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A Knowledge Governance Framework for RAG-Based AI and Personalized Learning in Higher Education

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Abstract

Background: Artificial intelligence (AI) is increasingly used in higher education, yet its educational value depends on whether outputs are grounded in reliable academic knowledge, aligned with course competencies, and reviewed by educators.
Aims: This study proposes a conceptual Knowledge Management (KM) framework integrating academic knowledge sources, a governed repository and representation layer, AI-based processing using retrieval-augmented generation (RAG), personalized learning services, and evaluation with lecturer feedback.
Methods: A focused narrative synthesis connected literature on KM, generative AI, RAG, personalization, learning analytics, and responsible AI governance. Unlike a systematic literature review, the study does not use a reproducible database-search and screening protocol and does not claim comprehensive coverage.
Result: The resulting model offers a course-level workflow, four research propositions, and indicators for future evaluation. The most important adoption priority is to establish a curated, version-controlled knowledge base linked to course learning outcomes before deploying AI-generated explanations or recommendations.
Conclusion: The framework has not been empirically validated; therefore, its effects on learning outcomes remain unknown. Future work should begin with expert validation and prototype testing of source traceability, answer accuracy, recommendation relevance, privacy safeguards, and lecturer oversight.

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1. Introduction

Higher education institutions function as knowledge-intensive organizations that create, organize, preserve, and disseminate knowledge through teaching, research, and community engagement (Nonaka & Takeuchi, 1995; Safrizal *et al.*, 2026). At the course level, academic knowledge is distributed across semester learning plans, teaching modules, presentations, textbooks, scholarly articles, recorded lectures, assessment questions, rubrics, and lecturers' professional experience. Without systematic knowledge management practices, including

consistent metadata, document version control, and clear ownership of academic resources, these materials may become fragmented and difficult to retrieve, update, and reuse. Such challenges can hinder students' access to authoritative learning resources and increase the effort required for lecturers to maintain instructional materials. These issues become particularly important when artificial intelligence (AI) is integrated into educational processes, as large language models can generate plausible but inaccurate responses and require appropriate human oversight (Kasneci *et al.*, 2023; Miao & Holmes, 2023). Retrieval-Augmented Generation (RAG) offers an architectural approach to grounding AI-generated responses in external knowledge sources; however, its reliability depends on the quality, relevance, and traceability of the retrieved evidence (Lewis *et al.*, 2020). Therefore, integrating knowledge governance, source-grounded AI, and competency-aligned personalized learning is a key design consideration for developing reliable AI-supported learning environments in higher education.

Knowledge Management (KM) provides a systematic approach to identifying, acquiring, storing, sharing, and using knowledge. Nonaka and Takeuchi's (1995) knowledge-creation model describes the interaction between tacit and explicit knowledge through socialization, externalization, combination, and internalization. In learning contexts, this model can help institutions understand how lecturers' experience is documented as teaching materials and how students internalize knowledge through practice and reflection.

AI can support document processing, semantic search, explanation generation, learning analytics, and recommendations. However, the literature also highlights concerns about answer reliability, transparency, bias, privacy, and the need for educator involvement (Bond *et al.*, 2024; Kasneci *et al.*, 2023; Miao & Holmes, 2023). Research reviews map applications of AI and generative AI in education, but a practical course-level design still needs to explain how governed academic knowledge, source-based AI responses, competency mapping, and feedback can work together (Wang *et al.*, 2024; Yusuf *et al.*, 2024; Zhang *et al.*, 2024). This is the problem addressed in the present study: AI functionality alone is insufficient if academic knowledge is not curated, traceable, and connected to learning objectives.

The central problem addressed in this study is the gap between the growing use of AI tools in higher education and the limited integration of those tools with governed, course-specific academic knowledge. Without knowledge governance, AI may produce answers that conflict with the curriculum or rely on unapproved sources. Conversely, a repository without intelligent retrieval may remain difficult to use. Retrieval-Augmented Generation (RAG) can connect generative models with external knowledge sources, but retrieval alone does not guarantee correctness; source quality, citation traceability, and procedures for handling insufficient evidence remain essential (Lewis *et al.*, 2020). Learning analytics can inform feedback and instructional design, but activity indicators should be interpreted alongside assessment evidence and pedagogical context rather than treated as direct measures of mastery (Banihashem *et al.*, 2022; Drugova *et al.*, 2024). This study therefore addresses the need for a course-level framework that connects knowledge curation, source-grounded AI, competency-aligned learning support, and lecturer-led evaluation.

