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AI-Driven Knowledge Sharing in the Banking Sector: Challenges and Approaches

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Abstract: Digitalization is becoming increasingly relevant for banking, hence the necessity for a practical Knowledge Management (KM) system that can facilitate rapid innovation and ensure proper regulatory compliance. While there is growing recognition of KM as a strategic driver of performance, it is implemented in a fragmented way within financial institutions and limited by technology, organizational and governance barriers. This paper presents a Systematic Literature Review (SLR) following the PRISMA 2020 protocol, aiming to identify, evaluate and synthesize the academic literature published between 2020 and 2025 on the integration of AI and KM in the banking context. Forty primary studies were examined via narrative synthesis to address two research inquiries: the challenges of AI-driven knowledge sharing (RQ1) and AI-based methodologies and best practices that enhance knowledge management processes (RQ2). The findings identify three main challenge domains data and technology infrastructure, organizational and human factors, and governance, security, and ethics constraints and six main solution categories, including NLP, machine learning, knowledge graphs, expert systems, human-AI hybrid collaboration, and ethical AI governance frameworks. These findings lead to the idea that the use of AI improves the accessibility of knowledge, learning and creativity and its efficiency depends on the capacity of the appropriate KM, absorptive capacity and maturity of governance. The study offers a cohesive framework linking AI innovation to organizational knowledge performance within the finance sector.

Keyword: Artificial Intelligence**,** Banking Sector, Knowledge Management, Knowledge Sharing, Systematic Literature Review

INTRODUCTION

The banking sector is currently experiencing rapid digital transformation, which significantly increases data volume and complexity and creates new challenges in how information is managed and utilized. However, large batches of data are only really valuable when they have been processed and the knowledge extracted and interpreted (Elgargough et al., 2024). Consequently, this shift is historically reshaping the operational patterns in which businesses build, exchange, and use knowledge. In a data-driven era, effective information management and organizational knowledge have been crucial for innovation, competitiveness, service quality, and agility and responsiveness to change (Founes & Boudabbous, 2025). However, Knowledge Management (KM) continues to be seen as a strategic enabler with the potential for diverse benefits. However, KM adoption remains very low in the banking sector due to either a lack of willingness or capability to generate, collect, and leverage organizational knowledge, especially in banks operating in developing countries. Largely, processes are still siloed in most banks; the ability to capture both tacit and explicit knowledge, transfer knowledge to other departments across the bank, and reuse the information gained has not been established. Consequently, both organizational learning and evidence-based decision-making have yet to be fully achieved.

In recent years, artificial intelligence (AI) has emerged as a disruptive force with the potential to revolutionize knowledge management systems, particularly information sharing (Jarrahi et al., 2023). For example, natural language processing, machine learning, and intelligent recommendation systems in practice enable the organization of large-scale data to derive useful insights, thereby automating complex information processing, making knowledge or information retrieval and use more efficient (Dwivedi et al., 2021). AI-based innovation helps firms address modern organizations knowledge management challenges, as highlighted in the literature by Xu, Ni, and Hu (Xu et al., 2025) through an adaptive construction grounded in the processes of acquiring, integrating, and utilizing knowledge across operations. AI integration with KM, also known as AI-driven Knowledge Management, helps improve the precision, relevance, and context of knowledge. Since vast amounts of operational and regulatory data are generated on daily basis, the use of AI helps learn quickly, duplicate less, and support compliance and innovation activities.

However, while the theoretical potential for AI for KM is acknowledged, there is little (quantitative or qualitative) empirical data regarding its actual adoption and impact. While AI technologies have the potential to support knowledge-based activities, research has generally indicated that uptake in organizations remains low, and many firms are struggling to integrate AI technology effectively into KM practices (Pai et al., 2022). Most research on AI applications is narrow; for instance, studying chatbots for customer support or ML for fraud detection, without linking these projects to useful information management processes such as knowledge collection, sharing, and consumption. As a result, there is no shared understanding of how AI technologies contribute to the development of knowledge management processes in the banking industry. This fragmentation emphasizes the need to conduct a Systematic Literature Review (SLR) in order to consolidate existing evidence, organize AI-based techniques, and identify theoretical and practical trends of AI-initiatives in knowledge management systems.

The research objectives of this study aim to systematically provide current information on the use of AI technologies for information management, especially in information-sharing systems within the banking domain. As banks continue to navigate digital transformation, this study is designed to systematically review existing literature on AI and KM to identify patterns of implementation, successful implementations (best practices), and conceptual frameworks that explain their relationship. The SLR will specifically conduct a systematic literature review to discover AI-based approaches supporting knowledge sharing, evaluate their effects on KM performance, and summarize the main conclusions that evolve scholarly and managerial implications.

To achieve this purpose, the study focuses on two main research questions :

RQ1: "What are the main challenges in implementing AI-driven knowledge sharing in the banking sector?"

RQ2: "What best practices or approaches have been successfully applied in implementing AI-driven knowledge in the banking sector?"

