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From Knowledge Management to Knowledge Intelligence: An AI-Enabled Framework for Business Performance, Decision Support, and Organizational Learning

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Abstract

Artificial intelligence is transforming how organizations manage, retrieve, interpret, and apply knowledge for business performance. While knowledge management has traditionally focused on knowledge capture, repositories, lessons learned, communities of practice, expertise sharing, and organizational learning, many organizations continue to experience fragmented knowledge assets, inconsistent reuse, weak metadata, limited expertise visibility, and poor feedback loops between knowledge creation and business application. These limitations affect proposal development, project execution, onboarding, innovation, operational decision-making, quality management, and organizational responsiveness. This conceptual article proposes an AI-Enabled Knowledge Intelligence Framework for improving business decision support, organizational learning, and knowledge-based performance. Drawing on the knowledge-based view of the firm, intellectual capital theory, dynamic capabilities, organizational learning, business intelligence, management information systems, and knowledge governance, the article positions artificial intelligence as an augmentation layer within a broader business management system. The framework includes six interdependent dimensions: knowledge sources, knowledge structuring, AI augmentation, human validation and sensemaking, knowledge application, and learning feedback. The article argues that AI-enabled knowledge management should not be treated as a technology implementation alone, but as a managerial capability that integrates people, processes, governance, information systems, and performance measurement. Research propositions and managerial implications are provided to support future empirical study and practical adoption in business and industrial management contexts.

Keywords

Knowledge Management, Artificial Intelligence, Decision Support, Organizational Learning, Knowledge Governance

1. Introduction

Organizations increasingly operate in environments characterized by information overload, distributed work, rapid technological change, competitive pressure, and growing demand for evidence-based decision-making. In such environments, knowledge is a critical business resource. Organizations rely on prior project experience, lessons learned, client knowledge, employee expertise, operational data, proposals, reports, market intelligence, process documentation, and decision histories to execute work, reduce risk, innovate, and improve performance (Choo, 1998; Davenport & Prusak, 1998; Grant, 1996).

However, many organizations struggle to convert existing knowledge into timely and actionable business insight. Knowledge is often distributed across repositories, emails, shared drives, collaboration platforms, project records, customer relationship management systems, enterprise resource planning systems, business intelligence dashboards, personal files, and informal networks. This fragmentation creates inefficiencies. Employees spend time searching for prior work, teams duplicate effort, lessons are not reused, expertise remains hidden, and managers make decisions without full access to relevant organizational knowledge.

Knowledge management has long addressed these challenges by promoting knowledge capture, sharing, reuse, governance, and organizational learning. Traditional knowledge management systems include repositories, taxonomies, communities of practice, lessons learned systems, and knowledge management systems designed to support knowledge processes (Alavi & Leidner, 2001; Markus, 2001; Wenger, 1998). Yet these systems often rely on manual tagging, static repositories, keyword search, voluntary contribution, and inconsistent governance. As organizational knowledge grows in scale and complexity, these approaches become difficult to maintain and apply.

Artificial intelligence offers new opportunities to improve knowledge management and business decision support. AI can support semantic search, summarization, content classification, expertise mapping, knowledge graph development, recommendations, predictive analytics, natural-language querying, and decision-support workflows. These capabilities can help organizations locate, interpret, and apply knowledge more effectively (Dwivedi et al., 2023; Faraj et al., 2018; Jarrahi, 2018).

At the same time, AI introduces risks. AI-generated outputs may be inaccurate, biased, outdated, unsupported, or disconnected from business context. AI systems may retrieve poor-quality content, obscure source provenance, or create misplaced confidence in automated answers. These risks are especially important because AI evaluation may fail when it treats expert knowledge as fully codified or objective (Lebovitz et al., 2021; Raisch & Krakowski, 2021). Therefore, AI does not eliminate the need for knowledge management. Instead, it increases the need for trusted sources, governance, human validation, quality management, and performance measurement.

This article proposes an AI-Enabled Knowledge Intelligence Framework for business management. The framework explains how organizations can integrate knowledge management and artificial intelligence to improve decision support, business performance, organizational learning, and knowledge reuse.

The central research question is: How can organizations integrate artificial intelligence into knowledge management to improve business performance, decision support, and organizational learning while maintaining trust, governance, and human judgment?

The theoretical gap is not the absence of research on knowledge management, business intelligence, or decision-support systems individually. Rather, established concepts do not fully explain the organizational capability required to activate heterogeneous knowledge at the point of work through AI while preserving provenance, governance, context, and accountable human judgment. Knowledge management explains how knowledge is created, organized, shared, and reused; business intelligence primarily converts structured data into analytical insight; and decision-support systems assist particular choices. Knowledge intelligence addresses the integrative capability that connects these functions in a governed, recursive system that transforms distributed data, documents, experience, and expertise into validated action and then learns from resulting outcomes.

Accordingly, this article makes three contributions. First, it defines knowledge intelligence as a construct distinct from, but dependent upon, KM, BI, and decision support. Second, it specifies a six-dimension causal architecture in which governed knowledge foundations enable AI augmentation, human validation conditions the reliability of application, and feedback renews the knowledge base. Third, it provides organization-level propositions and observable indicators that make the framework empirically testable.

2. Business Problem and Research Question

The practical problem addressed in this article is the persistent gap between organizational knowledge possession and organizational knowledge use. Many organizations have large volumes of information and knowledge assets, but they lack effective mechanisms to convert those assets into business value.

This problem appears in several common business situations. Proposal teams may struggle to find reusable content or past performance examples. Project teams may fail to apply lessons learned from previous work. New employees may struggle to locate trusted guidance and expertise. Managers may make decisions without complete access to relevant organizational knowledge. Operational teams may recreate deliverables that already exist. Experts may be identified through informal networks rather than enterprise systems. Business intelligence systems may present data but lack contextual knowledge.

These issues are not merely information management problems. They affect productivity, quality, cost, risk, innovation, customer responsiveness, and organizational performance.

