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Integration of Knowledge Management Systems (KMS), Artificial Intelligence (AI), and Machine Learning (ML) in Knowledge-Based Organizations: A Comparative Analysis of PT Telkom Indonesia Tbk and PT SMI Using the SECI and DeLone–McLean Models

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Abstract

Knowledge management systems (KMS) often end up as document repositories because search is inaccurate and content is not updated, while evidence on integrating artificial intelligence (AI) and machine learning (ML) into KMS in Indonesian organizations remains limited. This study explains the theoretical foundations of integrating KMS, AI, and ML; compares current theories, approaches, and research findings; analyzes integration practices at PT Telkom Indonesia Tbk, with PT Sarana Multi Infrastruktur (PT SMI) as a comparator; and formulates strategic recommendations. It is a literature review with a single case study and one comparative case, using secondary data (journal articles, conference proceedings, theses, and official news reports), with priority given to publications from 2021–2026. The qualitative analysis compares theories, approaches, and findings, then maps the cases onto the SECI model and the DeLone–McLean information systems success model. The literature agrees that AI improves the efficiency of knowledge access, search, and distribution, but differs in its emphasis on tacit knowledge, automation versus augmentation, and organizational culture. The Telkom case shows the potential of ML-based hybrid recommender systems, while the RAG chatbot prototype at PT SMI, tested with 10 respondents, shortened the learning curve of new employees; neither case has measured impact evidence. Integration is best understood as a socio-technical system. This study proposes a four-layer framework and a phased 0–24-month roadmap that begins with data governance and measurable pilots; future research needs to measure long-term impact on performance and innovation.

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Keywords: Knowledge Management System, Artificial Intelligence, Machine Learning, Knowledge-Based Organization, SECI Model, PT Telkom Indonesia Tbk

INTRODUCTION

In a knowledge-based economy, an organization's competitiveness is determined by what it knows and how quickly it puts that knowledge to use. Knowledge-based organizations place learning, innovation, and knowledge sharing at the core of their business processes. Knowledge scattered across individuals, documents, procedures, and operational data has value only if it can be found, understood, and applied when needed.

A Knowledge Management System (KMS) is the technological and organizational infrastructure for capturing, storing, sharing, and applying knowledge (Gelashvili-Luik et al., 2025). However, the volume of organizational knowledge is growing rapidly in the form of documents, conversations, meetings, and operational data, while employees struggle to find relevant knowledge. Many KMS end up as document repositories that are rarely opened because search is inaccurate, content is not updated, and the system is not connected to day-to-day work. A review of the public sector found a similar pattern: KMS still rely on manual input, have limited search capabilities, and hold data fragmented across departments (Telaumbanua, 2026).

Artificial intelligence (AI) and machine learning (ML) offer an answer to this problem through their ability to read unstructured data, learn from user behavior, and generate recommendations or answers automatically. Systematic reviews show that research interest in integrating AI into KMS continues to grow, but also note challenges such as data quality and employee resistance (Gelashvili-Luik et al., 2025; Pai et al., 2022). Large language models and the Retrieval-Augmented Generation (RAG) approach expand these possibilities (Dwivedi et al., 2023): employees can ask questions in everyday language and obtain answers sourced from the organization's official documents. Expanded technological capability, however, does not automatically produce organizational value (Enholm et al., 2022). AI is most beneficial when positioned as a partner to humans rather than a replacement, especially for tacit and contextual knowledge (Jarrahi et al., 2023).

The research gap arises from four issues. First, many empirical studies are single case studies or prototypes, so their generalizability is limited. Second, results are more often reported as system accuracy and user satisfaction than as impact on innovation or organizational performance (Enholm et al., 2022). Third, ethical issues, such as algorithmic bias, employee data privacy, and intellectual property, receive less attention than technical aspects. Fourth, organizational contexts in developing countries, including Indonesia,

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remain under-researched, and implementation frameworks for AI-based KMS are still dominated by studies of the private sector (Telaumbanua, 2026).

PT Telkom Indonesia Tbk is relevant for filling this gap because it has a large workforce, a complex business portfolio, and a digital transformation agenda. Telkom has been the object of research on ML-based knowledge recommender systems (Alberto & Kurniawan, 2022) and, in 2025, cited a knowledge management system as one of its strategic AI use cases (Pratama, 2025).

This study aims to (1) explain the theoretical foundations of KMS, AI, and ML in knowledge-based organizations; (2) critically analyze the comparison of theories, approaches, and research findings; (3) analyze integration practices at PT Telkom Indonesia Tbk, with PT Sarana Multi Infrastruktur (PT SMI) as a comparative case; and (4) formulate strategic recommendations so that the integration of KMS, AI, and ML is successful and sustainable.