The first research question is framed to ascertain and investigate the top hindrances that thwart and slow the adoption of AI-based knowledge-sharing systems in banking organizations. This question probes the organizational, technological, and contextual variables that influence AI adoption and integration into KM. This review aims to summarize the earlier studies and uncover how banks have either stood out or succumbed as they hybridize their AI techniques with time-honored, context-bounded KM practices. Understanding these matters is critical to understand under what circumstances AI will genuinely improve knowledge access, collaboration and utilization in heavily regulated data intensive fields such as the banking field.

The second research question aims to identify AI driven approaches that have been successfully used to improve information sharing in the banking industry. This involves looking at the various AI approaches, such as ML, natural language processing, expert systems and intelligent recommendation engines as they are used in practice and understanding how they have been used to make the transfer of information more efficient and effective. This research aims to identify best practices, innovative frameworks and success factors that will demonstrate how AI can enhance the process of knowledge management, increase the organizational learning and contribute to the digital transformation of financial institutions.

This study aims to provide a structured and evidence-based understanding of the adoption of AI and Knowledge Management initiatives in the banking sector, by addressing two research questions. The findings not only map the current research lines and methodological approaches, but also identify practical insights and theoretical gaps that can guide the development of AI-based Knowledge Sharing Systems in the future.

METHOD

This section presents the approach taken in the study to answer the identified research questions. The Systematic Literature Review (SLR) method is adopted in this study to identify, evaluate and synthesize the scientific literature on the application of Artificial Intelligence to knowledge sharing in the banking industry. SLR method was chosen as an appropriate tool for a systematic review to conduct a comprehensive evaluation of previous studies on this topic using well-defined and reproducible techniques. This review was conducted and reported in accordance with PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analyses). The review was conducted in three phases: Planning Phase, Implementation Phase and Reporting & Analysis Phase.

Planning

The planning phase is the first phase of the Systematic Literature Review (SLR). Its purpose is to determine how to conduct research and to define the direction and scope in a systematic way that ensures methodological rigor (Page et al., 2021). This stage consists of simple, general research questions, especially those based on frameworks such as PICOC. Additionally, exclusion and inclusion criteria were defined to filter the relevant studies in terms of publication year, research field, methodology and source quality (Page et al., 2021). Furthermore, a comprehensive search strategy was developed by selecting the appropriate database and constructing the search string using Boolean operators to maximize retrieval accuracy (Page et al., 2021). The planning part of the SLR is the most crucial and critical step, because inadequate planning may introduce bias, lead to false or invalid conclusions, and compromise the validity of SLR results.

Implementation

The implementation phase is the most important phase of the SLR process and follows the PRISMA framework to ensure transparent and systematic selection of studies (Page et al., 2021). This phase consists of four major stages: identification, screening, eligibility, and inclusion, which altogether constitute the literature selection process (Page et al., 2021), as shown in Figure.1. The figure summarizes the number of notes identified, screened, excluded and included in the final review.

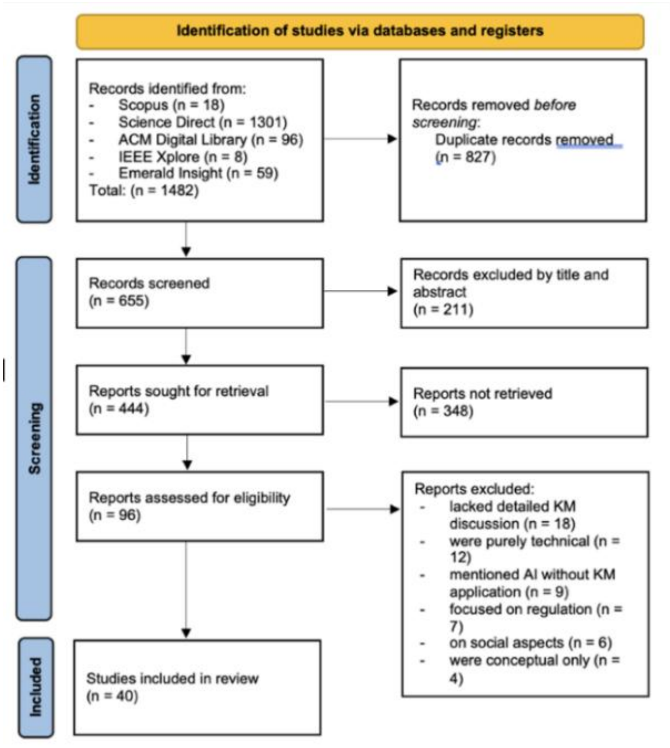

Figure 1. Systematic Literature Review Flow Process

Identification

The identification phase consists of systematically searching academic databases for all potentially relevant studies. During the identification phase, relevant notes were extracted from the selected database and other sources according to the established search strategy (Page et al., 2021).

1. Database Selection

   A literature search was performed using five major academic databases, which are commonly used in the research of computer science, information systems, and business management:
   a) Scopus
   b) Science Direct
   c) ACM Digital Library
   d) IEEE Xplore
   e) Emerald Insight

   These databases were selected for their extensive coverage and inclusion of peer-reviewed, high-quality publications.

2. Search String Formulation
   The search strategy was based on three main ideas: *(1) Artificial Intelligence, (2) Knowledge Sharing, and (3) Banking Sector*. Boolean operators were used to combine related keywords, as shown below (adjusted per database syntax):
   ("knowledge sharing" OR "knowledge management") AND ("artificial intelligence" OR "AI" OR "machine learning") AND ("banking" OR "financial services") AND ("challenges" OR "barriers" OR "approaches" OR "solutions").

