Jurnal Manajemen Bisnis Vol. 13, No.1 (2026) March, Page. 189-207
e-ISSN: 2621-1971 | p-ISSN: 2088-7086

From Walking Libraries to Answer Engines: Optimizing Knowledge Internalization in Public Financing with RAG-Based AI Chatbots

Debrian Ruhut Saragih[1*], Grisna Anggadwita[2],
[1,2] Universitas Telkom, Bandung, Jl. Telekomunikasi No. 1, Sukapura, Dayeuhkolot District, Bandung Regency, West Java 40257, Indonesia*

ARTICLE INFO

Correspondence Email:
debrianruhut.saragih@gmail.com

Keywords:
RAG; AI Chatbot; SECI Model; KMS Success Model; Knowledge Management; Knowledge Internalization.

DOI:
https:doi.org/10.33096/jmb.v13i1.1366

-

ABSTRACT

This research arises from the critical need to optimize knowledge internalization within the SECI Model, especially in organizations handling complex and regulated information such as public financing. The study aims to identify the limitations of the existing Knowledge Management System (KMS), implement a Retrieval-Augmented Generation (RAG)-based AI Chatbot prototype, and evaluate its effectiveness in facilitating knowledge internalization. A qualitative case study approach was employed using the Design Science Research Method (DSRM). Data were collected through in-depth interviews and prototype testing involving 10 purposively selected respondents from the Public Financing Division of PT SMI. Findings indicate that the conventional KMS is suboptimal, leading to high dependency on social learning and the "walking library" phenomenon, where critical knowledge is siloed within specific individuals rather than being institutionalized. The implemented AI Chatbot prototype successfully accelerated the learning curve for new employees, reduced cognitive load – the mental effort required to search for and synthesize information, and received positive evaluation based on the KMS Success Model dimensions. The study implies that organizations should transition their knowledge-sharing culture from individual dependency to smart system-based interactions.

ABSTRAK

Penelitian ini dilatarbelakangi oleh urgensi untuk mengoptimalkan internalisasi pengetahuan dalam Model SECI, khususnya pada organisasi yang mengelola informasi kompleks dan terstruktur seperti pembiayaan publik. Tujuan penelitian adalah mengidentifikasi keterbatasan sistem manajemen pengetahuan (KMS) yang ada, mengimplementasikan prototipe chatbot AI berbasis Retrieval-Augmented Generation (RAG), dan mengevaluasi efektivitasnya dalam memfasilitasi internalisasi pengetahuan. Metode yang digunakan adalah studi kasus kualitatif dengan pendekatan Design Science Research Method (DSRM). Data dikumpulkan melalui wawancara mendalam dan pengujian prototipe terhadap 10 responden terpilih dari Divisi Pembiayaan Publik PT SMI. Hasil penelitian menunjukkan bahwa KMS konvensional tidak optimal sehingga mengakibatkan ketergantungan tinggi pada pembelajaran sosial dan fenomena "walking library", dimana pengetahuan kritikal perusahaan tersimpan pada individu tertentu dan belum terdokumentasi menjadi aset perusahaan. Prototipe chatbot AI berhasil mempercepat pembelajaran karyawan baru, mengurangi beban kognitif – beban mental individu untuk mencari dan mensistesis informasi, dan mendapat evaluasi positif berdasarkan dimensi KMS Success Model. Implikasinya, organisasi perlu melakukan transisi budaya berbagi pengetahuan dari ketergantungan individu menuju interaksi berbasis sistem cerdas.

INTRODUCTION

Effective knowledge management is imperative for organizations operating in complex, information-intensive sectors such as infrastructure financing. The inability to internalize explicit knowledge—transforming documented procedures into tacit understanding—poses significant operational risks, including compliance failures, decision-making delays, and loss of institutional memory. This urgency is amplified in state-owned enterprises like PT Sarana Multi Infrastruktur (Persero) or PT SMI, where public financing commitments exceed IDR 38.53 trillion as of October 2024 (PT SMI, 2025), demanding meticulous knowledge handling and accountability.

PT SMI was selected as the research object due to its dual role as a Special Mission Vehicle of the Ministry of Finance and a leading infrastructure financing institution. Unlike typical commercial enterprises, PT SMI operates under stringent regulatory frameworks and manages multidisciplinary knowledge spanning finance, law, engineering, and public policy. Its existing KMS, InfraLib, represents a common yet underperforming archetype in the public sector—characterized by declining user engagement, fragmented information, and a reliance on social learning rather than systematic access.

Previous research has extensively documented the challenges of KMS in the public sector. Laihonen et al. (2023) observe that public sector KMS are often trapped in a reporting approach rather than becoming tools for meaning creation, thus losing relevance in facing the complexity of organizational tasks. Other challenges include the fragmentation of knowledge sources, reliance on social learning and individual expertise, as well as difficulties in accessing and synthesizing scattered (siloed) information quickly and accurately (Alavi & Leidner, 2001). To navigate these complexities, the successful implementation of a KMS as an effective knowledge-handling tool must be examined through the Technology-Organisation-Environment (TOE) framework, which emphasizes the critical interplay between technological features, internal organizational processes, and the external environment (Tornatzky & Fleischer, 1990).

On the other hand, advances in Artificial Intelligence (AI) offer transformative opportunities for modern Knowledge Management (KM) by mimicking human intelligence to solve complex organizational tasks. Integrating AI into KM, particularly through chatbots, significantly improves information access efficiency, making the stages of knowledge creation, sharing, and application more efficient and fosters organizational innovation (Jarrahi et al., 2022; Sundaresan & Zhang, 2021). Specifically, chatbots utilizing Natural Language Processing (NLP) alleviate the burden of manual information searching (Shawar & Atwell, 2007). Within this technological landscape, Large Language Models (LLM) and the Retrieval-Augmented Generation (RAG) architecture provide more accurate and contextual responses by combining generative capabilities with specific external knowledge bases (Lewis et al., 2020). Implementing a RAG-based chatbot into a KMS is predicted to address conventional system weaknesses by providing intuitive access and accelerating the internalization of explicit knowledge into tacit understanding in accordance with the SECI Model (Jais & Ngah, 2024; Sundaresan & Zhang, 2021). The role of such innovative technology is also vital for ensuring business resilience during global disruptions, such as the post-pandemic recovery era which demands highly adaptive organizational responses (Anggadwita et al., 2021).

However, a significant gap exists in empirical studies that specifically apply and evaluate a RAG-based AI Chatbot to support knowledge internalization within the highly regulated context of a state-owned infrastructure financing enterprise. Most existing studies focus on general chatbot adoption in commercial settings, leaving the unique complexities of public financing underexplored. Furthermore, while the KMS Success Model provides a robust evaluation framework (Jennex and Olfman, 2004), its application to assess an AI-driven knowledge internalization tool remains limited.

