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Utilizing Retrieval Augmented Generation (RAG)-Based Chatbots as an Innovative Learning Tool in Higher Education: A Case Study on the Use of Digital Learning Resources

Yusza Reditya Murti[1*], Dian Puteri Ramadhani[2], Herry Irawan[3]

[1,2,3]Universitas Telkom
Jawa Barat, Indonesia
yuszaa@telkomuniversity.ac.id*

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Abstract

Background: Higher education institutions face information fragmentation and cognitive overload as students struggle to access learning materials scattered across multiple digital platforms. Large Language Models encounter hallucination issues and static knowledge bases, limiting their educational application.
Aims: This research aims to design and evaluate a Retrieval Augmented Generation (RAG)-based chatbot system integrated with Learning Management Systems to address information fragmentation in educational environments
Methods: We employed Design Science Research Methodology (DSRM) to develop the RAG-based chatbot. Technology Acceptance Model (TAM) assessment with 267 undergraduate students and semi-structured interviews with five faculty members evaluate user acceptance and pedagogical perspectives.
Results: The RAG chatbot achieved strong initial user acceptance (mean score 4.097). Students valued perceived usefulness over ease of use, with high usage intentions and recommendation willingness. Faculty recognized pedagogical value while emphasizing quality assurance needs.
Conclusion: This exploratory study demonstrates technical feasibility and baseline user acceptance for RAG-based chatbots in education, showing promise for addressing information accessibility challenges. Demonstration-based evaluation requires validation through longitudinal field studies.

A. Introduction

Higher education institutions serve as fundamental catalysts for establishing knowledge economies in the 21st century (Bygstad et al., 2022). Contemporary universities face challenges as traditional pedagogical approaches prove increasingly inadequate for addressing diverse student learning expectations. The prevalence of standardized, one-size-fits-all instructional methodologies leads to significant inefficiencies in maximizing individual learning potential (Goyibova et al., 2025). This pedagogical inflexibility manifests in diminished student engagement and suboptimal academic outcomes. Traditional face-to-face learning methods often fail to accommodate different learning styles and individual student needs, creating barriers to effective knowledge acquisition.

Digital technologies represent a critical mechanism for realizing educational potential in modern academic environments (Bygstad et al., 2022). The progression of digital learning infrastructure shows identifiable developmental periods: administrative systems implementation during the 1980s-1990s, followed by educational platforms including Learning Management Systems (LMS), Massive Open Online Courses

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(MOOCs), and digital libraries after 2000 (Bygstad et al., 2022). Paradoxically, the technological proliferation has introduced new obstacles for information processing.

In higher education, the way we learn is facing some serious challenges due to the growth of digital information and learning resources scattered across various platforms. Access to learning materials now involved multiple systems, such as LMS, MOOCs, Digital Library Platforms, and other external materials. The fragmentation of learning materials across multiple unintegrated systems creates significant barriers for students seeking to efficiently locate relevant resources (Kaklij et al., 2019). Combined with limited time and cognitive capacity, this fragmentation triggers information overload that reduces decision-making accuracy and learning effectiveness. Educational stakeholders express serious concerns about digital overload's impact on students' psychological well-being and academic performance (Lauri et al., 2020; Upadhyaya & Vrinda, 2021). Faculty report additional technology-related challenges including digital assessment concerns, psychological barriers, technology intimidation and resistance, time constraints, and information overload (Al-Hail et al., 2024). Contemporary digital environments foster shortened attention spans and increased distractibility among learners.

Educational research indicates that dialogue serves as a fundamental catalyst for effective learning (Swacha & Gracel, 2025). In practice, many students are unable to engage in meaningful conversations with their instructors due to large class sizes that prevent individual attention, or with peers in asynchronous online learning environments where real-time interaction is limited. This limitation becomes particularly pronounced when students need assistance outside regular class hours, as faculty availability is restricted and individual consultation opportunities are limited. Furthermore, the absence of personalized learning approaches fails to accommodate individual student differences in learning pace, style, and comprehension levels. These conditions create significant barriers to optimal learning experiences.