Screening

The screening phase consists of reviewing titles and abstracts to exclude studies that do not fit within the research's scope (Page et al., 2021). The screening and management of the review process was carried out with Parsif.al, an online platform for systematic literature reviews. Parsif.al supported importing data, removing duplicates, filtering by inclusion/exclusion and tagging.

1. Duplicate Removal
   Parsif.al automatically detects and removes duplicate records to maintain database consistency.
2. Inclusion and Exclusion Criteria
   Titles / abstracts were screened in Parsif.al using the inclusion and exclusion criteria shown in Table 1.

Table 1. Inclusion and Exclusion Criteria

Criterion		Inclusion	Exclusion
1	Topic	Explicit discussion of AI, Knowledge Sharing, and Banking.	Focus only on AI (e.g., fraud detection) or KS without AI.
2	Context	Studies conducted in the banking or financial services sector.	Studies in unrelated domains (e.g., healthcare, education).
3	Type of Publication	Peer-reviewed journal or full conference paper.	Grey literature, editorials, posters, or abstracts only.
4	Language	English or Indonesian.	Other languages not covered in this review.
5	Publication Year	2015–2024 (to ensure technological relevance).	Published before 2015.

Eligibility

This stage involves a full-text review of the remaining studies to determine if they meet the inclusion and exclusion criteria (Page et al., 2021). In this stage, the full text of each article is checked to ensure that all inclusion criteria are met and that each included paper is directly relevant to the research objective. Articles that mentioned AI or knowledge sharing only superficially or lacked empirical and conceptual depth were excluded. This phase removes all low-quality primary studies of AI based knowledge sharing in banking sector leaving only the high-quality papers in the final synthesis.

Inclusion

The inclusion and exclusion phases resulted in a series of studies that will eventually be included in the review (Page et al., 2021).

1. Data Extraction
   Parsif.al is used to extract and summarize key information from each article. The data extraction form includes:
   a) Bibliographic data (author, year, title, source)
   b) Research objectives and methods
   c) Definition and implementation of AI and knowledge sharing

d) Identified AI challenge - KM (RQ1)
e) Proposed or implemented approach (RQ2)
f) Key findings and implications summary

All data were extracted into a spreadsheet prior to coding and thematic analysis.

2. Data Synthesis

The study employs Thematic Analysis to analyze the qualitative data and to identify common recurring patterns across the selected studies. The analysis included several phases:

a) Open Coding: Quotes related to challenges and approaches were coded.
b) Theme Development: Related codes are clustered into larger themes such as "Data Privacy and Security", "AI Adoption Barriers", and "Organizational Knowledge Culture".
c) Theme Refinement: The themes that came out of the analysis were looked at again and improved to make sure that the interpretation was still in line with the research questions and the study as a whole

The results of this stage are discussed in Chapter 4 (Findings and Discussion), which presents the main challenges and AI supported knowledge sharing approaches identified within the banking industry.

Reporting and Analysis Phase

The selected research data is analyzed to generate meaningful insights in this phase. In this stage, the data extraction is carried out to obtain research specifications, including research characteristics, methods, analysis/abstract, variables, and major results (Page et al., 2021). The results were analyzed to chart research trends, identify gaps and implications for future research and practice (Synder, 2019).

RESULTS AND DISCUSSION

Data Extraction

Data were extracted following the PRISMA 2020 protocol to search, screen, and summarize the literature published between 2020 and 2025 on artificial intelligence (AI) and knowledge management (KM) in the banking and finance service industry.

Overall, the systematic search retrieved 1482 records from five major databases: Scopus (n=18); ScienceDirect (n=1301); ACM Digital Library (n=96); IEEE Xplore (n=8), and Emerald Insight (n=59). After deleting 827 duplicate records, 655 papers were advanced to the screening stage. Of these, 211 papers were excluded based on title and abstract review because not relevant to AI–KM contexts. Of these, 444 articles were screened for retrieval, of which 96 full texts were assessed for eligibility.

After screening, 56 studies were excluded, and 40 were included in the final synthesis. Reasons for exclusion included the following:

1) Lacked detailed KM discussion (n=18)
2) Purely technical (n=12)
3) AI applications unrelated to KM (n=9)
4) Focused on regulation (n=7)
5) Focused on social aspects (n=6)
6) Conceptual or social-only analyses (n=4)

Descriptive Analysis of the Included Studies

A descriptive analysis of the distributional characteristics of the 40 selected studies was conducted prior to performing thematic synthesis. This is a descriptive overview:

1. Publication Year Distribution

Figure 2 shows an overview of the distribution of publication years for the included papers. The results show that scientific interest in AI-based knowledge management (KM) in the banking sector increased from 2020 to 2024, with the most publications in 2024 (n=8) and the second most in 2023 (n=8), followed by 2020/2022 (n=7). The increase in adoption shows the significance of AI in financial knowledge processes.

