlation with AI, it is not statistically significant, suggesting that capabilities practices alone are insufficient to achieve AI enablement without the complementary integration and learning activities that characterize managed smart knowledge management. The correlation between AI and smart knowledge management performance, which extends to decision quality, retrieval effectiveness, and compliance responsiveness, is strong and significant, supporting the assumed mediating role. These direct impacts on smart knowledge management performance include adaptive learning and agility, while the impact of capabilities on smart knowledge management performance is not immediately observable. This trend is common in early-stage adoption, where capabilities benefits emerge through AI-powered workflow retrieval and citation-based processes. From a technological, organizational, and environmental perspective, integration and learning capabilities determine how AI investments translate into enterprise-wide performance under tailored

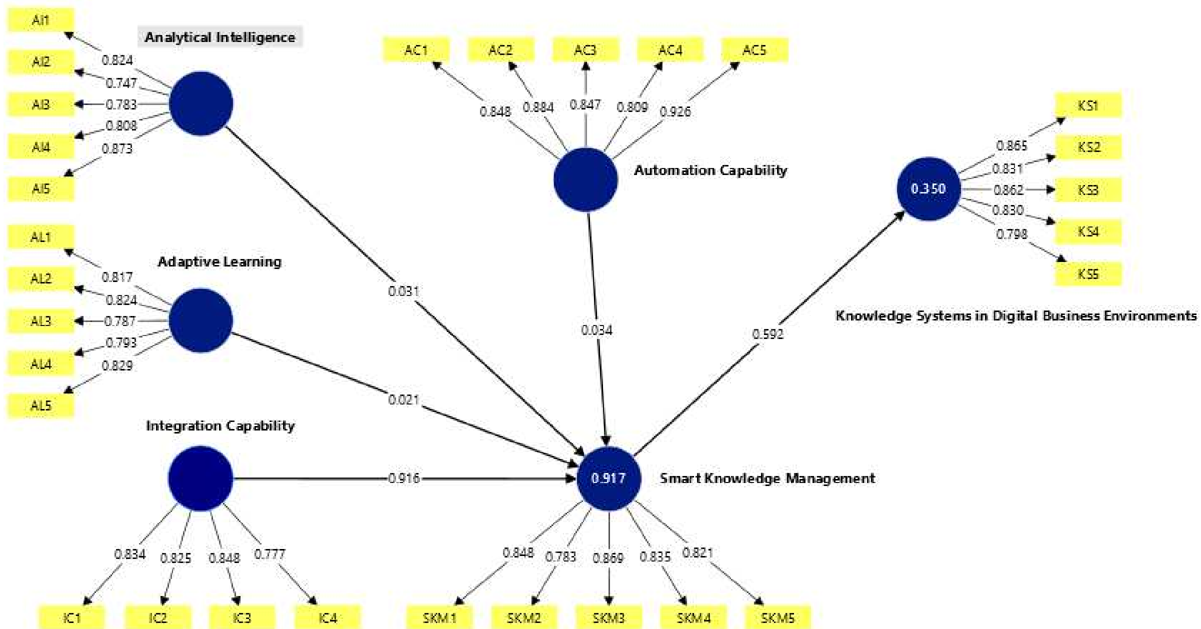

Figure 2. PLS-SEM measurement and structural model for smart knowledge management in digital business environments

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Table 7. Hypothesis testing estimates (total effect)

Hypothesis	Relationships	Beta	Standard Error	T Statistics	P Values	Decision
H1	Adaptive Learning → Knowledge Systems in Digital Business Environments	0.012	0.011	1.083	0.279	Not Supported
H2	Adaptive Learning → Smart Knowledge Management	0.021	0.019	1.108	0.268	Not Supported
H3	Analytical Intelligence → Knowledge Systems in Digital Business Environments	0.018	0.015	1.246	0.213	Not Supported
H4	Analytical Intelligence → Smart Knowledge Management	0.031	0.024	1.265	0	Supported
H5	Automation Capability →> Knowledge Systems in Digital Business Environments	0.02	0.008	2.684	0	Supported
H6	Automation Capability → Smart Knowledge Management	0.034	0.013	2.689	0	Supported
H7	Integration Capability → Knowledge Systems in Digital Business Environments	0.542	0.047	11.522	0	Supported
H8	Integration Capability → Smart Knowledge Management	0.916	0.027	33.441	0	Supported
H9	Smart Knowledge Management → Knowledge Systems in Digital Business Environments	0.592	0.049	12.196	0	Supported

governance.