This research addresses the gap by offering a novel methodological application of the *Design Science Research Method (*DSRM) to develop and test a RAG-based AI Chatbot artifact. The novelty lies in its specific contextual focus, its theoretical integration of the SECI Model and KMS Success Model, and its empirical insights from a state-owned enterprise. The benefits include both theoretical contributions to knowledge management and artificial intelligence literature, and practical implications for organizations seeking to modernize their KMS. Based on this background, the objectives are threefold: (1) to identify the current state of PT SMI's KMS in supporting SECI internalization; (2) to implement a RAG-based AI Chatbot prototype tailored for public financing knowledge; and (3) to evaluate the prototype's success using the KMS Success Model framework.

According to the Knowledge-Based View (KBV), knowledge is the most strategically significant resource of a firm; thus, competitive advantage is achieved through the effective integration and application of both tacit and explicit knowledge (Grant, 1996). Effective knowledge management is positively correlated with innovation capability, particularly when fostered by a supportive organizational culture (Lam et al., 2021). This strategic alignment presents vast opportunities for service innovation, which carries broad potential to contribute to sustainable economic growth (Anggadwita & Dhewanto, 2013).

The SECI Model further describes four modes of knowledge conversion (Figure 1): Socialization (tacit-to-tacit), Externalization (tacit-to-explicit), Combination (explicit-to-explicit), and Internalization (explicit-to-tacit) developed by Nonaka and Takeuchi (1995). Socialization involves sharing tacit knowledge through direct experience and social interaction, while Externalization articulates tacit knowledge into explicit concepts. Combination involves systemicizing different bodies of explicit knowledge. Finally, Internalization, which is the primary focus of this research, is the process of embodying explicit knowledge into tacit knowledge, akin to "learning by doing" or understanding documented procedures deeply.

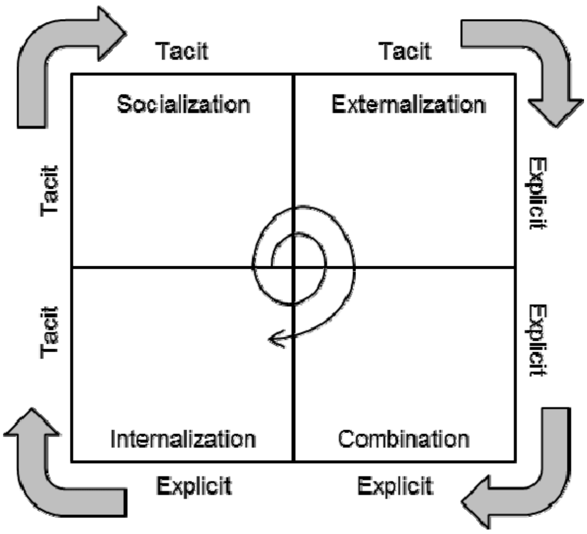

Figure 1. SECI Model – Nonaka
Source: Nonaka & Takeuchi (1995)

Davenport and Prusak (1998) state that the ultimate goal of internalization is for knowledge to be learned and developed according to individual capabilities. In the model, this is visualized as a directional flow from the explicit domain to the tacit domain, emphasizing how individuals learn and internalize structured information through use and experience. The chatbot is positioned as a facilitative tool within this process, accelerating and supporting the internalization of complex public financing documents into actionable insights for employees. The integration of such chatbots into a KMS not only enhances data-driven decision-making (Zhao et al., 2023) but also facilitates more structured management of both explicit and tacit knowledge (Moghadam & Sadeghi, 2022). Furthermore, chatbots act as catalysts for continuous organizational learning within dynamic work environments (Chen et al., 2022).

Figure 2 illustrates the operational architecture of the Retrieval-Augmented Generation (RAG)-based AI Chatbot implemented in this study. The process begins with user queries, which are processed by a retriever module that searches a vector database (ChromaDB) containing preprocessed organizational documents. Retrieved contexts are then passed to a large language model (OpenAI) to generate accurate and source-grounded responses. This integrated workflow—spanning data collection, embedding creation, retrieval, and generation—ensures that the chatbot provides relevant and verifiable answers, thereby reducing AI hallucinations and enhancing the reliability of knowledge delivery in public financing contexts. By leveraging external knowledge bases to enhance the generation process, the RAG model significantly improves the relevance and accuracy of the chatbot's responses (Zhang & Sun, 2020).

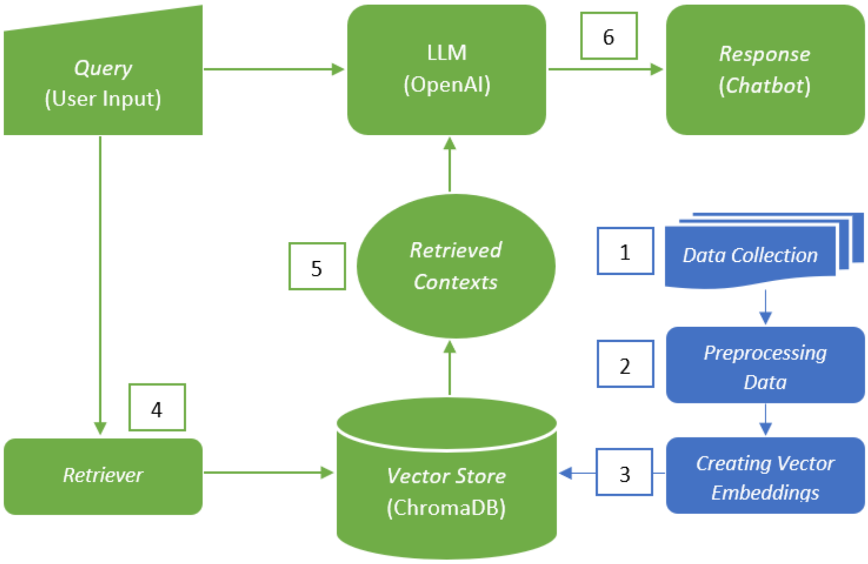

Figure 2. RAG System Architecture
Source: Lewis et al. (2020)

RESEARCH METHOD

This study employs the DSRM to create and evaluate a technological artifact—a RAG-based AI Chatbot prototype—intended to solve the identified organizational problem of ineffective knowledge internalization (Gregor & Hevner, 2013). The research paradigm is pragmatism, with an abductive theory development approach that combines empirical field observations (induction) with the application of existing theories such as the SECI Model and the KMS Success Model (deduction) (Saunders et al., 2015). The type of research is qualitative with a single-case study strategy, focused on the Public Financing Division of PT SMI

(Sugiyono, 2020; Yin, 2014). The research focus is strictly defined to prevent bias and ensure a detailed examination of knowledge internalization (Moleong, 2021). The unit of analysis is the individual employee within the Public Financing Division, as their responses represent the core data for assessing knowledge management practices (Sekaran & Bougie, 2016). The research location is the natural work setting at the PT SMI office in Jakarta, and the study was conducted cross-sectionally from June to October 2025.