This study proposes an AI-based Knowledge Management framework to support higher education learning. It addresses three research questions: (1) How can KM and AI components be integrated into a course-level learning workflow? (2) How can this integration support source-grounded knowledge retrieval and competency-aligned personalization? and (3) Which technical, pedagogical, and governance aspects should be evaluated before implementation? The article contributes a conceptual model, a methodological workflow, four research propositions, and proposed evaluation indicators. Its central practical recommendation is to begin implementation with a lecturer-curated, version-controlled repository linked to course learning outcomes, then add RAG-based support and personalized recommendations under human oversight.

2. Methods

This study uses a conceptual research design based on a focused narrative literature synthesis. The purpose is to formulate and position a framework integrating Knowledge Management (KM) and AI for higher education learning, not to estimate the effects of an intervention. The method is therefore not a systematic literature review (SLR): the study did not apply a reproducible database-search strategy, formal screening protocol, PRISMA flow, or systematic quality appraisal. The findings should be interpreted as a reasoned conceptual synthesis rather than an exhaustive account of all relevant studies.

The framework was developed through five stages, summarized in the methodological flowchart in Figure 1. First, the educational problem was specified: academic resources are fragmented, learning needs vary, and AI outputs may be unreliable without source governance. Second, a focused body of literature was selected purposively across KM and knowledge creation, AI and generative AI in education, RAG and source-grounded systems, personalization and learning analytics, and responsible AI governance. Third, the selected literature was read thematically to identify knowledge sources, AI mechanisms, educator roles, evaluation approaches, and governance risks. Fourth, these themes were mapped into a five-component framework. Fifth, research propositions and possible evaluation indicators were derived for future empirical testing.

Sources were selected for relevance to the research questions, with priority given to peer-reviewed journal articles, systematic reviews, foundational works, and relevant institutional guidance. Foundational sources were included where they explained core concepts, such as the SECI model and RAG. The article does not report a total number of records identified or screened because a formal systematic search was not conducted. This limitation is made explicit to avoid implying that the method is an SLR.

The thematic synthesis examined each source in relation to its contribution to the framework: (a) what knowledge or data are managed; (b) which AI mechanism or learning-analytics approach is discussed; (c) how educators or learners are involved; (d) how outputs or learning processes may be evaluated; and (e) what ethical, privacy, transparency, or governance risks arise. Themes were mapped to the framework's five components—academic knowledge sources, repository and representation, AI processing, learning services, and evaluation and feedback. Relationships were retained when supported by the literature or when they represented an explicit design requirement.

The synthesis distinguishes three types of statements. First, established concepts are drawn from prior literature, including SECI and RAG. Second, design choices proposed by the authors include course metadata, competency mapping, document versioning, and lecturer review. Third, propositions about the expected performance of the integrated framework remain hypotheses for future testing. This distinction prevents a conceptual design from being presented as an empirical finding.

The main methodological limitations are the absence of a reproducible search protocol, formal source-quality appraisal, and expert validation. The framework is consequently an initial conceptual proposal. A future SLR would need to specify databases, search dates and strings, inclusion and exclusion criteria, records at each screening stage, and a quality-appraisal procedure.

No respondent data, experiments, statistical tests, or prototype results are reported in this study. The unit of analysis is the knowledge-management process within a single higher education course. Potential implementation inputs include the syllabus, modules, presentations, authorized references, question-to-learning-outcome mappings, quiz responses, and assignment scores. Student data should only be processed for a defined learning purpose, with appropriate access controls, data minimization, and compliance with institutional policy.