THEORETICAL REVIEW

No single framework is sufficient. The SECI model explains the types of knowledge and the modes that AI can support, but does not address AI technology specifically (Sumbal & Amber, 2025). The DeLone–McLean information systems success model provides evaluation indicators in the form of system quality, information quality, service quality, use, user satisfaction, and net benefits (Maftuhah et al., 2023), but focuses on the system and less on social dynamics. The implication is that an AI-based KMS should not be assessed solely on algorithmic accuracy; content quality, ease of use, and real benefits for work must also be measured. The automation–augmentation paradox (Raisch & Krakowski, 2021) explains how to divide roles between humans and AI, although it is conceptual and not specific to knowledge.

METHOD

Research Design

This study is a literature review with a single case study, reinforced by one comparative case. The analysis is qualitative.

Setting and Case Subjects

The primary case is PT Telkom Indonesia (Persero) Tbk, a state-owned enterprise in telecommunications and digital services. Telkom was chosen because it has a large workforce, a complex business portfolio, and a record of academic research on knowledge

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management, so its data can be traced. The comparative case is the Public Financing Division of PT Sarana Multi Infrastruktur (PT SMI).

Data Collection

The study uses only secondary data in the form of journal articles, conference proceedings, theses, and official news reports. Literature was selected for its relevance to the topic, with priority given to publications from 2021–2026. Data for the Telkom case come from Alberto and Kurniawan (2022), a case study of a corporate learning platform (Universitas Gadjah Mada [UGM], 2025), and 2025 news reports (Pratama, 2025). Data for the PT SMI case come from Saragih and Anggadwita (2026).

Data Analysis

The analysis was carried out in three steps: (1) comparing theories, approaches, and findings in the literature; (2) mapping the Telkom case onto the four modes of the SECI model and onto the dimensions of the DeLone–McLean information systems success model (Maftuhah et al., 2023; Sumbal & Amber, 2025); and (3) comparing the Telkom case with PT SMI as the basis for critical analysis and recommendations. Because the data are secondary, this study does not measure quantitative impact and does not claim implementation results that have not been documented.

RESULTS

The Role of AI in the Knowledge Cycle

The integration of KMS, AI, and ML is mapped onto four dimensions of knowledge management according to Jarrahi et al. (2023): creation, storage and retrieval, sharing, and application (Table 1). In each dimension, the role of AI has clear limits.

Table 1: The Role of AI in the Knowledge Cycle

Dimension	Role of AI/ML	Example techniques	Limitations
Creation	Discovers new patterns and insights from data	Clustering, predictive analytics	Insights must be interpreted and validated by humans
Storage and retrieval	Classifies, indexes, and finds content	NLP, semantic search	Depends on data quality and completeness

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Dimension	Role of AI/ML	Example techniques	Limitations
Sharing	Recommends relevant materials or experts	Hybrid filtering, knowledge graphs	Tacit knowledge is not shared automatically
Application	Delivers contextual answers while people work	RAG chatbots, expert systems	Risk of erroneous answers if sources are not up to date

A systematic review of 30 articles on the use of AI in public-sector KMS found ML to be the dominant method (36.7%), followed by NLP (26.7%), chatbots/LLMs (16.7%), and expert systems (13.3%) (Telaumbanua, 2026).

Key Study Findings

Table 2 summarizes the main findings of the key studies.

Table 2: Main Findings of Key Studies

Study	Approach	Main findings
Pai et al. (2022)	Systematic review	AI and knowledge management are interrelated; knowledge sharing is associated with communication, trust, information systems, incentives, and organizational structure
Jarrahi et al. (2023)	Conceptual review	AI plays a role in four dimensions of knowledge management; AI excels at specialized intelligence, while strategic judgment, empathy, and general intelligence remain human; the roles of *knowledge scientist* and *AI champion* emerge
Gelashvili-Luik et al. (2025)	PRISMA systematic review, 40 publications	The role of AI is shifting from supporting routine tasks to enabling dynamic, real-time knowledge flows; challenges: data quality, employee resistance, alignment with workflows
Telaumbanua (2026)	Systematic review, 30 public-sector articles	KMS still rely on manual input, limited search, and fragmented data; implementation frameworks for AI-based KMS are dominated by private-sector studies

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Study	Approach	Main findings
Alberto & Kurniawan (2022)	Development of a hybrid recommender system	The model uses Telkom's knowledge stock and human capital development data and considers the ideal competencies for a position, user preferences, and learning history
Saragih & Anggadwita (2026)	*Design Science Research*, RAG chatbot prototype, 10 respondents	Conventional KMS are suboptimal, giving rise to the *walking library* phenomenon; the prototype shortens the learning curve of new employees and reduces cognitive load
Raisch & Krakowski (2021)	Conceptual	Automation–augmentation paradox: automating and augmenting human work are interdependent, not separate choices

Taherdoost and Madanchian (2023) also discuss the impacts, benefits, and implementation of AI in knowledge management.