Rather than aiming for statistical generalization across the entire organization, this study seeks analytical generalization (Yin, 2014), where empirical results are used to expand the theoretical applicability of the SECI and KMS Success Models in high-compliance contexts. Consequently, the population of interest is specifically narrowed to the Public Financing Division, which represents the core knowledge-intensive unit handling complex infrastructure projects. From this specific domain, a purposive sampling technique was employed to select respondents with direct experience in public financing knowledge work (Patton, 2015). The final sample consisted of 10 respondents—8 Relationship Managers (RMs) and 2 Team Leaders (TLs)—from Public Financing Divisions are presented in Tabel 1. This sample size was determined not by statistical representativeness, but by theoretical saturation—the point at which incremental data collection yields no new insights into the specific research questions (Guest et al., 2006) and the consideration that usability testing with 5–10 users is sufficient to identify the majority of problems (Virzi, 1992). The homogeneity of the sample in terms of work context ensures depth and relevance of the data.

Table 1. Respondent Demographics

Respondent Id	Age	Role	Years of Experience
01-DPPU-1	29	Relationship Manager	5
02-DPPU-1	38	Relationship Manager	8
03-DPPU-1	27	Relationship Manager	4
04-DPPU-1	33	Relationship Manager	9
05-DPPU-1	35	Relationship Manager	9
06-DPPU-1	35	Relationship Manager	3,5
07-DPPU-1	35	Team Leader Analyst	7
08-DPPU-1	43	Team Leader Relationship Manager	10
01-DPPU-3	31	Relationship Manager	5
02-DPPU-3	36	Relationship Manager	7

Source: Processed Data (2025)

The research procedure follows the six stages of DSRM according to Peffers et al. (2007):

1. Problem Identification: Exploring the pain points of the existing KMS (InfraLib) through in-depth interviews, document studies, and analysis of user interaction data.
2. Solution Objective Definition: Formulating the objectives and scope of the AI Chatbot implementation, as well as determining success metrics based on the KMS Success Model framework.
3. Design and Development (Conducted outside the focus of this article): System design using Entity Relationship Diagrams (ERD) to visualize data structures (Elmasri & Navathe, 2020) and Data Flow Diagrams (DFD) to map the interaction and data paths between system components (Satzinger et al., 2019), as well as prototype development using the Python programming language and relevant libraries.
4. Demonstration (Demo): Introducing and demonstrating the developed AI Chatbot prototype to the sample users.

5. Evaluation: Conducting functional testing (black-box testing) and an in-depth evaluation of the prototype from the user perspective, guided by the dimensions of the KMS Success Model (Wang & Yang, 2016).
6. Communication: Documenting the research findings and conclusions.

Primary data were collected through semi-structured in-depth interviews (Boyce & Neale, 2006) conducted in two phases: (1) problem identification and (2) prototype evaluation. Data collection utilized open-ended interviews, allowing participants the freedom to respond in their own natural language and providing deeper insights into their experiences (Rapley, 2001; Purandare & Patil, 2023). Secondary data included internal documents (procedures, guidelines), academic literature, and usage analytics from the InfraLib platform. Qualitative data from interviews were analyzed using the interactive model by Miles and Huberman (1994), conducted through three concurrent flows:

1. Data Reduction: This phase involved open coding of interview transcripts to identify recurring keywords and phrases (e.g., 'always asking seniors,' 'hard to find specific clauses').
2. Data Display: Codes were clustered into categories to construct major themes. For instance, the recurring pattern of reliance on verbal confirmation from seniors was categorized into the 'Walking Library' phenomenon, while the user desire for direct solutions was mapped to the 'Answer Engine' requirement.
3. Conclusion Drawing & Verification: Themes were synthesized and verified through triangulation across different respondent levels (Junior RMs vs. TLs) to ensure the findings represented collective organizational challenges rather than individual biases."

Analytical Dimensions

Table 2 outlines the sensitizing concepts derived from the theoretical framework. These dimensions serve as a guide for data collection and thematic analysis, rather than as statistical variables for hypothesis testing. Key conceptual constructs definitions are as follows: Knowledge Internalization (The process of embodying explicit knowledge into tacit understanding), RAG-based AI Chatbot (A conversational agent utilizing Retrieval-Augmented Generation to fetch specific organizational data), and KMS Success (multi-dimensional assessment of the system based on six dimensions: System Quality, Knowledge Quality, Service Quality, Knowledge Use, User Satisfaction, and Net Benefit).

Table 2. Key Conceptual Constructs and Analytical Dimensions

Construct / Focus	***Conceptual Definition***	***Qualitative Indicator (Interview Focus)***
Knowledge Internalization (Target Process)	The process of embodying explicit knowledge into tacit understanding.	Perceived ease of understanding complex documents; Reduction in asking colleagues.
RAG-based AI Chatbot (Technological Intervention)	A conversational agent utilizing Retrieval-Augmented Generation to fetch specific organizational data.	User experience regarding query accuracy, citation visibility, and hallucination reduction.
KMS Success (Evaluation Framework)	Multidimensional assessment of the system's impact on individual and organizational work.	Narrative feedback across six dimensions: SQ, KQ, SvQ, KU, US, NB (Wang & Yang, 2016).

Source: Processed Data (2025)

RESULTS AND DISCUSSION

Results

Data collection involved 10 respondents from PT SMI's Public Financing Division. The sample included 8 RMs (with 3,5–9 years of experience) and 2 TLs (with 7–10 years of experience). This composition ensured insights from both operational and strategic levels of knowledge work.

The analysis of current practices reveals that knowledge transfer activities within the division are heavily skewed towards socialization and externalization and/or combination, with significant barriers in internalization. As illustrated in the analysis of division activities, Relationship Managers predominantly rely on Socialization (tacit-to-tacit) processes. Due to the fragmentation of knowledge sources and limited accessibility, these employees tend to acquire knowledge through informal social learning—asking colleagues or seniors directly—rather than utilizing formal documentation. This behavior has led to a "walking library" phenomenon, a condition where critical institutional knowledge is siloed in specific individuals rather than being effectively captured by the system. These findings support and enrich several previous theories and studies. The identified reliance on social learning reflects the socialization phase in the SECI Model (Nonaka & Takeuchi, 1995), which becomes the primary workaround when formal systems fail. The existing KMS's failure to support internalization (transferring explicit to tacit knowledge) aligns with criticisms of KMS that serve merely as passive repositories without a focus on effective knowledge presentation (Alavi & Leidner, 2001).