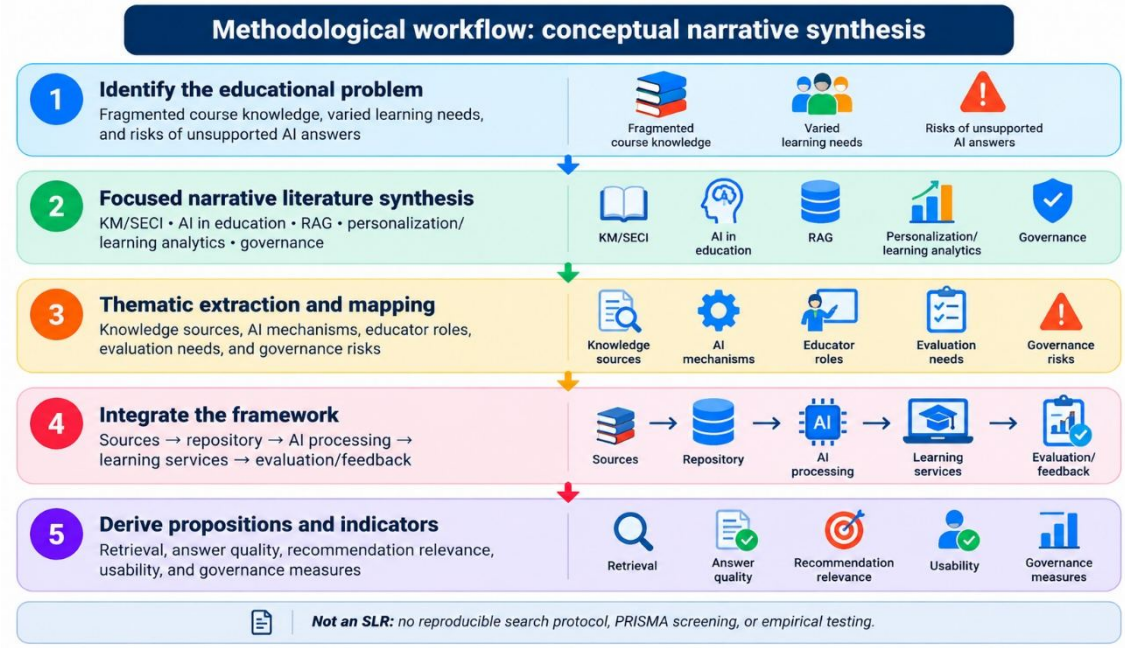


Figure 1. Methodological workflow of the focused narrative synthesis

3. Results and Discussion

3.1 Conceptual Architecture of AI-Based Knowledge Management

The proposed framework contains five interconnected components (Figure 2 and Table 1). Academic knowledge sources provide approved course materials; the repository and representation layer organizes them with metadata, indexing, version control, and concept or competency links; AI processing supports retrieval, summarization, and explanation; learning services present source-grounded answers and competency-aligned resource recommendations; and evaluation and feedback support review of answers, recommendations, and source updates. This architecture responds to research that identifies diverse AI applications in education while also calling for attention to ethics, collaboration, and methodological rigour (Bond *et al.*, 2024; Wang *et al.*, 2024). The framework's distinctive contribution is the proposed integration of these elements into one course-level knowledge-governance cycle, rather than the invention of a new AI algorithm.

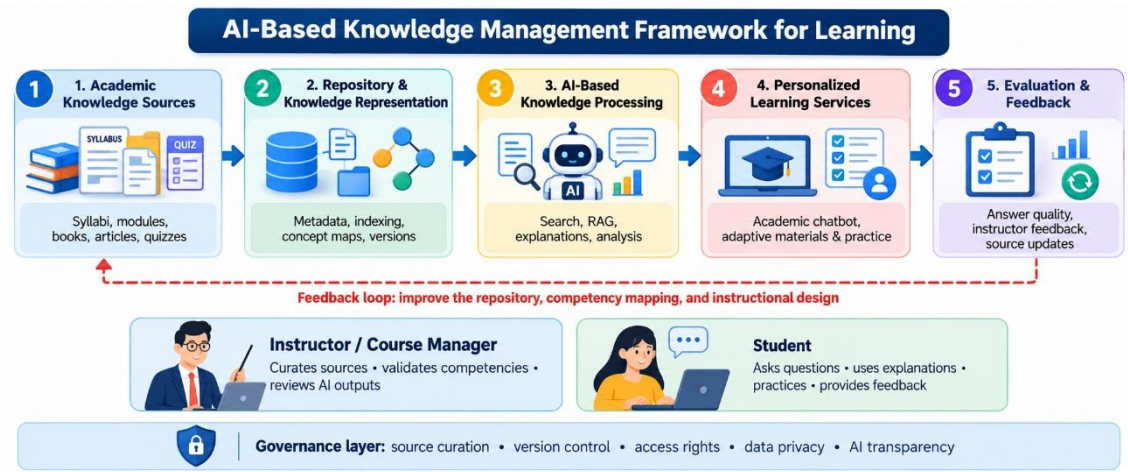


Figure 2. Conceptual framework of AI-based Knowledge Management for learning
Source: Authors' design.