AI can improve these conditions, but only if implemented within a structured knowledge management environment. Connecting AI tools to disorganized repositories may increase speed without improving accuracy. This concern is consistent with socio-technical research showing that information systems fail when designers focus on technical capability without accounting for organizational context, people, work processes, and governance (Bostrom & Heinen, 1977). AI-enabled knowledge systems therefore require a managerial framework that integrates technology, governance, business workflows, knowledge quality, human validation, and performance measurement.

This article addresses the following research question: How can AI-enabled knowledge management be structured as a business management capability that improves decision support, knowledge reuse, and organizational performance?

3. Literature Review

3.1. Knowledge Management in Business Organizations

Knowledge management refers to the systematic process of creating, capturing, organizing, sharing, transferring, and applying knowledge to improve organizational performance. In business organizations, KM supports innovation, quality improvement, operational efficiency, employee development, customer responsiveness, and strategic decision-making (Alavi & Leidner, 2001; Davenport & Prusak, 1998; Nonaka & Takeuchi, 1995).

Traditional KM approaches include repositories, lessons learned systems, taxonomies, expertise directories, communities of practice, after-action reviews, and governance structures. These practices help organizations preserve institutional knowledge and reduce duplication of effort by supporting knowledge reuse across different users and business situations (Markus, 2001; Wenger, 1998).

However, KM systems often fail when they are treated as document storage platforms rather than business performance systems. A repository may contain useful content, but if employees cannot find it, trust it, or apply it in the flow of work, the knowledge does not create value. For KM to influence performance, knowledge must be connected to business processes, decision points, and measurable outcomes.

3.2. Business Intelligence and Decision Support

Business intelligence systems help organizations collect, analyze, and present data for decision-making. Dashboards, analytics platforms, performance reports, and forecasting tools support managerial decision processes. However, business intelligence often emphasizes structured data more than contextual knowledge, while organizational knowing also depends on sensemaking, knowledge creation, and decision processes (Choo, 1998).

Business decisions frequently require more than data. Managers also need lessons learned, assumptions, expert judgment, client history, operational context, prior decisions, and organizational memory. AI-enabled knowledge management can complement business intelligence by connecting data-driven insight with knowledge-based context.

This connection is important because many business problems are not solved by information access alone. They require interpretation, prioritization, comparison, judgment, and application. Knowledge intelligence strengthens decision support by combining structured business data with organizational experience and human expertise.

3.3. Artificial Intelligence and Management Information Systems

Artificial intelligence is increasingly embedded in management information systems. AI can classify information, generate summaries, detect patterns, recommend content, automate workflows, and support natural-language interaction. In the context of KM, AI can help organizations retrieve, synthesize, and reuse knowledge at scale while also reshaping expertise, work boundaries, coordination, and management practices (Faraj et al., 2018; Jarrahi, 2018; Raisch & Krakowski, 2021).

Generative AI expands these possibilities by allowing users to ask natural-language questions and receive synthesized responses. Semantic search, retrieval-augmented generation, and knowledge graphs can help connect users to relevant documents, people, prior decisions, and lessons learned.

However, AI also creates new management concerns. These include accuracy, explainability, source transparency, information security, privacy, bias, ethical use, and accountability. Effective AI-enabled KM therefore requires governance and human review, especially because generative AI creates opportunities for productivity gains while also introducing risks related to misinformation, bias, privacy, and misuse (Dwivedi et al., 2023; Lebovitz et al., 2021).

3.4. Knowledge Governance and Quality Management

Knowledge governance includes the policies, standards, roles, and accountability mechanisms used to manage knowledge assets. In business settings, governance helps ensure that knowledge is accurate, current, accessible, secure, and relevant. Knowledge governance also concerns how governance mechanisms influence knowledge sharing, retention, and creation (Foss, 2007; International Organization for Standardization [ISO], 2018).

Quality management is also essential. Knowledge assets must be reviewed, maintained, retired, or updated. Metadata must be consistent. Trusted sources must be defined. Ownership must be clear. Without governance and quality management, AI-enabled systems may amplify poor-quality knowledge.

3.5. Organizational Learning and Dynamic Capabilities

Organizational learning occurs when organizations capture experience, interpret it, and apply it to future action. Dynamic capabilities refer to the ability of organizations to sense changes, seize opportunities, and transform resources. AI-enabled KM can support both organizational learning and dynamic capabilities by improving the speed and quality of knowledge reuse (Argyris & Schon, 1978; Crossan et al., 1999; Teece, 2007; Teece et al., 1997).

When lessons learned, project records, expertise, and business intelligence are connected through AI-enabled systems, organizations can adapt more quickly and make better-informed decisions. This positions AI-enabled KM as a strategic management capability rather than a back-office information function.

4. Theoretical Foundation

The proposed framework draws on several theoretical foundations relevant to business and management.

4.1. Knowledge-Based View of the Firm

The knowledge-based view argues that knowledge is a strategic resource and that organizational advantage depends on the ability to integrate and apply knowledge. From this perspective, AI-enabled KM is not merely a technical tool. It is a capability that helps organizations convert distributed knowledge into business value (Grant, 1996; Spender, 1996).

4.2. Intellectual Capital Theory

Intellectual capital includes human capital, structural capital, and relational capital. Human capital includes employee expertise and experience. Structural capital includes processes, systems, repositories, methods, and documented knowledge. Relational capital includes client, partner, supplier, and stakeholder knowledge. These dimensions connect individual and collective knowledge to organizational advantage and business performance (Bontis, 1998; Nahapiet & Ghoshal, 1998).

AI-enabled KM can strengthen intellectual capital by making expertise more discoverable, improving the structure of organizational knowledge, and connecting relational knowledge to business decision-making.

4.3. Dynamic Capabilities

Dynamic capabilities explain how organizations adapt to changing environments by sensing opportunities, seizing them, and transforming resources. AI-enabled KM supports dynamic capabilities by improving knowledge discovery, learning feedback, decision speed, and organizational responsiveness (Teece, 2007; Teece et al., 1997).