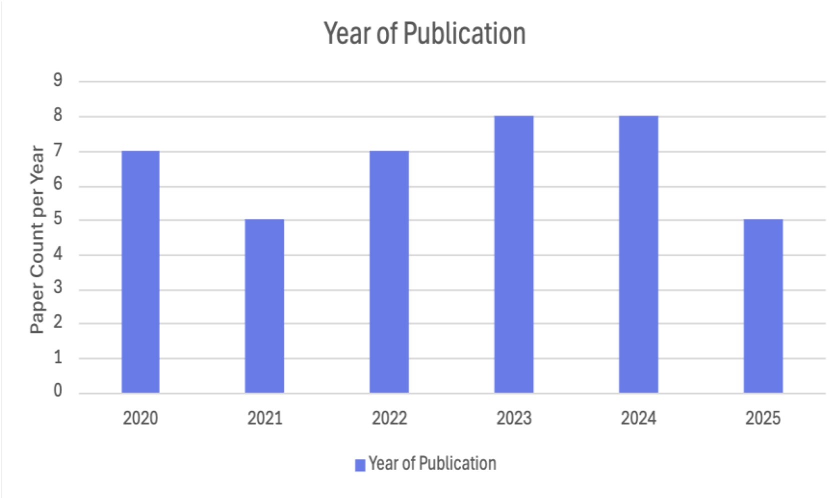

Figure 2. Publication year distribution of the selected studies

2. Research Methodologies Used

Figure 3 illustrates the methodological approaches adopted in the selected studies. Quantitative methods are most prevalent (n=15), followed by experimental designs (n=12). Qualitative studies (n=6), case studies (n=6), and design science research (n=4) provide complementary insights. A single mixed methods study was identified. This distribution indicates that AI–KM research is still mostly dependent on empirical and model-based validation methods.

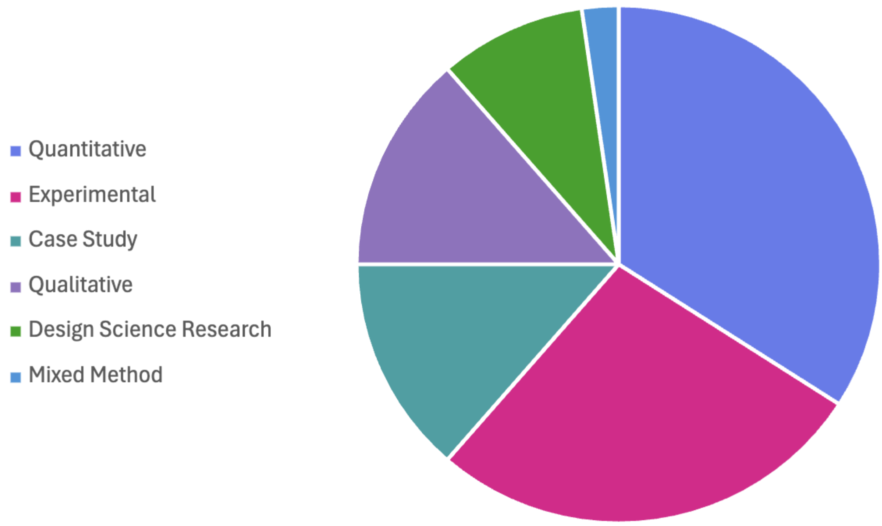

Figure 3. Research methodologies adopted across the selected studies.

3. Knowledge Sharing Process Stages Addressed

Each study was analyzed based on the knowledge sharing (KS) process stages shown in Figure 4. Knowledge Application (n=34), Knowledge Integration(n=28), and Knowledge Capture (27) appear most frequently. Stages like Knowledge Transfer (n = 4), Knowledge Extraction (n = 3), Knowledge Storage (n = 2), Knowledge Creation (n = 2), and Knowledge Retrieval (n = 1) are less commonly addressed. That is an indication that the current research is more prioritizing on operationalization and integration of knowledge rather than on generative or transfer based processes.

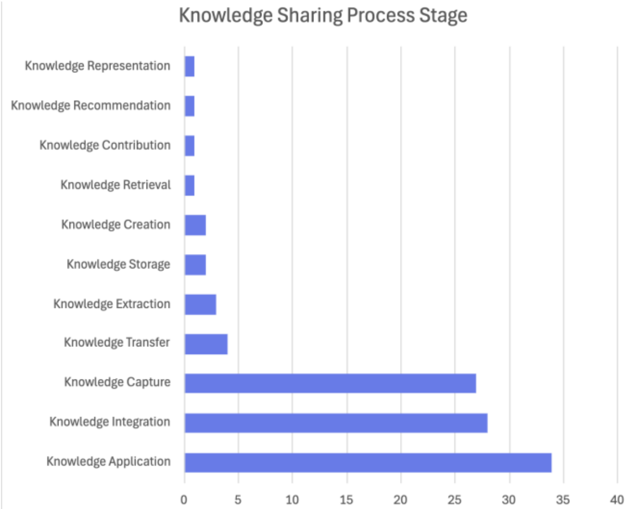

Figure 4. Distribution of Knowledge Sharing Process Stages in the reviewed literature.