Conversely, TLs play a crucial role in externalization and/or combination, translating tacit field experiences into explicit knowledge such as new procedures and guidelines to ensure regulatory compliance. However, the existing KMS, known as InfraLib, has failed to support the internalization process effectively. The study identified that the platform is underutilized due to the high volume of multidisiplinary data and the complexity of retrieving relevant information.

The gap analysis between the current state and user needs indicates a critical demand for a system transformation. Users expressed a strong preference for shifting from a static repository to a dynamic "answer engine"—a system capable of synthesizing scattered information into direct, actionable responses. Figure 3 below visualizes the mapping of current activities against the SECI model.

Socialization ***(Tacit – Tacit)***	***Externalization*** ***(Tacit – Explicit)***
• Conducting socialization regarding public financing. • Coordinating meeting preparations. • Participating in training. • Providing direction and team coordination.	• Creating field visit reports. • Compiling minutes of financing decision meetings.
Internalization ***(Explicit – Tacit)***	***Combination*** ***(Explicit – Explicit)***
• Accessing and studying the latest procedures and regulations. • Accessing and studying up-to-date documentation on financed activities. • Studying recent cases related to public financing.	• Drafting public financing proposal memos. • Preparing presentation materials for the Board of Directors and stakeholders. • Drafting public financing guidelines and procedures.

Figure 3. SECI Model of Public Financing Division Activities

Source: Processed Data (2025)

The researcher established a threshold criterion wherein responses shared by at least 50% (or 5 out of 10 respondents) were quantified to form the focal themes or conclusions. The results of this identification are detailed in Table 3.

Table 3. Problem Identification and Needs Analysis

Respondent Statements	Focal Themes
5 out of 10 respondents (50%) identified the primary challenge as the fragmentation of abundant yet sporadic information. They emphasized that the complexity of knowledge in public financing is driven by product diversification, a multi-stakeholder ecosystem, and the specific, case-by-case nature of projects. Furthermore, this knowledge is inherently multidisciplinary—spanning regional finance, technical engineering, and social contexts—and dynamic, requiring constant adaptation to shifting public needs, particularly in the post-pandemic era.	High volume of knowledge and multidisciplinary complexity
5 out of 10 respondents (50%) identified the core problem as the fragmentation and disorganization of organizational knowledge. Although the majority of this knowledge exists in written form, it is scattered across informal channels—such as WhatsApp groups and emails—or buried within lengthy procedural documents. The lack of a centralized repository forces employees to resort to inefficient manual searches, create siloed personal archives, or rely on verbal inquiries to colleagues in other divisions, significantly hindering information accessibility	Fragmentation of knowledge sources and limited access
The majority of respondents (60%) indicated a critically low engagement with the existing system, citing a combination of technical and content-related barriers. Primary deterrents include a lack of awareness, cumbersome access (absence of a dedicated app), and 'application overload,' which drives users toward alternative platforms like Microsoft Teams and OneDrive. Furthermore, even users who initially showed enthusiasm eventually abandoned the system due to outdated content and a perceived lack of value or urgency in their daily workflows.	Adoption failure of the existing KMS (InfraLib)
The majority of respondents (60%) indicated that knowledge acquisition relies heavily on social interaction and collaborative learning models. This	Dependency on social learning

dynamic ranges from new hires directly questioning seniors to a 'reactive collaboration' approach where employees facing specific challenges seek out experienced colleagues who have successfully resolved similar issues (metaphorically described as a 'sufferer' seeking a 'cured patient'). In terms of workflow, a dichotomy exists: some employees prefer a 'social-first' strategy (ask then search) to establish context, while others adopt a 'document-first' strategy (read then ask) to validate their understanding.	(Informal)
5 out of 10 respondents (50%) emphasized the critical strategic value of knowledge management versus the operational costs of its current fragmented state. While institutional knowledge is recognized as a key competitive advantage essential for compliance, audit functions, and the DFI mandate, the lack of a systemized approach has created significant issues. Knowledge asymmetry across divisions has turned RMs into overburdened 'walking libraries' (increasing cognitive load) and fostered operational inefficiencies, often resulting in unproductive conflicts during cross-functional collaborations.	Strategic value of cross-divisional knowledge
The majority of respondents (80%) identified three critical success factors for the proposed system: quality, simplicity, and efficiency. First, content must not only be accurate and up-to-date but ideally integrated with the data warehouse in real-time. Second, the User Experience (UX) requires a simplified, mobile-friendly interface. Finally, users strongly emphasized the need to eliminate technical barriers, specifically demanding a seamless 'one-click' login process to replace the cumbersome 'access bureaucracy' of the current system.	The need driving the adoption of a more effective new system
5 out of 10 respondents (50%) articulated a clear demand for advanced AI capabilities that transcend traditional document storage. The consensus points towards an intelligent system analogous to ChatGPT, capable of summarizing documents, analyzing data, and answering ad-hoc leadership queries with direct, actionable insights. Furthermore, respondents emphasized the need for a shift from process-oriented to outcome-based knowledge presentation, utilizing algorithms to surface relevant content and provide immediate answers rather than mere document links	Shift in KMS user expectations towards an "answer engine"

Source: Processed Data (2025)

The RAG-based AI Chatbot prototype was developed by processing 21 core public financing documents into a vector database. The prototype evaluation was conducted qualitatively using semi-structured interviews guided by the six dimensions of the KMS Success Model (Wang & Yang, 2016). Rather than seeking numerical satisfaction scores (e.g., Likert scales), this approach aimed to map user narratives to understand how and why the system impacts their workflow. The findings are summarized in Table 4.

Table 4. Summary of Qualitative Evaluation Findings based on KMS Success Model

KMS Dimension	Evaluation Focus	Key Qualitative Findings
System Quality (SQ)	Access speed, ease of use, and user interface.	• **Speed:** 8 out of 10 respondents provided responses such as "Very Fast," "Fast," or "Less than 30 seconds" (01-DPPU-1; 02-DPPU-1; 03-DPPU-1; 04-DPPU-1; 05-DPPU-1; 8-DPPU-1; 01-DPPU-3; 02-DPPU-3). • **Ease of Use**: 5 out of 10 respondents provided responses such as "Very Easy," "User Friendly," or "Familiar like other AI programs" (02-DPPU-1; 04-DPPU-1; 06-DPPU-1;