4.4. Organizational Learning

Organizational learning theory emphasizes how organizations learn from experience, create knowledge through interaction, and improve future action. AI-enabled KM can support organizational learning by capturing lessons, recommending prior knowledge, enabling knowledge conversion, and feeding outcomes back into knowledge systems (Argyris & Schon, 1978; Crossan et al., 1999; Nonaka et al., 2000).

4.5. Knowledge Governance

Knowledge governance provides the managerial controls needed to ensure that knowledge is trustworthy and usable. In AI-enabled KM, governance is essential because AI systems depend on source quality, metadata, access controls, lifecycle management, and validation processes (Foss, 2007; International Organization for Standardization, 2018).

5. Conceptual Development Approach

This article uses an integrative conceptual framework-development approach rather than an empirical systematic review. The objective is theory building: to connect established management constructs with recurring organizational problems introduced or intensified by AI-enabled knowledge work. Literature domains were selected purposively when they explained one of four requirements of the focal phenomenon: knowledge as an organizational resource, technology-supported retrieval and decision support, human interpretation and learning, or governance and performance control. The resulting theoretical domains were the knowledge-based view, intellectual capital, dynamic capabilities, organizational learning, business intelligence and management information systems, socio-technical systems, human-AI collaboration, and knowledge governance.

The synthesis proceeded in four stages. First, the literature was examined for established constructs and causal mechanisms relevant to knowledge creation, integration, reuse, sensemaking, decision support, organizational learning, and governance. Second, recurring practitioner problems were used as problem anchors: fragmented content, weak findability, limited expertise visibility, inconsistent reuse, disconnected lessons learned, uncertain source authority, and weak feedback between knowledge use and business outcomes. These problems were retained when they represented an organization-level barrier addressed by more than one theoretical domain and could plausibly be influenced by KM and AI capabilities. Third, AI capabilities—including semantic search, summarization, classification, recommendation, knowledge graphs, expertise mapping, and natural-language interaction—were mapped to the mechanisms they could augment rather than treated as independent solutions. Fourth, the constructs were organized into the smallest coherent sequence that preserved inputs, enabling conditions, transformation mechanisms, application, and recursive learning.

The six dimensions were then checked for conceptual completeness and managerial interpretability. Knowledge sources and knowledge structuring represent the foundation; AI augmentation represents the scalable transformation mechanism; human validation and sensemaking provide contextual and accountability controls;

knowledge application represents proximal use; and learning feedback connects outcomes back to the knowledge base. The framework is therefore an analytically derived model intended to support falsifiable propositions and future empirical testing, not a claim of causal effects already demonstrated by the present article.

6. From Knowledge Management to Knowledge Intelligence

Traditional knowledge management often focuses on storing, organizing, and sharing knowledge. While these functions remain important, they are no longer sufficient for organizations facing complex business decisions and rapidly expanding knowledge assets. Prior KM research shows that knowledge management systems must support knowledge processes and reuse situations rather than merely store content (Alavi & Leidner, 2001; Markus, 2001).

This article defines knowledge intelligence as: the organizational capability to convert distributed knowledge into trusted, contextualized, and actionable business insight through the combined use of human expertise, structured knowledge practices, governance, analytics, and artificial intelligence.

Knowledge intelligence shifts KM from a repository-centered activity to a business performance capability. Traditional KM asks: Where is the knowledge stored? Knowledge intelligence asks: How can knowledge improve decisions, execution, learning, and performance? Traditional KM emphasizes access to documents. Knowledge intelligence emphasizes the activation of knowledge in business workflows. Traditional KM often measures system usage. Knowledge intelligence measures reuse, decision quality, operational improvement, innovation, and business impact (Choo, 1998; Davenport & Prusak, 1998).

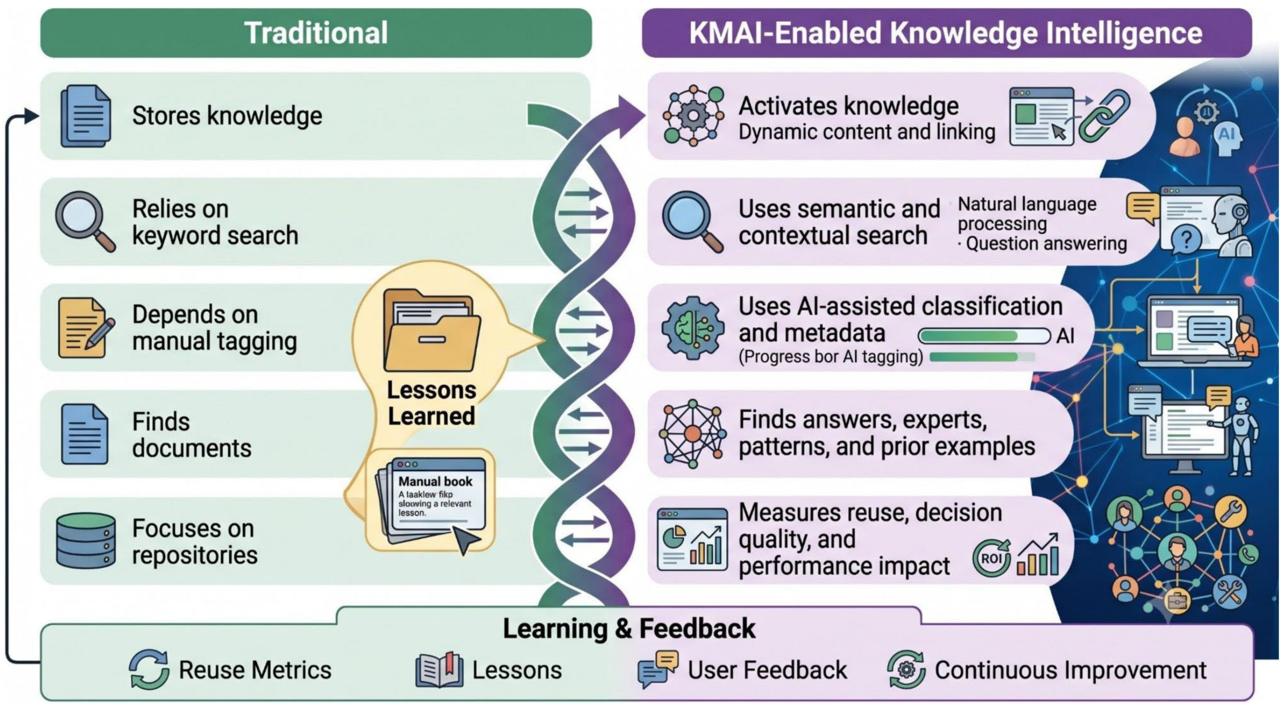

Figure 1. Evolution from traditional KM to AI-enabled knowledge intelligence.