The workflow is cyclical rather than purely linear. Assessment results, student feedback, and lecturer review may reveal that a topic needs clarification, a question is misaligned with a learning outcome, or a source is outdated. These signals can prompt revisions to the repository and instructional design. This feedback logic is consistent with research emphasizing formative feedback (Hattie & Timperley, 2007; Shute, 2008) and with reviews linking learning analytics to feedback and learning-design improvement (Banihashem *et al.*, 2022; Drugova *et al.*, 2024). These are theoretically supported design expectations; the present study has not measured their effect in a deployed system.

Table 1. Components of the AI-based Knowledge Management framework

Component	Primary Inputs	Function	Output
Academic knowledge sources	Syllabus, modules, books, articles, questions	Collect valid and relevant sources	Selected document collection
Repository and representation	Documents and metadata	Indexing, classification, concept mapping	Structured knowledge base
AI processing	Questions and learning context	Search, RAG, analysis, explanation generation	Answers and recommendation candidates
Learning services	Answers and available competency profiles	Academic chatbot, adaptive materials and practice	Relevant learning experience
Evaluation and feedback	Assessment, lecturer input, user feedback	Check quality and update sources	System and material improvements

3.2 Knowledge Acquisition and Representation

Knowledge management begins by selecting authoritative sources. Lecturers or course managers determine which documents the system may use, verify document versions, and identify outdated materials. Minimum metadata should include document title, course, topic, learning outcome, update date, source type, owner, and access rights. This governance layer is important because AI-supported learning systems depend not only on model capability but also on the quality and traceability of the knowledge supplied to them (Bond *et al.*, 2024; Miao & Holmes, 2023).

Documents can be divided into text units small enough for retrieval without breaking conceptual meaning or context. Each unit should remain linked to its source document so that the system can identify the origin. If a concept map is available, materials can also be linked to prerequisite competencies and subsequent concepts. Concept mapping should not rely solely on word similarity; lecturer validation is needed to ensure that relationships between topics are academically sound.

The SECI model offers a useful lens for connecting lecturers' tacit teaching experience with explicit learning resources. Experience can be documented through cases, explanations, and reflections (externalization); materials from multiple sources can be integrated (combination); and students can develop understanding through practice and reflection (internalization) (Nonaka & Takeuchi, 1995). AI may assist with processing and organizing documents, but it cannot fully replace dialogue, mentoring, or pedagogical judgment. This distinction is consistent with the human-centred approach recommended for generative AI in education (Miao & Holmes, 2023).