		01-DPPU-3). • **User Interface (UI) Design**: 2 out of 10 respondents offered specific feedback on the layout, noting that the bullet-point format greatly facilitated understanding (03-DPPU-1), alongside criticism that the AI Chatbot appearance was "too boring" (02-DPPU-1)
Knowledge / Information Quality (KQ)	Accuracy, relevance, and regulatory compliance.	• **Accuracy & Relevance**: 8 out of 10 respondents provided responses such as "Accurate," "Relevant," or "Very Accurate" (01-DPPU-1; 02-DPPU-1; 04-DPPU-1; 05-DPPU-1; 06-DPPU-1; 8-DPPU-1; 01-DPPU-3; 02-DPPU-3). • **Trust Building (Source Citation):** 2 out of 10 respondents highlighted the high reliability attributed to the inclusion of source citations and page numbers, which facilitated verification (04-DPPU-1; 01-DPPU-3). • **Trust Building (Anti-Hallucination):** 2 out of 10 respondents expressed appreciation for the AI's ability to "honestly" answer "I don't know" rather than "fabricating" answers (02-DPPU-3; 08-DPPU-1). • **Critical Attitude (Verification):** 2 out of 10 respondents noted that the information output still requires re-confirmation against source documents and cannot serve as the sole basis for decision-making (03-DPPU-1; 06-DPPU-1). • **Identification of Limitations**: 2 out of 10 respondents noted that the quality of information output is limited to the uploaded documents (01-DPPU-3), and identified instances of context error/bias (specifically regarding PEN vs. Regular cases) (08-DPPU-1).
Service Quality (SvQ)	Reliability and role as an intelligent assistant.	• **No Technical Training Required:** 10 out of 10 respondents agreed that technical assistance or training is unnecessary because the user interface (UI) is highly intuitive. • **Need for Prompt Engineering Training:** 1 out of 10 respondents stated that non-technical training on "how to craft good and correct prompts" is needed to ensure optimal results (02-DPPU-1). • **Need for Orientation/Guidance:** 2 out of 10 respondents expressed the need for an introductory narrative or explanation to manage user expectations regarding the limitations and scope of knowledge contained within the AI Chatbot (06-DPPU-1; 07-DPPU-1).
Knowledge Use (KU)	Frequency and dependency in daily workflow.	• **Encouraging Usage**: 5 out of 10 respondents stated that the system would be used more intensively because it drastically reduces the barriers or "hassle" of searching for information. They mentioned using the chatbot to cross-check compliance with procedures, stating it "will definitely be used to assist with disbursement based on referenced regulations," and that "this chatbot will strongly encourage usage, especially for new employees" (02-DPPU-1; 03-DPPU-1; 05-DPPU-1; 06-DPPU-1; 08-

		DPPU-1). • **Reducing Cognitive Load**: 2 out of 10 respondents stated that the system would encourage searching because "it (the system) does the thinking," thereby delegating the search task to the AI Chatbot (02-DPPU-1; 06-DPPU-1). • **Workflow Shift**: 1 out of 10 respondents predicted that the system would shift the workflow to a "chatbot first, then documents" approach to obtain summaries (04-DPPU-1). • **Key Target Users:** 3 out of 10 respondents stated that the system provides the greatest impact for new employees (onboarding), auditors, and cross-divisional employees (01-DPPU-1; 03-DPPU-1; 08-DPPU-1). • **New Use Cases:** 1 out of 10 respondents noted the potential for using the system as a real-time aid during meetings with clients or Regional Governments (02-DPPU-3).
User Satisfaction (US)	User comfort	• **Satisfaction and Enthusiasm:** 9 out of 10 respondents stated they were "Satisfied," "Quite Satisfied," or that the prototype was "Sufficiently representative" (01-DPPU-1; 02-DPPU-1; 03-DPPU-1; 04-DPPU-1; 05-DPPU-1; 06-DPPU-1; 7-DPPU-1; 01-DPPU-3; 02-DPPU-3). • **Conceptual Success**: 1 out of 10 respondents stated that the system could serve as an "informational tool for leadership" (08-DPPU-1), thereby rating it as "successful" as an idea and breakthrough, although the expectation for comprehensive implementation is "still far off" and requires further refinement.
Net Benefits (NB)	Impact on individual and organizational performance.	• **Time Efficiency and Productivity Enhancement:** 8 out of 10 respondents confirmed the primary benefit is time efficiency, specifically cutting work duration and eliminating the need to "scour through procedures," thereby increasing productivity (01-DPPU-1; 02-DPPU-1; 03-DPPU-1; 04-DPPU-1; 05-DPPU-1; 06-DPPU-1; 01-DPPU-3; 02-DPPU-3). • **Cognitive Benefits (Synthesis & Generation)**: 3 out of 10 respondents stated the system aids in synthesizing information from multiple documents (05-DPPU-1), as well as assisting in drafting Financing Proposal Memos (MIP) (04-DPPU-1) or presentations (08-DPPU-1). • **Empowerment Benefits (Independence)**: 2 out of 10 respondents stated the system increases independence by reducing reliance on other divisions (02-DPPU-1) or on superiors for basic questions (06-DPPU-1). • **Strategic Benefits (New):** 1 out of 10 respondents identified a system use case as an assistant for responding to recurring questions from clients or Regional Governments (01-DPPU-3). • **Psychological Benefits**: 1 out of 10 respondents noted the AI Chatbot's benefit in reducing the hesitation or

	reluctance of new employees to ask questions to their superiors (05-DPPU-1).

Source: Processed Data (2025)

Its evaluation using the KMS Success Model (Wang & Yang, 2016) yielded the following key findings:

1. System Quality (SQ): The prototype was perceived as very fast (response <30 seconds), user-friendly, and intuitive. Users reported the system is highly responsive and user-friendly, significantly reducing the time spent searching through server folders.
2. Knowledge Quality (KQ): Outputs were rated as accurate and relevant. A critical trust-building feature was the inclusion of source citations and page numbers, along with the system's ability to state "I don't know" when information was unavailable, minimizing hallucinations. The RAG-based engine provided context-aware answers cited from valid regulations, minimizing the risk of using outdated information.
3. Service Quality (SvQ): The system required no technical training due to its intuitiveness, though guidance on prompt engineering was suggested. The chatbot functioned effectively as an "Answer Engine" rather than just a search tool, handling complex queries reliably.
4. Knowledge Use (KU): Respondents indicated a high intention to use the system as it reduced information-search "hassle" and cognitive load, promoting a "chatbot first" workflow. High intention to use was observed, particularly for "cognitive offloading" when senior mentors are unavailable.
5. User Satisfaction (US): Feedback was universally positive ("satisfied," "excellent"). Management viewed it as a successful proof-of-concept.
6. Net Benefit (NB): Identified benefits included time efficiency, cognitive offloading (synthesis), reduced expert dependency, and potential as a strategic tool for client inquiries. It also provided psychological safety, encouraging new employees to ask questions without hesitation.