The construct is differentiated by its focal object, mechanism, and outcome. KM's focal object is organizational knowledge and its lifecycle; BI's focal object is predominantly structured data and analytical patterns; and decision support focuses on improving a decision episode. Knowledge intelligence focuses on the organization-level capability that assembles heterogeneous knowledge, uses AI to retrieve and synthesize it, subjects outputs to governed human sensemaking, embeds the validated result in work, and updates the knowledge environment from observed outcomes (Figure 1). Thus, knowledge intelligence does not replace the established fields. Its theoretical value lies in specifying how their mechanisms must be orchestrated when AI simultaneously expands the scale of knowledge activation and the need for provenance, validation, and accountability.

7. AI-Enabled Knowledge Intelligence Framework

The AI-Enabled Knowledge Intelligence Framework includes six interdependent dimensions: knowledge sources, knowledge structuring, AI augmentation, human validation and sensemaking, knowledge application, and learning feedback.

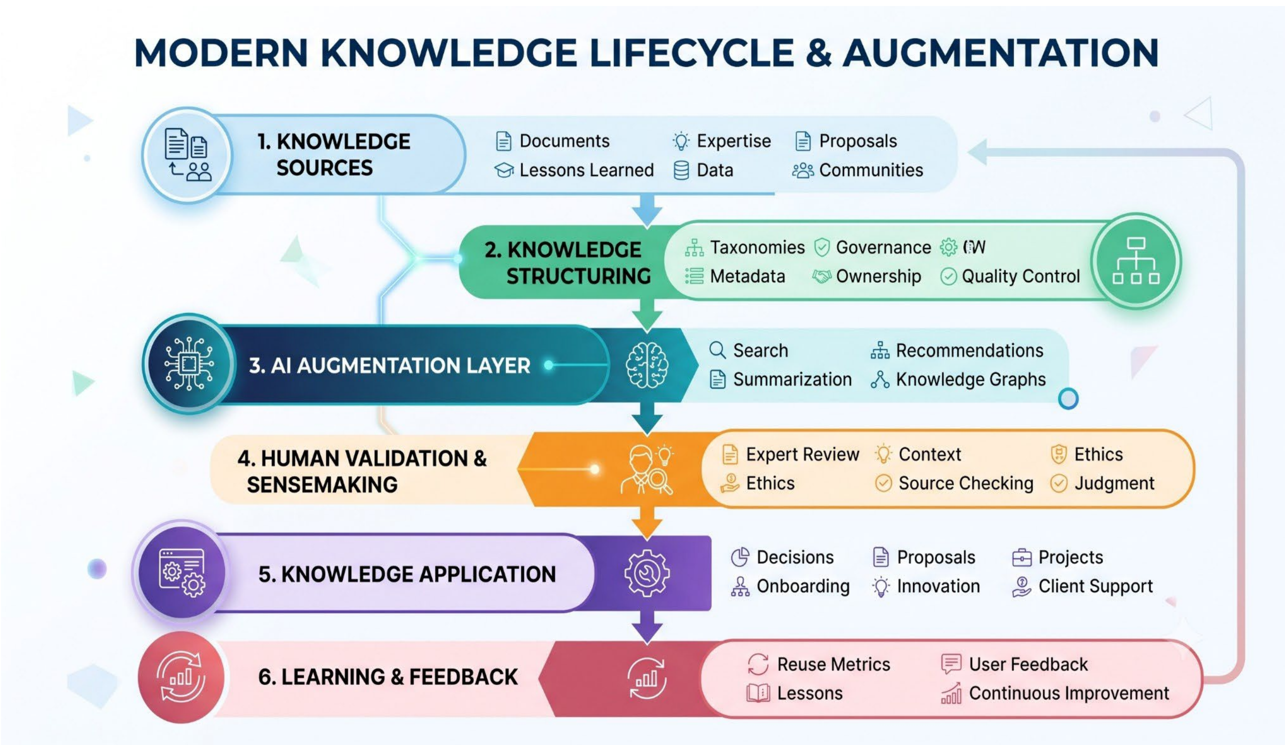

Figure 2. Modern knowledge lifecycle and AI augmentation framework.

The dimensions have distinct causal roles rather than forming a simple checklist. Knowledge sources and knowledge structuring are antecedent conditions because they determine the accessible, authorized, and interpretable knowledge available to the system. AI augmentation is the principal transformation mechanism that increases the scale and speed of retrieval, synthesis, classification, and recommendation. Knowledge application is the proximal outcome through which validated insight enters decisions and workflows. Learning and feedback form a recursive mechanism: evidence from use updates content, metadata, models, rules, and practices, thereby changing the antecedent conditions for subsequent cycles.

Governance and human validation operate as cross-cutting controls, but at different levels. Governance is both an antecedent and an embedded control: policies, ownership, source authority, access rules, and quality standards shape every dimension before AI output is produced and while it is used. Human validation is an embedded control and proposed moderator between AI augmentation and knowledge application; stronger expert review, contextual interpretation, and source checking should strengthen the positive effect of AI-generated outputs on decision and work quality, particularly as task uncertainty or consequence increases. Figure 2 depicts the process sequence.