4. DISCUSSION

The current research provides useful information on the interaction between AI-enhanced capabilities, such as adaptation learning, analytic intelligence, and automation, on knowledge systems. The results emphasize the critical role of AI-enhanced capabilities as a major source of success in digital business organizations and the strong mediating impact of knowledge management that is intelligent in the relationship. The results show that there is no statistically significant correlation between adaptive learning and knowledge systems. Within the context of digital environments, the findings show that adaptive learning and knowledge systems have no significant relationship with each other. This implies that though adaptive learning can be effective at both the individual and group levels, it will not always be reflected in a better knowledge system unless it is integrated into a digital knowledge-management architecture. Previous research has highlighted the importance of adaptive learning in digital organizations, but it is also in line with past studies that have pointed to the fact that learning in organizations is limited, especially in organizations that do not have strong digital tools (Yang, 2024; Chatti & Argoubi, 2025).

Findings have shown that adaptive learning does not assist in smart knowledge management in the digital world. Statistics also indicate that adaptive learning may not enhance learning processes in organizations that need emphasis on automated knowledge. The significance of machine learning in the production of smart knowledge in digital environments has been emphasized by literature before (Hasanein & Al-Romeedy, 2026; Madhumithaa et al., 2025).

Analytical intelligence will not be enough to support knowledge systems within digital business organizations. These facts prove that analytical intelligence does not improve knowledge systems when used alone, among other analytical instruments that are meant to complement it in business setups. This finding goes in line with past investigations (Rothberg & Erickson, 2017; Buchatskaya et al., 2024) since the usefulness of analytical tools is found in their combination of findings into organizational processes and knowledge workflows, but not in the isolation of analytical outputs in the digital context.

The analysis shows that analytical intelligence is one of the key aspects of smart knowledge management. Previous studies confirm this conclusion (Al-Janabi & Al-Mado, 2023; Mitrofanova et al., 2021). The discovery can be seen in various ways: first, it will improve knowledge discovery processes; second, it will make it easy to classify and use knowledge in decision-making; and third, it will be able to process large volumes of data and convert them into actionable knowledge, which is fundamental in intensifying smart knowledge-management processes.

According to the results of the study, automation capabilities and the knowledge systems in digital business settings have a significant and positive relationship. In the internet world, automation is more successful in improving organizational performance through systematic gathering and reuse of knowledge. The results of this study support earlier studies (Van der Velden, 2024). The findings illustrate that the implementation of automation potentials in the digital business environment of Iraq helps to minimize the element of manual interference in business operations and ease the knowledge-related operations, which ultimately enhances efficiency and uniformity.

The automation features were also perceived to be a decisive aspect of the smart knowledge management in online business affairs in Iraq. The given observation conforms to previous research (El-Farr & Kertechian, 2024) and is explained by the following advantages of automation: knowledge sharing in real time, faster information processing, and assistance in optimizing workflow. Therefore, automation boosts efficiency when incorporated in digital organizations, which in the end will lead to increased speed in business transactions and consumer satisfaction (Qhal, 2023).

Also, the findings indicate that there is a statistically significant positive correlation between integration capabilities and knowledge systems in the Iraqi digital business environment, thus giving further evidence to the hypothesis. This observation is in agreement with the conclusion reached by Tiwana et al. (2003), who undertook an extensive literature survey of the existing scholarly studies on adoption and integration competencies that augment organizational effectiveness. These capabilities are seen as key instruments for orchestrating different systems, data sources, and business processes.