4. Geographic Distribution of Studies

The geographical origins of the primary studies are shown in Figure 5. China has the highest number of publications (n=14), followed by India (n=6) and the U.S. (n=5). Other countries include the United Kingdom, Australia, Taiwan, Singapore, Japan, South Korea, Indonesia, Morocco, and several regions of Europe and Africa. This indicates the global spread of AI based KM research with a special focus on Asia and North America.

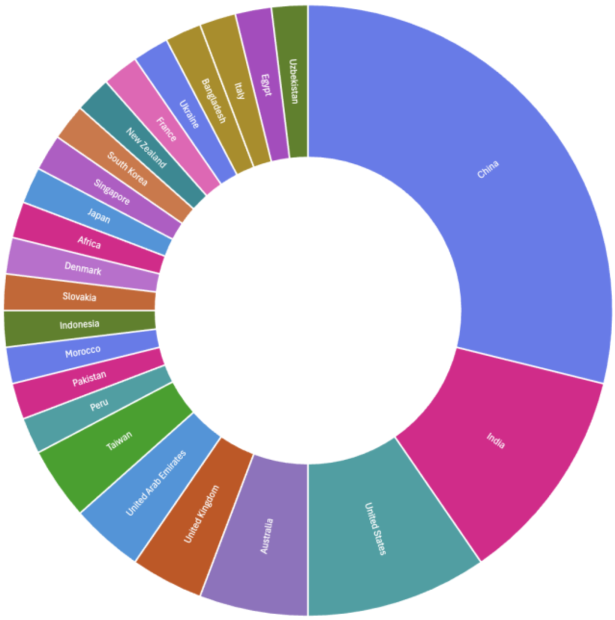

Figure 5. Geographical distribution of the selected studies

These descriptive findings provide a foundation for understanding the thematic analysis presented in Section IV.

5. Data Synthesis

This narrative synthesis incorporates evidence from 40 studies (2020–2025) examining the application of Artificial Intelligence (AI) in Knowledge Management (KM), particularly in knowledge sharing systems in the banking and financial sector.

All extracted data were coded into two analytical dimensions according to research questions (RQs). The recurrent patterns were obtained by performing open coding of the extracted textual summaries from the 40 papers. These codes were subsequently clustered thematically under each RQ, resulting in the synthesis presented in Tables III and IV.

Table 2. Data Synthesis Results (RQ1)

RQ	Category	Description	Evidence (Code)
RQ1	**Data & Technological Infrastructure Barriers**	Data fragmentation, legacy systems, and low interoperability hinder the integration of AI with KM repositories. Poor data quality and limited explainability reduce users' trust in AI-driven knowledge systems.	(Huang et al., 2021), (Alashbani & Zheng, 2022), (Goto, 2023), (Gomes, 2020), (Kang & Cheung, 2022), (Singh et al., 2022), (Shi & Deng, 2024), (Yuan et al., 2021), (Mohan, 2025), (Grosen & Edwards 2023), (Chernyak & Fareniuk, 2020), (Mittal et al., 2023), (Condoro Alejo et al., 2021), (Molavi et al., 2025), (Kozak et al., 2021), (Mamadiyorov et al., 2024)
	Organizational, Human, and Cultural Factors	Adoption resistance, skill gaps (AI–KM–domain), weak knowledge-sharing culture, and misalignment between business and IT units reduce implementation effectiveness.	(Alasbhani & Zheng, 2022) (Goto, 2023), (Mohan, 2025), (Nayak et al., 2021), (Liu et al., 2024)
	Governance, Security, and Ethical Hurdles	The absence of AI/data governance frameworks, privacy and security risks, and high regulatory auditability requirements slow down enterprise-wide deployment. A need for Explainable AI is frequently emphasized.	(Mamadiyorov et al., 2024), (Ni et al., 2024), (Chang et al., 2020), (Elnaggar et al., 2025), (Pangavhane et al., 2023)

Table 3. Data Synthesis Results (RQ2)

RQ	Category	Description	Evidence
RQ2	**NLP for Unstructured Knowledge**	Text mining, semantic search, and Q&A/chatbots are used to extract and retrieve knowledge from unstructured text, improving access, reuse, and efficiency	(Huang et al., 2021), (Chen et al., 2021), (Chen et al., 2025)
	Knowledge Representation & Semantic Integration	Knowledge Graphs unify terms and entities (example: customers, policies, processes), providing context-aware recommendations and more accurate knowledge retrieval.	(Huang et al., 2021), (Kang & Cheung, 2022), (Yuan et al., 2021), (Mamadiyorov et al., 2024), (Chen et al., 2021), (Anning-Dorson et al., 2025), (Kelebercova & Zozuk, 2023), (Bunnell et al., 2020)
	Predictive Modeling for Insight Generation	Machine Learning and Deep Learning (example: GNN, SVR, RNN) transform operational signals into organizational knowledge for risk prediction, anomaly detection, and operational forecasting.	(Alasbani & Zheng, 2022), (Gomes et al., 2020), (Shi & Deng, 2024), (Molavi et al., 2025), (Uddin et al., 2021), (Zhu et al., 2024), (Liu et al., 2020), (Hu et al., 2020)
	Secure and Privacy-Preserving AI Architectures	A new architecture is proposed to address safety and privacy concerns. Federated Learning enables a collaborative model at different banks or branches without sharing sensitive raw data.	(Singh et al., 2022), (Shi & Deng, 2024), (Mamadiyorov et al., 2024), (Chang et al., 2020),