7.1. Knowledge Sources

Knowledge sources are the raw materials of knowledge intelligence. These include reports, proposals, project records, lessons learned, customer data, operational data, financial data, subject matter expertise, business intelligence dashboards, communities of practice, and external research.

The quality of knowledge intelligence depends on the quality of these sources. AI cannot reliably produce useful business insight if the underlying sources are incomplete, outdated, inaccessible, or poorly governed.

7.2. Knowledge Structuring

Knowledge structuring includes taxonomies, metadata, ontologies, tagging standards, ownership models, source authority, and quality controls. This dimension organizes knowledge so that it can be retrieved, connected, and reused. These structuring practices align with the need for governance and management-system controls in organizational knowledge management (Foss, 2007; International Organization for Standardization, 2018).

AI can assist with classification, metadata generation, duplicate detection, entity extraction, and content clustering. However, managers must define the standards that determine what counts as trusted, current, and relevant knowledge.

7.3. AI Augmentation Layer

The AI augmentation layer includes tools that support knowledge discovery, synthesis, and reuse. These may include semantic search, generative AI, retrieval-augmented generation, recommendation engines, knowledge graphs, predictive analytics, summarization tools, and expertise mapping. These capabilities reflect broader developments in generative AI, learning algorithms, and human-AI collaboration in organizations (Dwivedi et al., 2023; Faraj et al., 2018; Jarrahi, 2018).

This layer should be embedded into business workflows. For example, AI can support proposal development by surfacing prior content, project startup by recommending lessons learned, onboarding by creating role-specific knowledge paths, and management decisions by connecting data with contextual knowledge.

7.4. Human Validation and Sensemaking

Human validation is necessary because AI-generated outputs require interpretation. Business knowledge is contextual. Managers and experts must determine whether an AI-generated answer is accurate, relevant, ethical, and applicable. This need reflects the importance of human-AI complementarity and the risk of relying on codified AI outputs without expert judgment (Jarrahi, 2018; Lebovitz et al., 2021).

Validation may include expert review, source checking, peer review, decision rationale documentation, and confidence assessment. Human judgment is especially important when AI outputs affect strategic decisions, client commitments, financial choices, compliance, or operational risk. These validation requirements also reflect the automation-augmentation tension in AI-enabled management (Raisch & Krakowski, 2021).

7.5. Knowledge Application

Knowledge application is where value is created. AI-enabled KM should improve business processes such as decision-making, proposal development, project delivery, customer support, onboarding, innovation, and quality improvement.

Knowledge that is captured but not applied does not produce business value. Therefore, the framework emphasizes knowledge use in the flow of work.

7.6. Learning and Feedback

Learning and feedback allow the knowledge system to improve over time. Feedback mechanisms include user ratings, reuse metrics, project reviews, lessons learned, decision outcomes, content quality reviews, and AI output evaluations. Such feedback mechanisms support organizational learning by linking individual, group, and organizational knowledge processes (Argyris & Schon, 1978; Crossan et al., 1999).

These mechanisms help organizations identify which knowledge is useful, which content is outdated, and where new knowledge is needed.

8. Business and Industrial Management Use Cases

AI-enabled KM has several applications in business and industrial management (**Figure 3**).

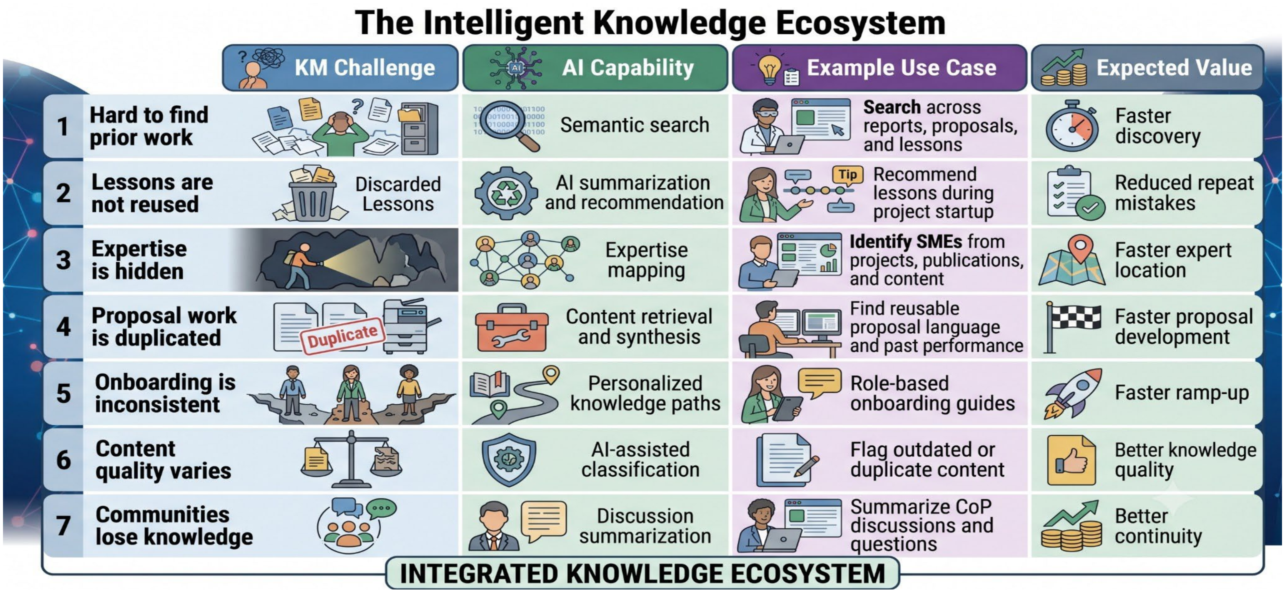

Figure 3. AI-enabled KM use case matrix.

8.1. Business Decision Support

AI-enabled KM can help managers access relevant data, lessons, prior decisions, expert input, and contextual information. This improves decision quality by connecting business intelligence with organizational knowledge, sensemaking, and decision processes (Choo, 1998).