At present, artificial intelligence has gained widespread adoption in educational settings (Chen et al., 2024; Chen et al., 2020) with Large Language Models (LLMs) are increasingly being explored to enhance learning and teaching processes through interactive dialogue capabilities (Li et al., 2025). LLM-powered chatbots function as virtual tutoring systems, providing real-time explanations and responding to student queries (Aleven et al., 2023). LLMs demonstrate remarkable proficiency in automated essay assessment and personalized feedback generation (Jeon & Lee, 2023). Their robust processing capabilities extend to multiple educational applications, including automated quiz development, intelligent content summarization, and comprehensive instructional planning support (Li et al., 2025). The adoption of LLM-powered conversational agents has been particularly promising due to their ability to provide natural and intuitive interaction through conversational interfaces, which represents a significant improvement over traditional search systems that often fail to meet user expectations (Klesel & Wittmann, 2025).

Despite technological advances, current applications encounter critical deployment challenges in authentic educational environments (Hwang et al., 2020). The hallucination phenomenon is a major concern, where models generate factually incorrect or misleading information due to probabilistic processing mechanisms (Ji et al., 2023). Hallucination was defined as content that is inconsistent with real-world facts or user inputs, is particularly problematic in educational settings because it undermines the trustworthiness of AI-generated responses (Klesel & Wittmann, 2025; Perković et al., 2024). In educational contexts requiring accuracy and reliability, errors might destruct learning outcomes. Additional limitations include static knowledge bases that are unable to incorporate current curricular updates or scientific developments (Li et al., 2025). LLMs also frequently lack explainability and personalization capabilities, failing to address diverse learner requirements and reducing confidence in AI-supported educational systems (Zhao et al., 2024).

To address identified limitations, researchers have introduced Retrieval-Augmented Generation (RAG), a hybrid framework combining LLM generative capabilities by incorporating an external knowledge base (Fan et al., 2024; Gao et al., 2023; Wan et al., 2025). RAG represents a significant advancement in AI architecture that integrates additional knowledge sources and enabling the generation of results that can be directly linked to verifiable knowledge sources while substantially reducing hallucination risks (Klesel & Wittmann, 2025). Unlike conventional LLMs relying exclusively on pre-trained knowledge, RAG systems retrieve relevant documents from external knowledge bases before response generation.

RAG operates through a two-step process: (1) a retriever component that searches and selects relevant documents from a knowledge database, and (2) a generator component that combines the retrieved information with the original query to produce contextually grounded responses. This hybrid approach allows the system to access both its pre-trained knowledge and real-time information from external sources, enabling more accurate and up-to-date responses while maintaining the natural language generation capabilities of LLMs (Lewis et al., 2021). This approach enhances factual accuracy, knowledge currency, and transparency, making it suitable for educational applications requiring precise and verifiable information. Through retrieval-based knowledge augmentation, RAG systems provide enhanced student explanations, adapt to curricular modifications, and mitigate misinformation risks (Li et al., 2025). RAG systems offer the flexibility to update knowledge by modifying the external database without retraining the entire model (Lewis et al., 2021), making them particularly valuable for educational environments where curricula and information frequently evolve. RAG-based chatbots can integrate diverse learning resources and provide students with unified access to comprehensive educational materials while enabling educators to efficiently manage and deliver personalized learning experiences.

Based on the current challenges in higher education technology integration, this research aims to design and evaluate a RAG system integrated with Learning Management Systems to enhance student learning experiences and address the critical issues of information fragmentation and overload in contemporary educational environments. This study represents a technology-driven exploratory investigation of RAG's potential for addressing well-documented challenges in higher education. Rather than claiming emergent problem discovery, our research was motivated by existing literature extensively documenting information fragmentation (Kaklij et al., 2019), cognitive overload (Shahrzadi et al., 2024), and limited student-faculty dialogue opportunities (Swacha & Gracel, 2025) as persistent problems in contemporary higher education. Given the recent advancement of RAG technology and its demonstrated effectiveness in reducing LLM hallucination while enabling knowledge-base integration (Klesel & Wittmann, 2025; Lewis et al., 2021), our research question emerged: Can RAG architecture provide a viable solution for these documented educational challenges? While simpler alternatives such as unified search portals or enhanced FAQ systems exist, these approaches address findability but not the cognitive synthesis burden where students still must navigate multiple documents and integrate information themselves. Unified search portals unable to provide conversational interaction or contextually adaptive responses that research identifies as fundamental for effective learning (Swacha & Gracel, 2025). RAG-based chatbots offer conversational interface and synthesized responses from multiple sources, directly addressing both information access and cognitive load simultaneously. This study focuses on showing technical feasibility and evaluating initial user acceptance and positioned as a technology evaluation study testing whether an emerging technology can address known problems in educational contexts.