Comparison of Research Approaches

The reviewed literature falls into three approaches (Table 3). All of it agrees that AI improves the efficiency of knowledge access, search, and distribution, and that technology alone is not enough: Pai et al. (2022) emphasize leadership and organizational arrangements, Gelashvili-Luik et al. (2025) emphasize human oversight, and Jarrahi et al. (2023) emphasize human–AI partnership. Survey evidence from 323 members of AI-focused digital groups in China also shows that AI-generated content has a positive effect on inter-organizational knowledge sharing, with knowledge digitization and cross-language collaboration as mediators (Cheng et al., 2025).

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Table 3: Comparison of Approaches in the Literature

Aspect	Technological (Alberto & Kurniawan, 2022; Saragih & Anggadwita, 2026)	Socio-technical (Jarrahi et al., 2023; Pai et al., 2022)	Systematic reviews (Gelashvili-Luik et al., 2025; Telaumbanua, 2026)
Focus	Building and testing systems (recommender, RAG chatbot)	Human–AI relationships, culture, leadership	Mapping opportunities, challenges, and success factors
Position of AI	A tool that improves access and efficiency	A partner, not a replacement	A supporting technology that requires oversight
Method	Prototype development, case studies	Conceptual and systematic reviews	PRISMA on scholarly databases
Strengths	Tangible, testable evidence	Rich conceptual frameworks	Broad and systematic coverage
Weaknesses	Single cases and prototypes; long-term performance impact rarely measured	Largely conceptual, with little empirical testing	Depends on the quality of the primary studies reviewed

The Case of PT Telkom Indonesia Tbk

Problem. Telkom has developed digital knowledge management practices for knowledge acquisition, inventory, and transfer, but adding to the knowledge stock alone is not enough for successful diffusion: the more learning options there are, the harder it is for employees to choose materials relevant to the ideal competencies of their positions (Alberto & Kurniawan, 2022).

Integration practices. Three practices are documented. First, ML-based knowledge recommendation: Alberto and Kurniawan (2022) designed a hybrid recommender system (content-based and collaborative filtering) that produces a model as the basis for a more personalized and efficient knowledge platform. Second, corporate learning platform: a qualitative case study of myDigiLearn, Telkom's Corporate Open Online Course (COOC) platform that functions as a knowledge management system, found two main knowledge

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management practices for mitigating operational and transformation risks (UGM, 2025). Third, strategic direction for AI: in 2025, Telkom's EVP of Digital Business and Technology described a collaboration with IBM on several strategic AI use cases and five AI business pillars (AI data centers, GPU chips, GPU services, cloud platform, and AI solution services). At an IBM forum on June 11, 2025, Telkom named three main use cases: an AI platform for human resources management, legal analytics, and a knowledge management system for corporate knowledge access, as well as the development of hyper-personalization, zero-touch network operations, and a study of agentic AI (Pratama, 2025).

Table 4 maps Telkom's practices onto the SECI model, and Table 5 assesses the case against the DeLone–McLean model dimensions.

Table 4: Mapping of Telkom's Practices onto the SECI Model

SECI mode	Practice in the Telkom case	Role of AI/ML	Notes
Socialization	Not a focus in the sources reviewed	Limited	Communities of practice and mentoring are needed
Externalization	Legal and HR documents are targeted by use cases	NLP to understand and summarize documents	Experts' tacit knowledge is not mentioned
Combination	Knowledge management system for corporate knowledge access	AI-based search and classification	Depends on data quality and governance
Internalization	COOC platform and learning-material recommendations	ML-based hybrid recommendation	Impact on performance is not documented

Table 5: The Telkom Case by DeLone–McLean Model Dimensions

Dimension	Finding in the case	Assessment
System quality	The hybrid recommendation model is designed for personalization	Sound in concept; full-scale test results are not documented
Information quality	Uses knowledge stock and human capital data	Data quality and content updating are not reported