8.2. Proposal and Business Development

Organizations can use AI-enabled KM to locate reusable proposal language, past performance examples, client context, pricing assumptions, technical approaches, and delivery lessons. This can reduce proposal development time and improve consistency.

8.3. Project and Operations Management

Project teams can use AI-enabled KM to identify prior project plans, risk registers, lessons learned, staffing models, deliverables, and closeout findings. This supports faster project startup and reduces repeated mistakes.

8.4. Expertise Discovery and Workforce Utilization

AI can help identify experts based on projects, publications, authored content, resumes, skills, and collaboration histories. This improves workforce utilization and reduces dependence on informal networks by making social and intellectual capital more visible (Nahapiet & Ghoshal, 1998; Wenger, 1998).

8.5. Onboarding and Workforce Learning

AI can generate role-based onboarding guides, recommend training materials, summarize key procedures, and connect new employees with relevant experts and communities. These practices can reinforce learning through participation in communities of practice and organizational routines (Wenger, 1998).

8.6. Quality Management and Continuous Improvement

AI can identify outdated documents, duplicate content, missing metadata, inconsistent procedures, and recurring lessons. This supports quality management and continuous improvement.

8.7. Innovation and Technology Management

AI-enabled KM can support innovation by connecting ideas, identifying patterns, surfacing emerging trends, and linking internal knowledge with external research. This use case aligns with dynamic capabilities because it helps organizations sense, seize, and transform knowledge resources in changing environments (Teece, 2007; Teece et al., 1997).

9. Knowledge Governance and Risk Management

AI-enabled KM requires governance because AI systems depend on the quality and authority of the knowledge they access. Governance helps ensure that AI-supported outputs are reliable, ethical, secure, and useful. This aligns with knowledge governance research and ISO 30401 guidance for establishing, implementing, maintaining, reviewing, and improving knowledge management systems (Foss, 2007; International Organization for Standardization, 2018). **Figure 4** depicts governance as a cross-cutting layer spanning the AI-enabled knowledge-management system.

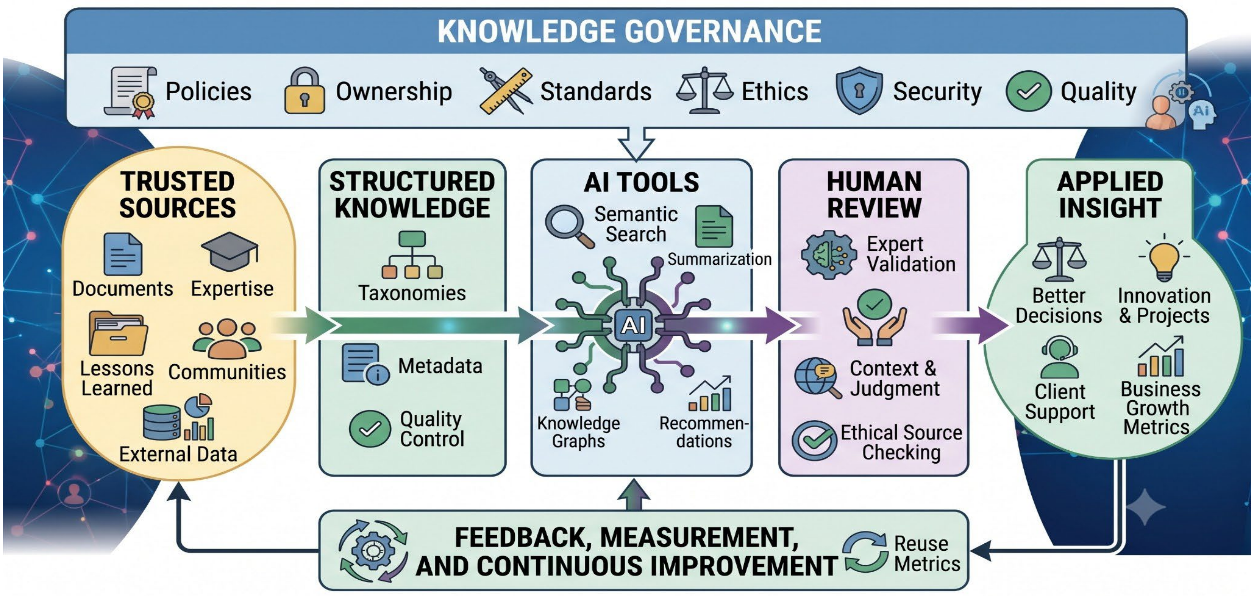

Figure 4. Knowledge governance layer for AI-enabled KM.

Key governance requirements include: Knowledge ownership, where each major knowledge domain should have an accountable owner; source authority, where organizations define approved and trusted sources; metadata standards, ensuring content is consistently tagged and classified; lifecycle management, so knowledge is reviewed, updated, archived, or retired; access control, protecting sensitive information; AI validation, ensuring high-risk AI outputs receive human review; ethical use, so AI is used transparently and responsibly; performance monitoring, evaluating AI-enabled KM against business outcomes; and risk management, monitoring bias, hallucination, outdated information, and misuse (Dwivedi et al., 2023; Foss, 2007; International Organization for Standardization, 2018).

Governance should not slow knowledge flow unnecessarily. Instead, it should create the trust necessary for employees and managers to use AI-enabled knowledge systems confidently.

10. Research Propositions

The primary unit of analysis for all propositions is the organization. A semi-autonomous business unit may be used as an equivalent unit when it possesses its own knowledge sources, governance, AI-enabled KM practices, workflows, and performance measures. Individual perceptions or behaviors may supply respondent-level data, but they are aggregated to characterize the organizational unit; the propositions do not infer organization-level effects from isolated individual use. Unless a study explicitly models multiple levels, predictors, mediators, moderators, and outcomes should be measured at this same organizational level.

Proposition 1: At the organizational level, higher knowledge-governance maturity will be associated with greater workforce trust in AI-enabled KM outputs.