The RAG prototype's success in providing centralized and easy knowledge access addresses the need to reduce barriers to knowledge retrieval, as advocated by Davenport and Prusak (1998). These findings align with the Information System Success Model, where system success is determined not only by information availability but also by the quality of the system and its ease of use (DeLone & McLean, 2003). Furthermore, the chatbot's ability as conversational AI to act as an answer engine substantiates claims by Dwivedi et al. (2023) regarding the significant efficiency potential of integrating AI into KMS. The findings on the importance of source citation and system honesty in building trust constitute a significant empirical contribution. This confirms that in the context of a highly-regulated organization like public financing, accountability and verifiability are not merely additional features but prerequisites for the successful adoption of an AI-based KMS. The warning from respondents to maintain manual verification also reinforces the position of the AI Chatbot as a Decision Support System (DSS), not an automatic decision-maker, which is a crucial principle in responsible AI implementation.

Figure 4 presents a representative screenshot of the RAG-based AI Chatbot interface, showcasing both the user’s question query and the system’s generated answer. The response is concise, well-structured, and directly addresses the user's inquiry regarding public financing procedures. Below the answer, the system provides transparent source citations—

including document names and page numbers—which enhance credibility and allow for verification.

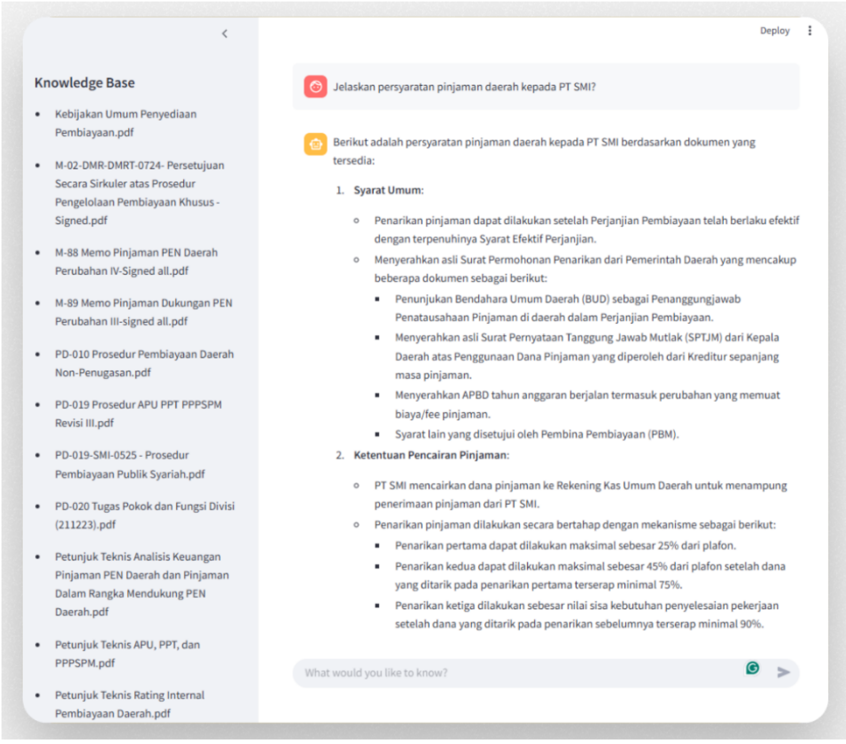

Figure 4. Screenshot of Question Query and AI Chatbot Answer Output
Source: Processed Data (2025)

Figure 5 further complements this by displaying the actual source documents retrieved by the chatbot, demonstrating how the system grounds its responses in specific, preprocessed organizational knowledge. Together, these visuals illustrate the chatbot's functionality as a reliable "answer engine" that synthesizes information from complex documents while maintaining traceability to original sources, thereby supporting trust and facilitating knowledge internalization.

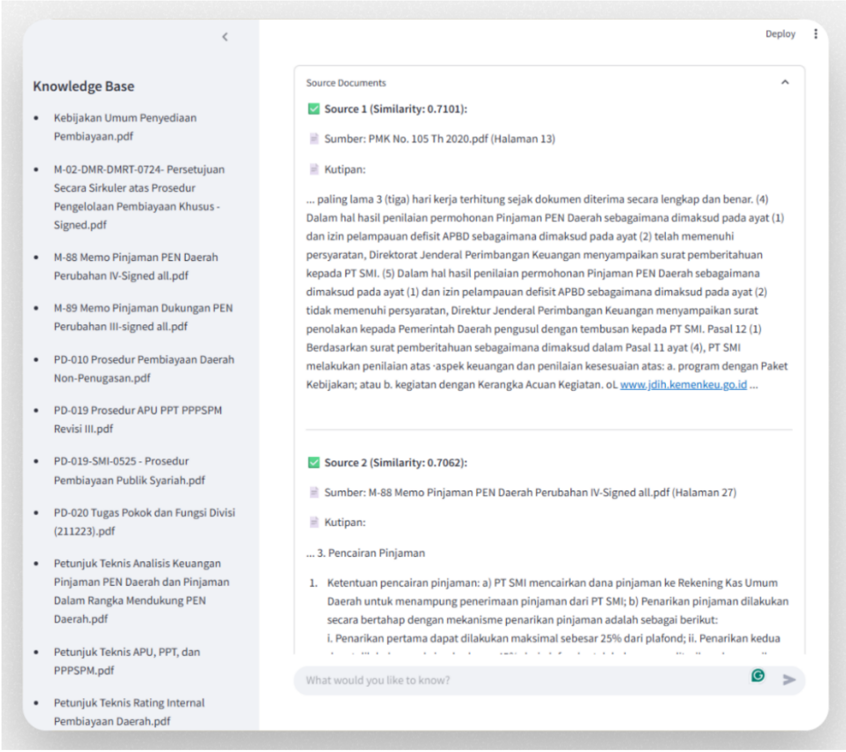

Figure 5. Screenshot of Source Documents for the AI Chatbot Prototype Answer
Source: Processed Data (2025)

These findings indicate that the AI Chatbot positively influences internalization and is evaluated successfully across all KMS Success dimensions. The study confirms that the conventional KMS failed to support the Internalization process, aligning with critiques of systems that function merely as passive repositories. The successful shift to an AI-driven "answer engine" demonstrates how technology can actively facilitate understanding in high-stakes, regulated contexts.

A key contribution is the empirical demonstration of how RAG architecture directly addresses the critical issue of AI hallucination in professional settings. The provision of source citations was a fundamental prerequisite for user trust and adoption in a compliance-sensitive environment. Furthermore, the chatbot began to redistribute the cognitive load from individuals to the system, mitigating organizational risk associated with the "walking library" dependency. Its role as a non-judgmental query tool also enhanced psychological safety for new employees, positioning the chatbot as a catalyst for a more open and equitable knowledge-sharing culture.

Discussion

The evaluation of the prototype using the KMS Success Model highlighted high scores in Knowledge Quality, particularly regarding accuracy and relevance. A distinguishing feature of this research compared to general studies on Generative AI is the application of Retrieval-Augmented Generation (RAG) to mitigate "hallucinations." Lewis et al. (2020) established that RAG combines generative capabilities with specific document retrieval to enhance accuracy. This study confirms that theory in a practical, high-stakes public financing context. Respondents reported high trust in the system specifically because it provides citations and source page numbers for every answer, allowing for immediate verification.