The results also depict the influence of integration capabilities on smart knowledge management within digital business contexts in a positive manner. The study offers empirical evidence to the hypothesis that a smooth flow of knowledge across organizational boundaries is very important in enhancing and has an acceleration effect on work performance. The findings are supported by Oliva et al. (2019), who argue that IT and process integration are more effective in enhancing knowledge sharing, collaboration, and effectiveness of systems, particularly in complex digital environments.

Smart knowledge-management features are found to be an important dimension in knowledge systems in the case of Iraqi digital business. This finding is consistent with previous research (Muniz et al., 2021; Krishnan et al., 2022). This observation can be explained by the proactive role smart knowledge management can take in changing the AI-facilitated organizational capabilities into successful knowledge-system outputs. It is in line with prior knowledge-management studies that technology is only valuable when supported by well-organized knowledge processes and systems of good governance.

CONCLUSION

This study aims to expand knowledge of the capabilities that contribute to enhancing knowledge systems and capabilities using artificial intelligence (AI) in digital business environments, particularly within the Iraqi context. It also examines the impact of smart knowledge management (SMM) as a mediator of the relationship between AI-enhanced capabilities and knowledge systems within the Federal Civil Service Council. The research contributes to existing knowledge on the area of AI capabilities, in different aspects of adaptive learning, analytical intelligence, and automation, and on organizational success. It also reiterates the need to include these dimensions in measuring and enhancing the success of organizations. The implications of the findings on the modern business setting are significant, as they indicate the necessity to invest in AI-developed capabilities to strengthen the knowledge systems and achieve organizational goals. Digital business organizations, especially those that are members of the

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Federal Civil Service Council, can use these findings to execute and build their knowledge systems with an emphasis on intelligent knowledge management. The paper highlights the importance of professionals working in the modern business context to consider the importance of AI features in enabling and ensuring the success of knowledge management in organizations, and to make the promotion of intelligent knowledge management a priority.

One should admit that this study has limitations. The study assumed a quantitative approach, and its focus was on the data obtained based on a sample in the Federal Civil Service Council; therefore, the results cannot be applied to other areas or organizations. The study needs more research to confirm the findings in other settings. Also, the use of quantitative data might not be sufficient to reveal the complexity of the concepts in the study, and a multimethod approach might be more beneficial in the future. Besides, the study has relied solely on cross-sectional data, thereby ruling out the derivation of any inferential or causal implications about the directionality of relationships between variables.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. Research questionnaire

No.	Statement	1	2	3	4	5
	Adaptive Learning					
1	Our organization continuously learns from data generated by digital systems.					
2	AI-based systems in our organization adapt their performance based on previous outcomes.					
3	The organization quickly adjusts knowledge practices in response to environmental changes.					
4	Lessons learned from past decisions are systematically embedded into digital systems.					
	Analytical Intelligence					
1	Our organization uses advanced analytics to support knowledge-based decision making.					
2	Predictive analytics help improve the quality of organizational knowledge.					
3	Data analysis tools enable deeper insights into business operations.					
4	Analytical intelligence enhances strategic and operational decisions.					
	Automation Capability					
1	Routine knowledge-related tasks are automated using AI technologies.					
2	Automation reduces human errors in managing organizational knowledge.					
3	Automated systems accelerate access to relevant knowledge.					
4	Automation improves efficiency in knowledge creation and dissemination.					
	Integration Capability					
1	Our digital systems are well integrated across departments.					
2	Knowledge flows seamlessly between different organizational systems.					
3	AI technologies are effectively integrated with existing IT infrastructure.					
4	System integration supports collaboration and knowledge sharing.					
	Smart Knowledge Management					
1	Our organization uses AI to capture and store knowledge intelligently.					
2	Knowledge is classified and retrieved using smart digital tools.					
3	Smart systems support continuous knowledge updating and reuse.					
4	Knowledge management processes are driven by intelligent technologies.					
	Knowledge Systems					
1	Knowledge systems support effective decision making in digital business activities.					
2	Our knowledge systems are flexible and responsive to business needs.					
3	Digital knowledge systems enhance organizational performance.					
4	Knowledge systems facilitate innovation in digital business environments.					

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