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Dimension	Finding in the case	Assessment
Service quality	Plan for an AI-based KMS for corporate knowledge access	Still only a plan in the 2025 source
Use and satisfaction	No data on employee use or satisfaction	Needs to be measured
Net benefits	COOC is linked to risk mitigation and transformation	Quantitative impact is not available

The Comparative Case of PT SMI

Saragih and Anggadwita (2026) studied the Public Financing Division of PT SMI, an infrastructure financing institution that manages complex and regulated information. Using *Design Science Research*, they identified the limitations of the existing KMS, implemented a RAG chatbot prototype, and evaluated it through interviews and prototype testing with 10 selected respondents, using the SECI model and the KMS Success Model. The conventional KMS was suboptimal, so employees relied on social learning and the *walking library* phenomenon emerged. The prototype shortened the learning curve of new employees, reduced the cognitive load of searching for and synthesizing information, and was rated positively on the dimensions of the KMS Success Model (Table 6).

Table 6: Comparison of the Telkom and PT SMI Cases

Aspect	PT Telkom Indonesia Tbk	PT SMI (Public Financing Division)
Main problem	Many learning materials; hard to choose relevant ones	Knowledge locked in individuals (*walking library*)
AI technology	ML-based hybrid recommendation; planned AI-based KMS	RAG-based chatbot
SECI focus	Internalization and combination	Internalization
Scale of evidence	Model/prototype and qualitative study; strategic plan	Prototype tested with 10 respondents
Limitations	Measured impact is not documented	Small scale and a single division

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DISCUSSION

Interpretation of Findings

Both cases support the literature's finding that the initial value of AI lies in access to and personalization of explicit knowledge and in accelerating employee learning (Alberto & Kurniawan, 2022; Saragih & Anggadwita, 2026). Five differences in emphasis within the literature help interpret these findings.

Tacit versus explicit knowledge. Technological approaches tend to focus on explicit knowledge (documents, FAQs, training materials) that is easy to index, whereas tacit knowledge is hard to codify (Jarrahi et al., 2023). Sumbal and Amber (2025) propose that generative AI can improve all four SECI processes, but the evidence in both cases touches only combination and internalization (Tables 4 and 6). KMS play a role mainly in combination and internalization; in socialization, technology only facilitates, for example through expert directories and collaboration spaces. A RAG chatbot is only as good as its source documents, so it strengthens the internalization of knowledge that is already written down rather than replacing socialization among employees. The fact that RAG retrieves information from external databases allows knowledge to be updated and answers to be traced (Gao et al., 2024), consistent with the risk of erroneous answers when sources are not up to date noted in Table 1.

Automation versus augmentation. Raisch and Krakowski (2021) show that the two are in tension and must be managed together. Recent reviews indicate that practice is moving toward augmentation with human oversight rather than full automation (Gelashvili-Luik et al., 2025; Telaumbanua, 2026). Iaia et al. (2024) are consistent with this: from a knowledge management perspective, the application of AI in business communication needs to be centered on people, processes, and technology and should move toward augmented intelligence, because AI cannot fully replace humans.

Technology versus culture. Studies that build systems report improved access, but systematic reviews show that the main barriers are actually data quality and employee resistance. The success of a prototype therefore does not guarantee successful adoption. A qualitative study of 50 early ChatGPT users shows that employees' use of generative AI can come with side effects: strained knowledge-sharing relationships, declining knowledge quality, and shifting work roles (Retkowsky et al., 2024).

Personalization versus serendipity. Recommender systems that learn from learning history tend to suggest materials similar to what has already been studied. A hybrid approach reduces this problem, but the reviewed literature has not tested whether recommendations push employees beyond their areas of expertise, even though organizational development requires cross-disciplinary learning.

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Private versus public sector. Implementation frameworks for AI-based KMS are still dominated by studies of the private sector (Telaumbanua, 2026). As a state-owned enterprise, Telkom sits between the two, so findings from both sectors need to be read with care.

A Four-Layer Conceptual Framework

Based on this synthesis, this study proposes a conceptual framework for integrating KMS, AI, and ML that views integration as a socio-technical system. The framework consists of four layers. First, the data and knowledge layer is a clean, classified repository with content owners. Second, the technology layer consists of semantic search engines, hybrid recommender systems, and RAG chatbots connected to the repository. Third, the people and culture layer comprises communities of practice, mentoring, sharing incentives, and the roles of *knowledge scientist* and *AI champion*. Fourth, the governance and evaluation layer comprises policies on ethics and security, human oversight, and success indicators based on the DeLone–McLean model.