The practical implication of this research is the potential shift in culture from informal social learning toward system-mediated learning. This can mitigate the risk of organizational knowledge attrition and distribute cognitive load more evenly. However, this finding also presents a "paradox of openness" (Sitalaksmi et al., 2024): on one hand, the system encourages knowledge flow; on the other hand, it requires strict data governance and continuous content curation to maintain the quality and security of intellectual assets. In this context, the paradox lies in leveraging AI for speed while maintaining strict adherence to regulatory compliance through human oversight. Unlike previous studies that might position AI as a replacement for human analysis, this research positions the RAG-Chatbot strictly as a Decision Support System (DSS) that requires a "human-in-the-loop" for final validation.

The findings of this study reveal that the conventional KMS at PT SMI has been suboptimal in supporting the SECI model's Internalization process—the conversion of explicit knowledge into tacit understanding. The existing system, which functions primarily as a document repository, suffers from information fragmentation and high access barriers, causing users to abandon the system in favor of informal social learning. This aligns with the theory proposed by Alavi and Leidner (2001), who argue that an effective KMS must focus not only on storage but significantly on knowledge presentation to facilitate understanding and application.

By implementing the RAG-based AI Chatbot, this research demonstrates a successful transformation from a static repository to a dynamic "answer engine." This shift supports the findings of Dwivedi et al. (2023), who suggest that integrating conversational AI into KMS allows for the instant synthesis and analysis of large datasets, thereby significantly improving efficiency. However, unlike general implementation studies, this research specifically highlights that the "answer engine" capability is crucial for the public financing sector, where regulations are complex and multi-disciplinary. The AI Chatbot bridges the gap by synthesizing fragmented explicit knowledge (procedures, memos, regulations) into coherent answers, effectively accelerating the internalization process that was previously hindered by the cognitive load of manual document searching.

A critical discovery in this study is the prevalence of the "walking library" phenomenon, where knowledge is siloed within specific individuals (RMs), creating an organizational vulnerability regarding intellectual asset retention. The reliance on social learning (asking colleagues) was identified as a coping mechanism for the inefficiencies of the old system. The implementation of the AI Chatbot has begun to shift this culture from individual-dependency to system-dependency.

This transition is further strengthened by the aspect of psychological safety. The results indicate that the AI Chatbot provides a safe environment for new employees to seek information without the fear of appearing incompetent to senior colleagues (Edmondson, 1999). This finding adds a new dimension to the work of Jais and Ngah (2024), who discussed organizational readiness for AI primarily from a technological and capability standpoint. This research extends that perspective by showing that AI readiness also involves psychological factors; the chatbot acts as a non-judgmental mentor, thereby democratizing access to knowledge. This contrasts with the findings of Susanty et al. (2019), who focused on IT as an enabler for innovation performance; while this study supports that premise, it further specifies that the "enabling" factor in a high-compliance environment is the reduction of social barriers to information access.

CONCLUSIONS

This study concludes that: (1) The existing KMS at PT SMI is suboptimal for supporting the SECI Model's Internalization process, leading to over-reliance on social learning and individual expertise. (2) A RAG-based AI Chatbot prototype was successfully implemented as a dynamic "answer engine" that facilitates faster and more accurate knowledge internalization. (3) Evaluation based on the KMS Success Model confirms the prototype delivers significant net benefits, including time efficiency, reduced cognitive load, and lower expert dependency, though its accuracy remains contingent on the quality of the underlying knowledge base.

For management, the findings underscore the need to champion a cultural shift from person-to-person knowledge sharing to person-to-system interaction to safeguard institutional memory. Successful implementation necessitates robust data governance to ensure the knowledge base remains accurate and up-to-date.

This study is bounded by several limitations. Theoretically, it focused primarily on the Internalization mode, leaving the chatbot's impact on other SECI modes unexplored. Technically, the artifact remains a prototype with limitations in security, scalability, and full enterprise integration. Future research should expand the functional scope of such chatbots to actively support the Externalization process. Longitudinal studies are recommended to assess the long-term impact on knowledge-sharing culture.

REFERENCE

Abu Shawar, B., & Atwell, E. (2007). Chatbots: Are they Really Useful?. Journal for Language Technology and Computational Linguistics, 22(1), 29–49. https://doi.org/10.21248/jlcl.22.2007.88.

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. MIS Quarterly, 25(1), 107-136. https://doi.org/10.2307/3250961.

Anggadwita, G. and Dhewanto, W. (2013). Service innovation in public sector: a case study on PT. Kereta Api Indonesia. Journal of Social and Development Sciences, 4(7), 308-315. https://doi.org/10.22610/jsds.v4i7.766.

Anggadwita, G., Martini, E., Hendayani, R., and Kamil, M. R. (2021). The Role of Technology and Innovation Capabilities in Achieving Business Resilience of MSMEs During Covid-19: Empirical Study. 9th International Conference on Information and Communication Technology (ICoICT), Yogyakarta, Indonesia, 2021, 1-6. https://doi.org/10.1109/ICoICT52021.2021.9527464.

Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2021). Artificial intelligence in practice: Implications for information systems research. Journal of Enterprise Information Management, 34(1), 228-262. https://doi.org/10.1108/JEIM-11-2020-0448.

Boyce, C., & Neale, P. (2006). Conducting in-depth interviews: A guide for designing and conducting in-depth interviews for evaluation input (Vol. 2). Watertown, MA: Pathfinder international.

Chakraborty, S., Misra, B., Dey, N. (2024). AI-Based Knowledge Management Applications. In: AI-Empowered Knowledge Management in Education. SpringerBriefs in Applied Sciences and Technology(), 59-75. https://doi.org/10.1007/978-981-97-2574-8_4.