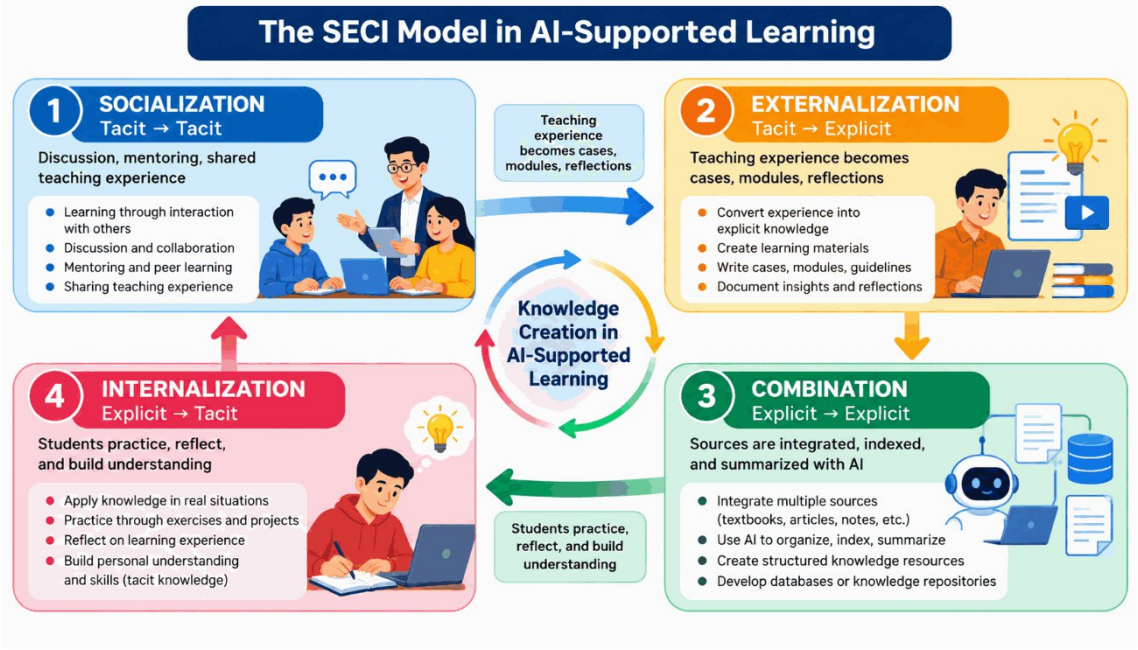


Figure 3. The SECI model and its role in AI-supported learning
Source: Adapted from Nonaka and Takeuchi (1995).

3.3 Knowledge Processing with Retrieval-Augmented Generation

RAG is one architectural option for connecting a language model to a governed knowledge repository. A student's question is converted into a query; relevant passages are retrieved; the passages are supplied as context to the language model; and the generated response identifies its supporting sources. Lewis *et al.* (2020) introduced RAG as a method combining generation with retrievable external memory. In this framework, RAG is a design component rather than a new technical contribution. Its educational value must be evaluated through answer correctness, evidence sufficiency, citation alignment, and the ability to abstain or refer a question to a lecturer when evidence is inadequate.

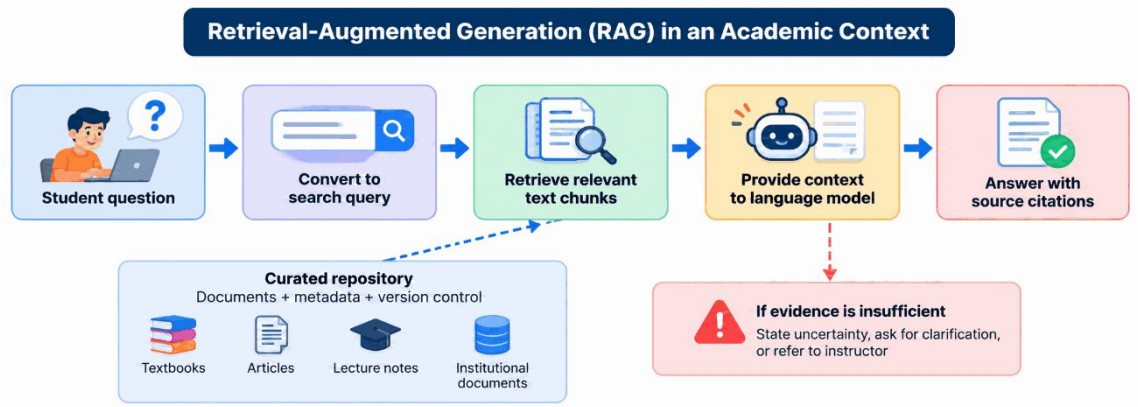


Figure 4. Retrieval-Augmented Generation workflow in an academic context
Source: Adapted from Lewis et al. (2020).

For academic use, answers should be grounded in approved sources and accompanied by source references. When retrieved evidence is insufficient, the system should communicate uncertainty, request clarification, or refer the student to a lecturer. These controls may reduce unsupported responses but cannot guarantee error-free output. Evaluation should examine factual correctness, relevance, evidence sufficiency, citation accuracy, and appropriate abstention. Such checks

respond to known opportunities and risks of large language models in education (Kasneci *et al.*, 2023) and to guidance on responsible generative AI use (Miao & Holmes, 2023).

Version control is also important. When lecturers update a module or syllabus, the knowledge index must be refreshed so that answers do not rely on obsolete materials. Search logs and AI outputs may be retained in a limited manner for quality auditing, while avoiding unnecessary storage of personal data.

3.4 Personalized Learning and the Lecturer's Role

Personalization can begin by mapping questions and activities to course learning outcomes or competencies. For example, a quiz question about the ETL process may be linked to a data-integration competency. Correct and incorrect answers, quiz scores, and relevant activity sequences can help identify topics for reinforcement; the system may then recommend foundational materials, worked examples, or more advanced exercises. Research on AI-based personalized learning and learning analytics supports the relevance of adaptive support as an area for development, while underscoring the need for careful evaluation (Farhood *et al.*, 2025; González-Pérez *et al.*, 2025; Rodríguez-Ortiz *et al.*, 2025).