RQ	Category	Description	Evidence
		Blockchain is used because it is transparent, immutable, and safe for sharing data, especially for AML/KYC and decentralized finance (DeFi) apps.	(Rabieinejad et al., 2022)
	Ethical/Strategic Governance	KM processes are supported by the integration of Explainable AI for transparency and Federated Learning and blockchain for privacy, integrity and auditability within ethical frameworks and secure architectures.	(Goto, 2023), (Kozak et al., 2021), (Ni et al., 2024), (Chang et al., 2020), (Elnaggar et al., 2025), (Pangavhane et al., 2023)

DISCUSSION

This section showcases the main findings obtained from the 40 selected studies, mapped to the formulated Research Questions (RQs) concerning the adoption of AI-driven knowledge sharing (KS) in the banking sector.

Challenges in AI-Driven Knowledge Sharing

The analysis identified that the key challenges can be categorized into three broad areas: (1) Data and Technological Infrastructure Barriers; (2) Organizational, People and Cultural Issues; and (3) Regulatory, Security, and Ethical Challenges.

1. Data and Technological Infrastructure Barriers

The big challenge is the prevalence of data fragmentation and organizational silo (Goto, 2023), (Singh et al., 2022), (Shi & Deng, 2024), (Yuan et al. 2021), (Chernyak & Fareniul, 2020), (Kozak et al., 2021). Different legacy banking systems operate independently, generating inconsistent, low-quality, or unstructured data (Alasbani & Zheng, 2022), (Gomes et al., 2020), (Kang & Cheung, 2022), (Molavi et al., 2025), (Mamadiyorof et al., 2024) that degrade AI performance. This fragmentation results in huge technical integration complexity since the new AI platforms need to be integrated into the core banking systems (Singh et al., 2022), (Mittal et al., 2023), (Alejo et al., 2021), (Mamadiyorov et al., 2024). In addition, several studies have identified scalability and system performance challenges, particularly because AI applications in the financial sector must handle large volumes of rapidly changing data (Shi & Deng, 2024), (Chang et al., 2020), (Rabienejad et al., 2022). Furthermore, several studies pointed out that advanced AI models often require considerable computational resources, which can create additional operational and infrastructure challenges for organizations (Shi & Deng, 2024), (Zhu et al., 2024), (Margiotta et al., 2023).

2. Organizational, Human, and Cultural Factors

Human-centric challenges are not just about technology. Poor AI adoption culture and employees' resistance to change (Goto, 2023), (Yuan et al., 2021), (Mamadiyorov et al., 2024), (Chang et al., 2020), (Elnaggar et al., 2025). This resistance is often due to a lack of trust in insights generated by AI (Sing et al., 2022), (Pangavhane et al., 2023), (Anning-Dorson et al., 2025) and professional cultures that tend to hoard information or fear losing their jobs (Goto, 2023), (Mittal, 2023), (Chang et al., 2020). This is further aggravated by a large digital skills gap, with severely limited numbers of people with hybrid skill sets across both banking and data science (Yuan et al., 2021), (Mamadiyorov et al., 2024), (Ngai et al., 2021). From a strategic perspective, misalignment between AI model objectives and organizational goals can occur through either building AI tools with unclear integration into business processes or failing to do so, as they did not attract use at all, thereby resulting in low ROI (Xu et al., 2025), (Kozak et al., 2021).

3. Regulatory, Security, and Ethical Hurdles.

This domain is non-negotiable based on the nature of this industry. Protecting data privacy and cybersecurity risks are top of mind in any system for accessing and sharing sensitive financial knowledge (Mamadiyorov et al., 2024), (Ni et al., 2024), (Chang et al., 2020), (Elnaggar et al., 2025), (Pangavhane et al., 2023). Changing this is not easy, as there are several higher barriers, with strict compliance requirements from regulators (e.g, GDPR, AML, KYC), making the decision needing to be explainable (Alojo et al., 2021), (Chang et al., 2020), (Elnaggar et al., 2025), (Pangavhane et l., 2023), (Abdurrahman, 2025). This is in clear contrast with the "black box" characteristic of many models, leading to a problem of low interpretability and explainability (XAI) (Goto, 2023), (Shi & Deng, 2024), (Zhu et al., 2024), (Margiotta et al., 2023), (Wang & Chen, 2024), (Rodgers et al., 2023). Lastly, algorithmic bias represents an ethical and regulatory risk particularly in cases such as credit scoring (Ni et al., 2024), (Pangavhane et al., 2023), (Rodgers et al., 2023), since these types of applications are known to embed many hidden biases in data.

AI-Driven Approaches and Solutions

There is a rich literature prescribing solutions that directly map to these challenges. These approaches are classified as a technical, architected and mega-strategy approach.