Proposition 2: At the organizational level, stronger AI-enabled knowledge structuring will be associated with higher knowledge reuse, and this relationship will be stronger when metadata standards, source authority, and human-validation controls are more mature.

Proposition 3: At the organizational level, the positive relationship between AI-enabled KM capability and business performance will be mediated sequentially by knowledge quality and effective knowledge application, conditional on knowledge-governance maturity.

Proposition 4: At the organizational level, AI-enabled KM will be more positively associated with decision-support effectiveness when it is integrated into business workflows than when it is deployed as a stand-alone technology.

Proposition 5: At the organizational level, human validation will positively moderate the relationship between AI augmentation and knowledge-application quality, with the moderating effect increasing in complex or high-consequence decision contexts.

Proposition 6: Organizations with more active learning-feedback loops will demonstrate greater longitudinal improvement in knowledge quality, reuse, and organizational-learning capability.

Proposition 7: At the organizational level, greater use of AI-enabled expertise discovery will be associated with improved workforce utilization through reduced dependence on informal networks.

Proposition 8: At the organizational level, AI-enabled lessons-learned systems will be more positively associated with aggregate project performance when relevant lessons are delivered during planning and execution than when lessons are stored only after closeout.

Table 1. Organization-level operationalization of the research propositions.

Prop.	Unit	Principal constructs	Example observable indicators
P1	Organization	Governance maturity; trust	Governance maturity assessment score; mean employee trust rating for AI-enabled KM outputs
P2	Organization	Knowledge structuring; reuse; controls	Metadata completeness/accuracy rate; percentage of retrieved assets reused; source-authority and validation-control maturity scores
P3	Organization	AI-enabled KM capability; knowledge quality; application; performance	Capability index; content accuracy/currency score; validated-use rate; change in cycle time, quality, cost, or revenue-related outcomes
P4	Organization	Workflow integration; decision-support effectiveness	Percentage of priority workflows with embedded AI-enabled KM; decision cycle time and decision-quality rating
P5	Organization	AI augmentation; human validation; application quality; task consequence	Percentage of AI outputs receiving expert review; validated-output accuracy or usefulness; proportion of high-consequence use cases
P6	Organization	Feedback-loop activity; quality; reuse; learning	Feedback closure rate; longitudinal change in knowledge-quality, reuse, and organizational-learning scores
P7	Organization	Expertise discovery; workforce utilization	Percentage of staffing searches using the system; time to identify qualified experts; assignment or billable-utilization rate
P8	Organization	Contextual lesson delivery; project performance	Percentage of projects receiving lessons during planning/execution; repeated-issue rate; aggregate schedule, cost, and quality performance

The indicators in Table 1 are illustrative operationalizations rather than a fixed measurement instrument. Future studies should establish construct validity, reliability, temporal ordering, and appropriate aggregation statistics before testing the propositions.

11. Measurement and Business Performance Evaluation

AI-enabled KM should be evaluated through both activity measures and business outcome measures. Table 1 links each research proposition to an organization-level unit and at least one observable indicator, providing a starting point for future scale development and empirical testing.

Activity measures include number of searches, AI summaries generated, knowledge assets classified, lessons captured, reusable assets accessed, expertise profiles created, and user feedback ratings. These measures help determine whether the system is being used.

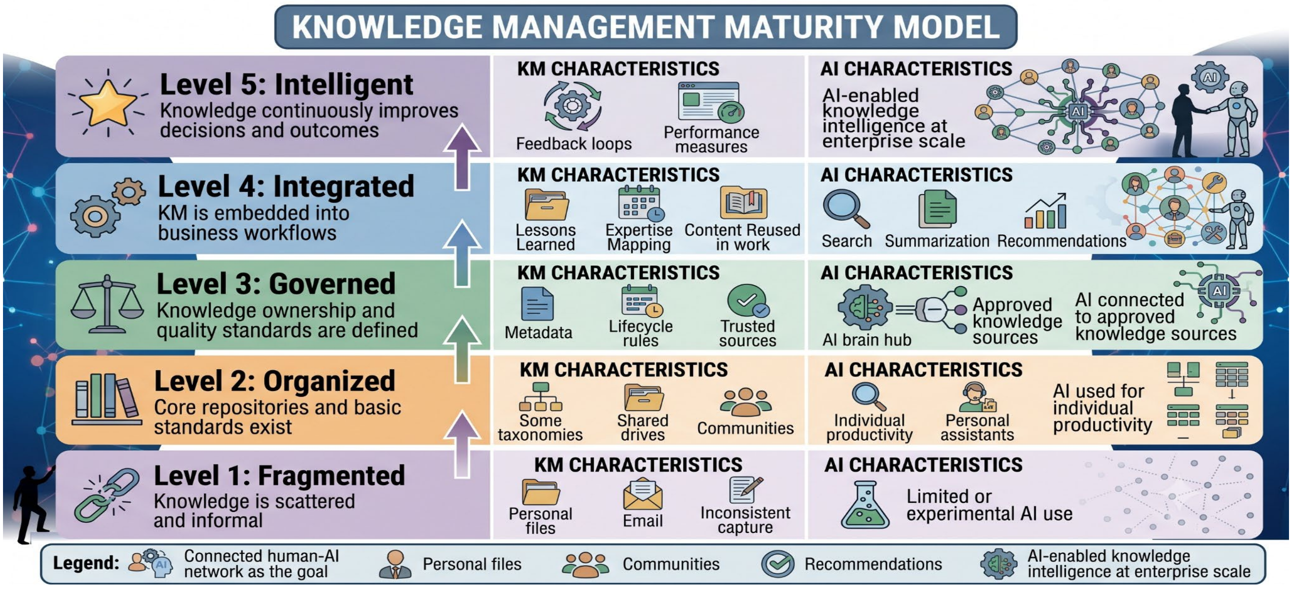

Figure 5. AI-enabled knowledge intelligence maturity model.