All three theoretical frameworks are represented: SECI in the people and technology layers, the information systems success model in the evaluation layer, and the automation–augmentation paradox in the governance layer.

CONCLUSION

KMS provide structure for the knowledge cycle, while AI and ML provide learning and automation capabilities; together they yield a more proactive KMS in the storage, retrieval, sharing, and application of knowledge. The literature agrees that AI improves knowledge access and efficiency, but differs in its emphasis on tacit knowledge, automation versus augmentation, and the role of organizational culture. The Telkom case shows the potential of AI for recommendation and knowledge access, while the PT SMI case shows the benefits of a RAG chatbot for new employee learning; both still have limited evidence of impact. Successful integration is determined by a combination of technology, data, culture, leadership, and ethics, so integration needs to be viewed as a socio-technical system.

In practical terms, organizations are advised to start with data governance and a limited pilot before expanding, involve employees from the design stage of the system, develop the roles of *knowledge scientist* and *AI champion*, and measure impact with consistent indicators.

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Recommendations

The evidence in the Telkom case consists of a model, a qualitative case study, and strategic statements; the 2025 news reports describe planned use cases, not implementation results, so claims of success must be avoided. With that caveat, the following ten recommendations are derived from the analysis.

First, priority should go to building the data and governance foundation. Data quality is the main barrier (Gelashvili-Luik et al., 2025); content owners, metadata standards, update cycles, and confidentiality classification should be established before AI is deployed. Second, technology should be chosen to fit the need: recommender ML for learning personalization (Alberto & Kurniawan, 2022); RAG chatbots for question answering based on official documents so that answers can be traced to their sources (Saragih & Anggadwita, 2026); and NLP for mining unstructured documents. Third, the human–AI partnership should be designed, keeping a *human in the loop* for important decisions and providing *knowledge scientist* and *AI champion* roles (Jarrahi et al., 2023; Telaumbanua, 2026).

Fourth, the tacit dimension should be preserved through social mechanisms. Communities of practice, mentoring, and *after-action reviews* should be maintained, and AI should be used to connect experts with those asking questions, which also addresses the *walking library* in the PT SMI case. Fifth, the sharing culture and incentives should be strengthened, since communication, trust, incentives, and organizational structure influence knowledge sharing (Pai et al., 2022); knowledge contributions should be linked to performance appraisal. Sixth, change and AI literacy should be managed through training, phased pilots, and user feedback.

Seventh, ethics and security should be applied through privacy policies, bias audits, access controls, and intellectual property protection, especially because recommender systems use employees' learning-history data. Eighth, cross-field learning should be encouraged by configuring recommender systems to also suggest materials on competencies required by employees' positions and career paths. Ninth, a measurable pilot should be started in one unit with clear indicators before expanding, as in the PT SMI case. Finally, impact, not just usage, should be measured, using the DeLone–McLean dimensions as the basis for indicators (Maftuhah et al., 2023).

Table 7 presents the implementation roadmap.

Table 7: Implementation Roadmap

Phase	Main activities	Evaluation indicators
0–6 months	Knowledge and data audit; governance policy; appointment of content owners	Percentage of content classified; policy ratified

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Phase	Main activities	Evaluation indicators
6–12 months	Pilot of a RAG chatbot or recommender in one unit; AI literacy training	Search time; user satisfaction; answer accuracy
12–24 months	Expansion to other units; integration with HR and business processes; impact evaluation	Knowledge reuse; onboarding speed; innovation ideas

The main risks and their mitigations are: low data quality (data governance, periodic content audits); employee resistance (training, involvement of *AI champions*, feedback); erroneous answers from generative systems (source tracing, human oversight; Dwivedi et al., 2023); data leakage and privacy violations (access controls, privacy policies, anonymization); and loss of tacit knowledge (mentoring, communities of practice, documentation of best practices).

Limitations and suggestions for further study

This study uses secondary data and therefore does not measure quantitative impact. The evidence for the Telkom case does not yet include data on use, satisfaction, or performance, and the evidence for the PT SMI case comes from 10 respondents in a single division. Both cases focus on explicit knowledge, so mechanisms for capturing experts' tacit knowledge cannot yet be assessed. Much of the reviewed literature consists of single case studies or prototypes, so generalizability is limited. The four-layer framework is conceptual and has not been empirically tested.

Future research needs to measure long-term impact on performance and innovation, test this integration in public organizations and MSMEs in Indonesia, and examine ethical and privacy issues in greater depth.

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