Activity data alone do not establish mastery. A student who rarely opens a resource may already understand a concept, while frequent access does not necessarily demonstrate understanding. Recommendations should combine multiple relevant signals, such as quiz answers, assignment results, and validated competency mappings. Lecturers should be able to inspect why a resource was recommended and override it when classroom context requires. This emphasis on interpretable, pedagogically grounded feedback is aligned with learning-analytics research (Banihashem *et al.*, 2022; Drugova *et al.*, 2024).

Lecturers are responsible for curating knowledge, defining learning objectives, validating competency maps, reviewing AI outputs, and deciding on pedagogical follow-up. This human-centered approach aligns with UNESCO guidance on the responsible use of generative AI in education and research (Miao & Holmes, 2023). Implementation should also inform students when they are interacting with AI and explain its limitations.

3.5 Conceptual Positioning and Distinctive Features of the Framework

Previous research has reviewed AI applications in higher education, generative AI in education, and learning analytics (Bond *et al.*, 2024; Wang *et al.*, 2024; Yusuf *et al.*, 2024; Zhang *et al.*, 2024). Work on RAG provides a technical foundation for retrieval-grounded generation (Lewis *et al.*, 2020), while studies of learning analytics address feedback, personalization, and learning-design improvement (Banihashem *et al.*, 2022; Drugova *et al.*, 2024). The proposed framework connects these areas by treating academic knowledge governance as the layer linking curated sources, course competencies, AI services, and lecturer feedback. These prior reviews contextualize the framework; they do not demonstrate that the integrated model has already been validated.

The framework's added value is conceptual and integrative. It treats source curation, metadata, versioning, access rights, and traceability as prerequisites for AI processing; links source-based retrieval to course learning outcomes and competency mapping; and closes the workflow through lecturer review of answer quality, recommendation relevance, and repository updates. This position is consistent with calls for stronger ethics, collaboration, and methodological rigour in AI-in-higher-education research (Bond *et al.*, 2024). It should not be interpreted as evidence that each element is individually new or that the integrated model is superior to existing systems.

Three design propositions follow from this integration. First, governance and version control should improve the ability to trace AI responses to approved course material. Second, mapping questions and learning resources to competencies may make recommendations more relevant than generic recommendations. Third, lecturer review and feedback may help detect unsuitable answers

and outdated materials. These propositions are testable expectations, not demonstrated outcomes. They should be examined through expert validation and comparative prototype evaluation.

This novelty claim should be interpreted proportionately. Several studies have broadly reviewed AI in higher education, generative AI, and learning analytics; therefore, this study does not claim to introduce a new AI or RAG technology. Its proposed added value lies in organizing these components into a single knowledge-governance cycle for course-level learning, with explicit links among curated sources, competency maps, AI services, evaluation, and knowledge revision. This proposed novelty can be investigated through expert validation and comparative prototype evaluation.

Table 2 summarizes the conceptual differences in focus. This comparison is a high-level synthesis of reported emphases in related publications, not the result of systematic coding of the entire literature. It should therefore not be interpreted as evidence that previous studies entirely lack any particular component.

Table 2. Conceptual positioning of the proposed framework in relation to related literature

Related literature focus	Reported emphasis	Position of the proposed framework
AI in education (Wang *et al.*, 2024; Bond *et al.*, 2024)	AI application categories, system design, adoption, impacts, and challenges	Positions academic knowledge governance as a connecting layer
Generative AI in education (Yusuf *et al.*, 2024; Kasneci *et al.*, 2023; Zhang *et al.*, 2024)	Pedagogical support, use, risks, AI literacy, and human oversight	Grounds AI answers in curated sources and lecturer validation
RAG (Lewis *et al.*, 2020)	Combines external-source retrieval with answer generation	Links retrieval to course metadata and competency maps
This article's framework	Conceptual synthesis, not yet empirically tested	Proposes a source–repository–AI–personalization–evaluation cycle

The following scenario illustrates how the framework could be used in a Knowledge Management course; it is not a report of an implemented system. A lecturer uploads the syllabus, a module on the SECI model, scholarly readings, and reviewed quiz questions. The repository organizes the files by topic and links them to learning outcomes. When a student asks about the difference between socialization and externalization, the system retrieves relevant passages and generates an explanation with source identification. This scenario shows how the framework combines knowledge curation with source-grounded AI support.