Chen, L., Zhang, X., & Xu, Y. (2022). Integrating chatbots into knowledge management: A case

study of organizational learning. Journal of Knowledge Management, 26(3), 567–582. https://doi.org/10.1108/JKM-05-2021-0397.
Davenport, T. H., & Prusak, L. (1998). Working knowledge: How organizations manage what they know. Harvard Business School Press.
DeLone, W.H., & McLean, E.R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. Journal of Management Information Systems, 19(4), 9 - 30. https://doi.org/10.1080/07421222.2003.11045748.
Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion paper: "so what if chatgpt wrote it?" multidisciplinary perspectives on opportunities, challenges and implications of Generative Conversational AI for Research, practice and policy. International Journal of Information Management, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642.
Edmondson, A. (1999). Psychological Safety and Learning Behavior in Work Teams. Administrative Science Quarterly, 44(2), 350-383.
Elmasri, R., & Navathe, S. B. (2020). Fundamentals of Database Systems (7th ed.). Pearson.
Gao, J., Galley, M., & Li, L. (2019). Neural approaches to conversational AI: Question answering, task-oriented dialogues and social chatbots. Foundations and Trends in Information Retrieval, 13(2-3), 127-298. https://doi.org/10.1561/1500000074.
Grant, R. M. (1996). Toward a Knowledge-Based Theory of the Firm. Strategic Management Journal, 17(S2), 109-122. https://doi.org/10.1002/smj.4250171110.
Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. MIS Quarterly, 37 (2), 337–355. https://doi.org/10.25300/MISQ/2013/37.2.01.
Guest, G., Bunce, A., & Johnson, L. (2006). How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability. Field Methods, 18(1), 59–82. https://doi.org/10.1177/1525822X05279903.
Jais, R., Ngah, AH. (2024). The moderating role of government support in chatbot adoption intentions among Malaysian government agencies. Transforming Government: People, Process and Policy, 18(3), 417–433. https://doi.org/10.1108/TG-02-2023-0026.
Jarrahi, M.H. et al. (2022). Artificial intelligence: a strategy to harness its power through organizational learning. Journal of Business Strategy, 44(3), pp. 126–135. https://doi.org/10.1108/jbs-11-2021-0182.
Jennex, M.E. and Olfman, L. (2004). Modeling Knowledge Management Success. Conference on Information Science and Technology Management, CISTM.
Kumar, A., & Singh, R. (2020). Software Testing: Principles and Practices. Pearson.
Laihonen, H., Kork, A. A., & Sinervo, L. M. (2023). Advancing public sector knowledge management: towards an understanding of knowledge formation in public administration. Knowledge Management Research & Practice, 22(3), 223–233. https://doi.org/10.1080/14778238.2023.2187719.
Lam, L., Nguyen, P., Le, N., & Tran, K. (2021). The Relation among Organizational Culture, Knowledge Management, and Innovation Capability; Its Implication for Open Innovation. Journal of Open Innovation: Technology, Market, and Complexity, 7, 66. https://doi.org/10.3390/joitmc7010066.
Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M.,

Yih, W., Rocktäschel, T., Riedel, S. and Kiela, D. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. In: Proceedings of the 34th international conference on neural information processing systems, Curran, Red Hook, NIPS '20, 9459–9474. https://doi.org/10.5555/3495724.3496517.

Miles, M. B., & Huberman, A. M. (1994). Qualitative Data Analysis: An Expanded Sourcebook. 2nd ed. Sage Publications.

Moghadam, M. R., & Sadeghi, H. (2022). The impact of AI-based chatbots on knowledge management in organizations. Journal of Artificial Intelligence Research, 45(4), 789–812.

Moleong, Lexy. (2021). Metodologi Penelitian Kualitatif. PT Remaja Rosdakarya.

Nonaka, I., & Takeuchi, H. (1995). The knowledge-creating company: How Japanese companies create the dynamics of innovation. Oxford University Press: New York, NY.

Patton, M. Q. (2015). Qualitative Research & Evaluation Methods: Integrating Theory and Practice (4th ed.). SAGE Publications.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. Journal of Management Information Systems, 24(3), 45-77. https://doi.org/10.2753/MIS0742-1222240302.

PT SMI. (2025). Mendorong pertumbuhan berkelanjutan lewat pembiayaan infrastruktur. Diakses 7 Maret 2025, dari https://www.ptsmi.co.id/mendorong-pertumbuhan-berkelanjutan-lewat-pembiayaan-infrastruktur

Purandare, S. V., & Patil, R. D. (2023). Open ended questionnaire for qualitative research. Journal of Advanced Multidisciplinary Research Studies and Development, 2(2).

Rapley, T. J. (2001). The art(fulness) of open-ended interviewing: Some considerations on analysing interviews. Qualitative Research, 1(3), 303–323. https://doi.org/10.1177/146879410100100303.

Ritala, P., Ruokonen, M. and Ramaul, L. (2024). Transforming boundaries: how does ChatGPT change knowledge work?. Journal of Business Strategy, 45(3), 214-220. https://doi.org/10.1108/jbs-05-2023-0094.

Satzinger, J. W., Jackson, R. B., & Burd, S. D. (2019). Systems analysis and design in a changing world (7th ed.). Cengage Learning.

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2015). Research Methods for Business Students (7th ed.). Essex, England: Pearson Education Limited.

Sekaran, U. and Bougie, R. (2016). Research Methods for Business: A Skill-Building Approach. 7th Edition. Wiley & Sons, West Sussex.

Sitalaksmi, S., Indarti, N., Anggadwita, G., & Sambudi, A. D. (2024). Knowledge leakage and collaborative innovation: a systematic literature review. Knowledge Management Research & Practice, 23(6), 732–748. https://doi.org/10.1080/14778238.2024.2431111.

Sugiyono. (2020). Metode penelitian kuantitatif, kualitatif dan R&D (2nd ed.). CV Alfabeta.

Sundaresan, S., & Zhang, Z. (2021). AI-enabled knowledge sharing and learning: Redesigning roles and processes. The International Journal of Organizational Analysis, 30(4), 983–999. https://doi.org/10.1108/IJOA-12-2020-2558.

Susanty, A. I., Yuningsih, Y., & Anggadwita, G. (2019). Knowledge management practices and innovation performance: A study at Indonesian Government apparatus research and training center. Journal of Science and Technology Policy Management, 10(2), 301–318. https://doi.org/10.1108/JSTPM-03-2018-0030.

Taherdoost, H., & Madanchian, M. (2023). Artificial intelligence and knowledge management: Impacts, benefits, and implementation. Computers, 12(4), 72.

https://doi.org/10.3390/computers12040072.
Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.
Virzi, R. A. (1992). Refining the Test Phase of Usability Evaluation: How Many Subjects Is Enough? Human Factors: The Journal of the Human Factors and Ergonomics Society, 34(4), 457-468. https://doi.org/ 10.1177/001872089203400407.
Wang, M., & Yang, T. (2016). Investigating the success of knowledge management: An empirical study of small- and medium-sized enterprises. Asia Pacific Management Review, 21(2), 79–91. https://doi.org/10.1016/j.apmrv.2015.12.003.
Yin, R. K. (2014). Case study research: Design and methods (5th ed.). Sage.
Zhang, Y., & Sun, A. (2020). A Survey on Retrieval-Augmented Generation Models for Text Generation. ACM Computing Surveys, 53(6), 1-35. https://doi.org/10.1145/3414686.
Zhao, L., Wang, Y., & Li, X. (2023). Enhancing knowledge management through chatbot integration: A study on decision-making processes. Information Systems Frontiers, 25(3), 765–780. https://doi.org/10.1007/s10796-022-10279-0.