B. Research Methods

This study employed Design Science Research (DSR) methodology which is suitable for developing and evaluating technological artifacts that address real-world problems in educational settings. The research followed the Design Science Research Methodology (DSRM) as the primary methodological framework to develop and evaluate a RAG-based chatbot system integrated with Learning Management Systems for higher education environments. DSRM framework provides a structured approach that aligns with the technology-focused nature of this study, enabling the creation of innovative artifacts that address real-world educational challenges while contributing to both practical and theoretical knowledge. The design science research method phase of DSRM is illustrated in Figure 1.

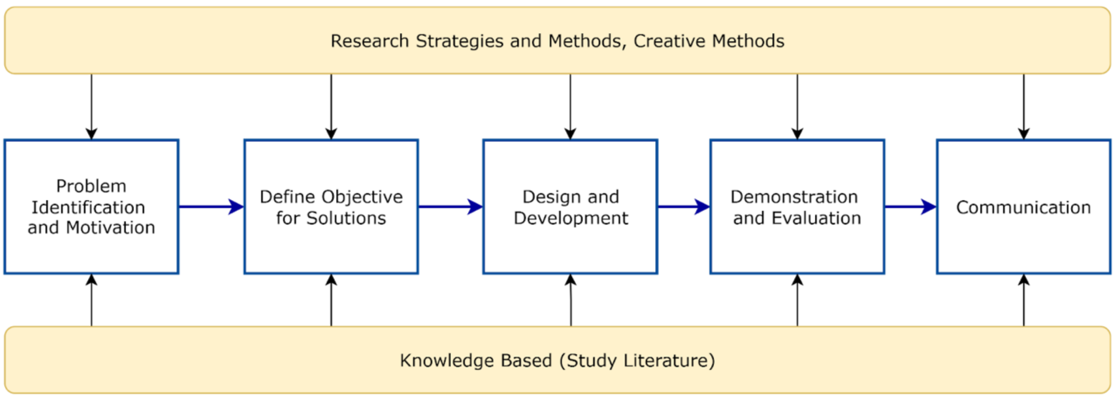

Figure 1. Design Science Research Method

The problem identification and motivation phase involved extensive literature review and needs assessment surveys to establish the foundation for RAG-based chatbot development. During the define objective for solutions phase, specific goals were established for system functionality, user experience, and educational effectiveness. The design and development phase implemented the RAG workflow for chatbots is shown in Figure 2.