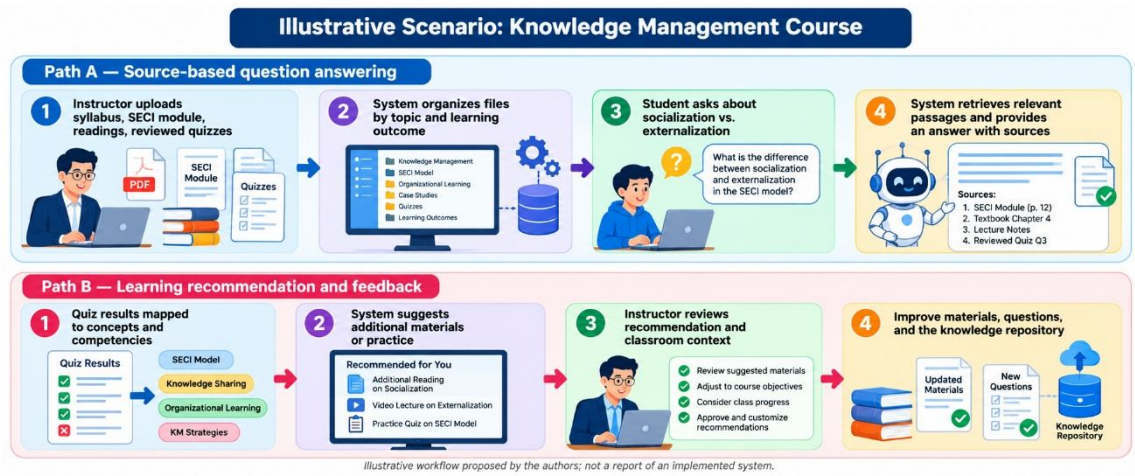


Figure 5. Illustrative use scenario in a Knowledge Management course
Source: Authors' design.

If quiz results indicate that a student answers several questions incorrectly about a concept, the system may suggest an alternative explanation or additional practice. The recommendation should remain provisional because errors may result from question wording, time constraints, or inaccurate competency mapping. Lecturers should review the evidence before changing instructional strategies or making judgments about student mastery. This is consistent with formative-feedback principles (Hattie & Timperley, 2007; Shute, 2008), but the proposed workflow requires empirical evaluation to establish whether it improves learning.

This scenario clarifies the relationship between KM and AI. KM ensures that sources, metadata, versions, and competency mappings are managed systematically; AI supports retrieval and explanation generation; and evaluation checks whether sources and recommendations are appropriate. Without the KM layer, AI outputs may become disconnected from the curriculum. Without evaluation, unsuitable recommendations may recur. Lecturer feedback and version management are therefore core design elements rather than optional features.

3.6 Research Propositions and Evaluation

Four propositions are proposed for future testing (Table 3). P1 concerns the relationship between repository structure and retrieval relevance; P2 concerns whether RAG with curated sources improves answer traceability compared with generation without retrieval; P3 concerns whether competency-based recommendations are rated as more relevant than generic recommendations; and P4 concerns whether lecturer validation and governance controls support implementation feasibility. These propositions are derived from the conceptual synthesis and should not be interpreted as tested findings.

Table 3. Proposed research propositions and evaluation designs

Code	Proposition	Possible evaluation approach
P1	Repository structure is associated with the relevance of search results.	Test search using a query set and expert relevance ratings.
P2	RAG with curated sources improves answer traceability compared with a model without retrieval.	Compare source support, answer accuracy, and citation alignment.
P3	Competency-based recommendations are more relevant than generic recommendations.	Use lecturer/student ratings and analyze the relevance of recommended materials.
P4	Lecturer validation and data governance support system implementation feasibility.	Conduct expert evaluation, access audits, and implementation-risk assessment.

Prototype evaluation should cover at least three groups of measures. First, retrieval performance can be assessed with Precision@k, Recall@k, and normalized Discounted Cumulative Gain (nDCG@k). Second, answer quality should include factual correctness, relevance, source support, citation alignment, and appropriate abstention. Third, recommendation quality and usability can be assessed through lecturer/student ratings and task-based usability measures. If learning outcomes are examined, pre-test/post-test scores or a suitable comparison design may be used. Metric selection should match the research question and available data.