However, activity measures alone are insufficient. Business outcome measures are more important. Outcome measures may include reduced time to find information, reduced duplication of work, faster proposal development, faster project startup, improved onboarding speed, improved decision cycle time, increased reuse of prior deliverables, improved quality of project outputs, reduced operational risk, improved customer or client responsiveness, better workforce utilization, increased innovation activity, and improved organizational learning maturity.

A maturity model (Figure 5) can help organizations assess progress from fragmented knowledge practices to enterprise-level knowledge intelligence. At lower maturity levels, knowledge is scattered and AI use is experimental. At higher maturity levels, knowledge is governed, AI is integrated into workflows, and feedback loops continuously improve knowledge quality and business performance.

12. Discussion

The proposed framework advances the argument that AI-enabled KM should be understood as a business management capability rather than a technology project. AI can improve the speed and scale of knowledge retrieval and synthesis, but it cannot replace the managerial work of defining knowledge priorities, governing trusted sources, validating outputs, and measuring business value (Bostrom & Heinen, 1977; Raisch & Krakowski, 2021).

The framework also bridges knowledge management and business intelligence. Business intelligence provides data-driven insight, while knowledge management provides context, experience, lessons, and expertise. AI-enabled knowledge intelligence integrates these functions by connecting structured data, unstructured knowledge, human expertise, and decision-support processes (Alavi & Leidner, 2001; Choo, 1998; Davenport & Prusak, 1998).

The discussion also highlights the importance of human judgment. AI can generate recommendations and summaries, but managers and experts must determine whether those outputs are relevant, accurate, ethical, and actionable. This is especially important in complex business environments where decisions involve uncertainty, tradeoffs, relationships, and risk (Jarrahi, 2018; Lebovitz et al., 2021).

Finally, the framework suggests that organizations should begin with business problems rather than AI tools. High-value starting points include proposal reuse, project startup, lessons learned, expertise discovery, onboarding, quality management, and decision support.

13. Managerial Implications

This article offers several implications for managers. First, leaders should treat AI-enabled KM as a strategic business capability. It should be connected to organizational goals such as improved decision-making, faster execution, better quality, innovation, and operational efficiency (Grant, 1996; Spender, 1996).

Second, organizations should identify priority use cases before selecting technology. AI-enabled KM should solve real business problems, not simply introduce new tools.

Third, managers should invest in knowledge foundations. These include taxonomies, metadata, trusted repositories, content ownership, lifecycle management, and quality controls (Foss, 2007; International Organization for Standardization, 2018).

Fourth, human expertise should remain central. AI should augment expert judgment by reducing search burden and improving access to relevant knowledge (Jarrahi, 2018; Raisch & Krakowski, 2021).

Fifth, organizations should establish governance before scaling AI. Employees need clarity about approved sources, validation requirements, security rules, and appropriate use.

Sixth, organizations should measure outcomes rather than activity alone. The success of AI-enabled KM should be evaluated by whether it improves business performance and strengthens intellectual capital, knowledge reuse, and organizational learning (Bontis, 1998; Markus, 2001; Crossan et al., 1999).

14. Limitations and Future Research

This article presents a conceptual framework and does not empirically test the proposed relationships. The framework is most applicable when an organization has recurring knowledge-intensive work, a sufficiently accessible digital knowledge base, identifiable business workflows, and authority to govern both knowledge and AI use. Its propositions therefore require empirical examination through case studies, surveys, design science research, longitudinal designs, and mixed-methods studies.

Several boundary conditions may weaken or alter the proposed relationships.

In highly regulated or safety-critical settings, mandatory controls, documentation, and approval requirements may reduce speed benefits while increasing the value of provenance and validation. In domains containing classified, personal, proprietary, or otherwise sensitive knowledge, access restrictions may limit the sources available to AI and require isolated technical environments. Where work depends heavily on tacit, embodied, relational, or locally negotiated expertise, codified sources and AI synthesis may represent only part of the knowledge required for action. The framework may also yield limited value when source quality is poor, the task is genuinely novel, feedback is delayed or ambiguous, or the organization lacks sufficient scale and resources to maintain governance, metadata, and evaluation.

These conditions do not necessarily make knowledge intelligence inapplicable; they change its expected mechanisms and outcomes. In high-consequence or tacit-intensive contexts, the framework predicts greater dependence on expert participation and more conservative automation. The proposed performance effects would be weakened or falsified if governed knowledge foundations, human validation, workflow integration, and feedback did not improve—or if they imposed costs that consistently exceeded gains in decision quality, reuse, learning, or operational performance.

Future studies could test whether AI-enabled KM reduces search time, improves proposal efficiency, increases lessons learned reuse, accelerates onboarding, or improves decision quality. Researchers could also examine how knowledge governance maturity affects trust in AI outputs.

Additional research is needed across different industries, including consulting, manufacturing, healthcare, logistics, education, public sector organizations, and research-intensive firms. Comparative studies could identify which industries benefit most from AI-enabled knowledge intelligence and which governance models are most effective.

Future research should also examine the relationship between AI-enabled KM and business intelligence. This includes how organizations integrate structured data, unstructured documents, tacit expertise, and AI-generated insight into decision-support systems.

15. Conclusion

Artificial intelligence is changing the future of knowledge management, but it does not replace the need for KM. Instead, AI increases the importance of knowledge governance, structure, quality, human validation, and business alignment (Alavi & Leidner, 2001; Foss, 2007; International Organization for Standardization, 2018; Lebovitz et al., 2021).

This article proposed an AI-Enabled Knowledge Intelligence Framework for business performance, decision support, and organizational learning. The framework includes six dimensions: knowledge sources, knowledge structuring, AI augmentation, human validation and sensemaking, knowledge application, and learning feedback.

The central contribution of the article is the concept of knowledge intelligence. Knowledge intelligence extends traditional KM by emphasizing the conversion of distributed organizational knowledge into trusted, contextualized, and actionable business insight. Organizations that develop this capability will be better positioned to improve decision-making, reduce duplication, accelerate work, strengthen innovation, and learn continuously from experience.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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