1. Advanced Natural Language Processing (NLP) for Unstructured Knowledge

Advanced models in natural language processing can primarily address unstructured data in reports and documents. It ranges from text mining (Huang et al., 2021), (Chen et al., 2021) and sentiment analysis (Alzamil et al., 2020) to complex deep learning approaches like BERT-BiLSTM-CRF (Kang & Cheung, 2022) and organization-specific transformers (e.g., ABILaBERT) (Margiotta et al., 2023). These techniques automate the extraction of knowledge and provide backbone to internal search engines (Mittal et al., 2023) and customer facing chatbots (Singh et al., 2022), (Elnaggar et al., 2025), (Pangavhane et al., 2023).

2. Knowledge Representation and Semantic Integration

Semantic technology is a key area of focus for breaking down data silos. KGs (Kang et al., 2022) and ontologies (e.g., FIBO) (Huang et al., 2021), (Chen et al., 2025), (Kelebercova & Zozuk, 2023) show how different entities (e.g., customers, policies, and employees) are related to one another. This enables more complex retrieval of data by considering the context of the information as opposed to simple keyword searches. In many cases this capability is enabled by the use of comprehensive data integration frameworks that connect information from multiple sources (Yuan et al., 2020), (Mamadiyorov et al., 2024), (Anning-Dorson et al., 2025).

3. Advanced Predictive Modeling for Insight Generation

The models used for machine learning to create predictions. Graph Neural Networks (GNNs) have been applied to various tasks on complex multirelational data, e.g., loan default (Shi et al., 2024), financial targeting (Liu et al., 2020), and asset pricing (Uddin et al., 2021). IGRU and other specialized models, such as improved RNNs, can be used to predict stock prices (Zhu et al., 2024). Several studies also applied Support Vector Regression (SVR) for operational forecasting tasks, such as predicting queue times (Gomes et al., 2020), and ML for credit scoring automation (e.g., automated credit grading) (Alasbani & zheng, 2022), (Molavi et al., 2025)

4. Secure and Privacy-Preserving AI Architectures

New architectures are shown to deal with privacy and security issues. Federated Learning (FL) allows model training across multiple banks or branches of the same bank without sharing the original, private data (Shi & deng,2024). Blockchain is used for sharing data because it is transparent, unchangeable, and safe, especially for AML/KYC and DeFi

(DeFi) (Singh et al., 2022), (Mamadiyorov et al., 2024), (Chang et al., 2020), (Rabieinejad et al., 2022).

5. Ethical AI and Strategic Governance Frameworks

Strategic frameworks accompany technical solutions to help mitigate regulatory and human challenges. While some focus on building fair-aware models (Ni et al., 2024) others focus on Explainable AI (XAI) applications to build trust and meet mammoth compliance needs (Pangavhane et al., 2023). At the organizational level, models such as the Technology Acceptance Model (Elnaggar et al., 2025) and the Technology Organization People framework (Chang et al., 2020) are applied to lead implementation and change management. Lastly, in order to ensure AI solutions meet and address an actual business need, practices such as goal-oriented learning (Kozak et al., 2021) and internal R&D units specifically designed for this purpose have been proposed (Goto, 2023).

AI Implementation Regulations in Indonesia

Indonesia is currently strengthening the foundations of its AI policy ecosystem, although it is still in an early developmental stage. As a way to encourage the establishment of transparent, accountable and human-centred AI, the government has introduced major regulatory pillars such as: National AI Strategy (STRANAS KA 2020-2045); Personal data protection law (UU No.27/2022) which formulates the collection, storage, and protection of private data; and Ethical AI Guidelines (SE Kominfo No.9/2023).

Indonesia is now among the top 10 countries worldwide in daily generative AI usage and ranks 4th in Southeast Asia in the Government AI Readiness Index. According to UNESCO’s 2024 assessment, 75.6% of organizations already use AI and 69.6% of the public believe AI has a positive impact. These developments suggest that AI governance is receiving greater attention in Indonesia, in terms of political commitment, as well as the strengthening of supporting institutions and policy frameworks (Kementerian Komunikasi dan Informasi Republik Indonesia, 2020).

Even so, several challenges remain. At present, AI-related responsibilities are spread across different ministries and institutions, which often creates coordination difficulties. Indonesia still lacks a national regulation or an independent body dedicated to AI governance. Although the Personal Data Protection Law (UU PDP) has already been enacted, many aspects of its implementation are still being developed, especially those related to technical guidance and enforcement mechanisms. In addition to regulatory issues, AI adoption also raises several ethical concerns that continue to become part of the broader discussion. Only 45% of organizations report understanding ethical AI practices, while only 24% state that they already have formal governance procedures for AI implementation. Concerns related to privacy and misinformation are also becoming more apparent. A UNESCO report found that 21.7% of IT stakeholders consider AI to pose risks to personal data protection (Kementerian Komunikasi dan Informasi Republik Indonesia, 2020)

The same issue is also reflected in the academic landscape. The systematic literature review conducted in this study shows that research on AI-enabled Knowledge Management in the Indonesian banking sector remains very limited. None of the 40 published studies between 2020 and 2025 studied the specific context of Indonesia. Most of the studies were conducted in other countries. However the organizational conditions, regulations and technological readiness might be very different in Indonesia. Therefore, empirical evidence on how AI-based knowledge management can be effectively implemented in Indonesian banking institutions remains limited.