To test effects on learning outcomes, future research could compare students using the prototype with a comparison group using conventional learning resources, subject to ethical approval and institutional requirements. Learning materials, duration, and assessment instruments should be comparable. Reports should include sample characteristics, missing data, effect sizes, and limits to generalizability. Without such a design, changes in scores cannot confidently be attributed to the AI system.

3.7 Governance Principles for Implementation

To support responsible implementation of the conceptual framework, governance should begin during source selection. Each document should have an owner or responsible person, version status, access rights, and review date. Unverified sources should not be treated as authoritative

references for AI-generated answers. These practices help maintain consistency with the syllabus and academic policy.

At the output level, AI answers should be distinguishable from original sources. The system should display the title or identity of the supporting document, warn users when evidence is insufficient, and provide a route for escalation to a lecturer. Kasneci *et al.* (2023) discuss the opportunities of language models for interaction and personalization as well as risks involving bias, unstable outputs, and the need for human oversight. UNESCO also emphasizes a human-centered approach, privacy protection, and institutional readiness for generative AI (Miao & Holmes, 2023).

For student data, collection should be limited to what is necessary for the stated learning purpose. Access to scores, activities, and competency profiles should be role-based. The use of data for analytics or model development should comply with institutional policies and applicable data-protection requirements. The framework does not prescribe a specific technology or legal policy; implementation details should be adapted to the institutional context.

3.8 Implementation and Governance Challenges

The first challenge is source quality. Incorrect, duplicated, incomplete, or outdated documents can reduce retrieval and answer quality. Content owners should therefore establish review procedures, version labels, and update schedules. The second challenge is erroneous generation. The system should cite sources, undergo periodic testing, and provide a mechanism for reporting unsuitable answers.

The third challenge is privacy and security. Student data should be limited to what is necessary, protected through access controls, and not used for other purposes without an appropriate basis. Where possible, identity data should be separated from analytics data. The fourth challenge is bias and accessibility; the system should be tested to ensure that students with different needs and learning backgrounds can access adequate support.

The fifth challenge is integration with academic systems. Implementation should consider authentication, access rights, LMS interoperability, and long-term maintenance. Finally, educational effectiveness cannot be determined solely by model sophistication. The system should be evaluated based on its support for learning outcomes, usability, user trust, and the quality of interactions between lecturers and students.

4. Conclusion

This study addressed its three research questions by proposing a conceptual framework that integrates Knowledge Management and AI in a course-level workflow. First, it shows how academic knowledge sources can be connected to a governed repository, AI-based processing, personalized learning services, and evaluation with lecturer feedback. Second, it explains how source-grounded retrieval and competency-aligned recommendations can be supported by linking approved materials and learning data to course outcomes. Third, it identifies evaluation priorities before implementation: retrieval performance, answer accuracy and traceability, recommendation relevance, usability, and data governance. The most important adoption priority is to establish a lecturer-curated, version-controlled repository mapped to course learning outcomes before enabling RAG-based answers and personalized recommendations.

The contribution is a conceptual integration, methodological workflow, four testable propositions, and a proposed evaluation plan. The study is not a systematic literature review (SLR), and the framework has not yet been validated through expert assessment, a working prototype, or student experiments. Consequently, the study cannot conclude that the framework improves learning outcomes. Future research should validate the model with experts, develop a prototype, compare it with appropriate baseline approaches, and evaluate technical quality and pedagogical usefulness while maintaining privacy, transparency, and lecturer oversight.

5. Recommendations for Future Research

Future research should proceed in stages: (1) obtain expert review of framework completeness and course alignment; (2) create a prototype using curated sources, metadata, and version control; (3) link questions and materials to validated learning outcomes; (4) test retrieval, answer correctness, source traceability, recommendation relevance, and usability; and (5) conduct an appropriately designed study of learning outcomes if justified. Governance checks should cover access rights, data minimization, transparency about AI use, and a clear route for lecturer intervention.

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7. Declaration of Generative AI

The authors used artificial intelligence (ChatGPT, Claude and Gemini) to assist with the analysis, editing, and language translation of the manuscript.

8. Conflict of Interest Declaration

The authors declare that there are no conflicts of interest regarding the publication of this article. The authors also confirm that this manuscript is original, has not been published previously, is not under consideration for publication elsewhere, and is free from plagiarism.

9. Author Contribution Statement

All authors contributed equally to the conduct research project, data analysis, and writing and preparation of this article.

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