CONCLUSION

This systematic literature review examined 40 studies on AI-driven knowledge sharing in the banking sector. Overall, the results indicate that the potential of AI as a support for knowledge-sharing practices in financial institutions is increasingly being acknowledged.

This study complements the above challenges and their solutions by providing a fundamental contribution in consolidating them. We identify not only technical challenges but also a service landscape with (1) Data-Related Challenges (e.g., silos, quality), (2) Technological Barriers (e.g., integration, XAI), (3) Human and Cultural factors (e.g., resistance, trust, skills gap), (4) Organizational Strategy (e.g., goal-alignment), and finally (5) Regulatory and Ethical Hurdles e.g., privacy compliance bias.

Consequently, the solutions proposed in the literature are also diverse and multidimensional. The studies reviewed indicate that a single algorithm or technology cannot be relied upon for effective implementation. Instead, organizations often mix several approaches to address various operational and organizational needs. Some studies have investigated how Natural Language Processing (NLP) and Knowledge Graphs (KGs) can improve the retrieval and application of information (Huang et al., 2021), (Kang & Cheung, 2022), (Chen et al., 2021), (Kelebercova & Zozuk, 2023), (Margiotta et al., 2023). Other works have shown that Graph Neural Networks (GNNs) and Machine Learning (ML) can help us understand complex financial data (Shi & Deng, 2024), (Uddin et al., 2021), (Zhu et al., 2024), (Liu et al., 2020). Federated Learning and Blockchain were also often recommended as ways to improve data security and aid in compliance with the rules (Shi & Deng, 2024), (Mamadiyorov et al., 2024), (Rabieinejad et al., 2022). At the same time, the literature consistently emphasizes that technological capability alone is not enough. However, the literature is consistent in showing that these technologies will not work effectively without strong organizational and governance support. Several studies have identified change management (Goto, 2023), explainable AI (XAI), and alignment of AI initiatives with organizational objectives (Kozak et al., 2021), (Ni et al., 2024), (Chang et al., 2020), (Elnaggar et al., 2025), (Pangavhane et al., 2023) as important. In other words, the challenges of implementing AI are not only technical, but also linked to organizational, human, and regulatory factors.

The results finally indicate that enhancing knowledge sharing capabilities with AI is not simply a matter of deploying new technologies into banking practices. In other words, the challenges of implementing AI are not only technical, but also closely linked to organizational, human and regulatory factors.

This study also has several limitations. Although the SLR process was systematic, the choice of databases and keyword combinations may have affected the studies included in the review. Therefore, we may have missed some relevant sources, particularly grey literature such as industry white papers and central bank reports. In addition, because the synthesis process relied on qualitative interpretation, the analysis remains subject to a certain degree of researcher subjectivity.

The synthesized literature also has its own limitations. Many of the studies examined are conceptual, prototype, or small-scale case studies (Goto, 2023), (Kang & Cheung, 2022), (Shi & Deng, 2024), (Chang et al., 2020), (Elnaggar et al., 2025), (Pangavhane et al., 2023), (Kelebercova & Zozuj, 2023), (Abdurrahman, 2025), (Hakmaoui et al., 2022). The reviewed literature also highlights the lack of large scale, longitudinal and empirical validation of AI systems in real banking environments (Ni et al., 2024), (Kelebercova & Zozuk, 2023), (Margiotta et al., 2023). Furthermore, many of the findings are highly dependent on the context of a specific country or financial institution ((Xu et al., 2025), (Gomes, 2020), (Yuan et al., 2021), (Chernyak & Fareniuk, 2020), (Molavi et al., 2025), (Mamadiyorov et al., 2024), (Elnaggar et al., 2025), (Chen et al., 2021), (Margiotta et al., 2023), (Alzamil et al., 2020) , which makes it hard to generalize the results to other contexts.

Based on these gaps, this review identifies some important directions for future research.:

1. Empirical Validation and Socio-Technical Adoption.

These findings point to the need for further empirical large-scale studies, which should go beyond prototype development and assess the real impact and return on investment (ROI) of AI-supported knowledge sharing in real organizational settings. Future research should also consider a socio-technical perspective to understand better how systems can be designed to foster employee trust and reduce resistance to AI adoption, including approaches such as human-in-the-loop systems (Singh et al., 2022), (Yuan et al., 2021), (Mamadiyorov et al., 2024), (Elnaggar et al., 2025), (Anning-Dorson et al., 2025).

2. Explainability (XAI) for Tacit Knowledge and Compliance.

The practical application of Explainable AI (XAI) needs more attention in the future (Shi & Deng, 2024), (Margiotta et al., 2023), (Wang & Chen, 2024). Further research is required to meet the increasing regulatory demands for transparency and to gain a better understanding of how XAI can help to capture, validate and disseminate tacit knowledge of human experts (Goto, 2023), (Kang & Cheung, 2022).

3. Scalable Governance and Privacy-Preserving AI.

Further research is required on the practical scalability and interoperability of privacy-preserving architectures like Federated Learning (Shi & Deng, 2024) and Blockchain (Chang et al., 2020) in real world bank systems. This requires to be combined with holistic governance frameworks that cover the entire life cycle of AI produced knowledge and prevent potential ethical hazards, such as algorithmic bias (Ni et al., 2024), (Rodgers et al., 2023).

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