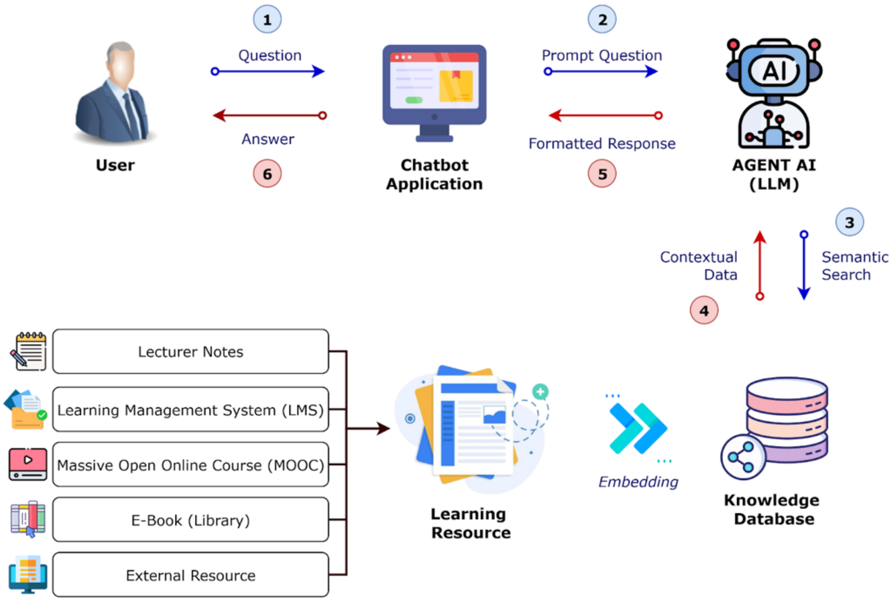

Figure 2. Conceptual Workflow for Chatbots

Figure 2 presents the high-level Retrieval Augmented Generation (RAG) workflow designed for educational chatbots, showing the conceptual flow of information from user query to final response. The workflow follows a six-step process: (1) user submits a question to the chatbot application (2), which forwards the query as a prompt to the Agent AI powered by Large Language Models (3). The Agent AI performs semantic search to identify relevant information from the knowledge database (4), where learning resources from diverse educational sources including lecturer notes, Learning Management Systems, Massive Open Online Courses, e-books, and external resources have been processed through embedding and stored as searchable vector representations. The retrieved contextual data informs the Agent AI's response generation (5), which is then delivered back to the user through the chatbot interface (6).

It is important to clarify that this diagram presents a simplified conceptual overview. The term "contextual data" (step 4) refers to the retrieved relevant information from the knowledge database. Learning materials undergo a multi-stage processing pipeline before becoming searchable content in the knowledge database. The detailed technical architecture, including the complete extraction, preprocessing, chunking, and embedding pipeline, is comprehensively illustrated and explained in Figure 3 (System Architecture) in the following section.

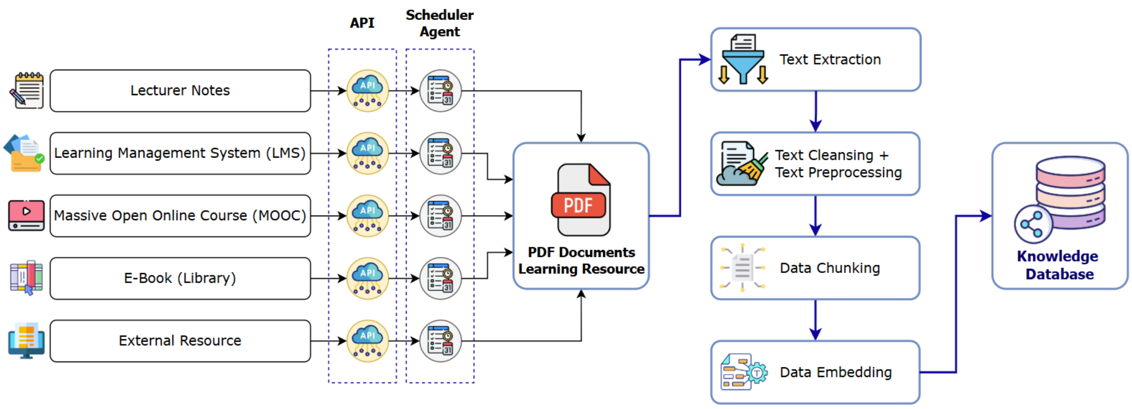

Figure 3. Retrieval Augmented Generation (RAG) Workflow for Chatbots

Figure 3 provides the detailed technical architecture that operationalizes the conceptual workflow presented in Figure 2. This architecture illustrates the Knowledge Base Construction Pipeline. The knowledge database is populated through a structured, multi-stage embedding pipeline that transforms raw institutional documents into searchable vector representations. The mechanism is explained below:

Step 1 - API Integration

Source applications including Lecturer Notes, LMS, MOOC, E-Books from institutional libraries, and External Resources are connected to the RAG chatbot system via Application Programming Interfaces (APIs). These APIs act as standardized bridges enabling automated data transfer from diverse platforms with different native formats and structures.

Step 2 - Automated Scheduling

A scheduler agent automates the synchronization process by periodically triggering the APIs to fetch new or updated documents from source platforms. This automation ensured the knowledge base remains current with institutional learning resources without requiring continuous manual intervention. The scheduling frequency can be configured based on institutional needs and content update patterns (e.g., daily synchronization during active teaching periods, weekly updates during breaks).

Step 3 - Format Standardization and Text Extraction

All retrieved content, regardless of original format, is converted to PDF format for uniform processing. Subsequently, automated text extraction pulls the raw textual content from these PDF documents, converting formatted documents into machine-readable plain text. This extraction handles various file types including native digital PDFs, scanned documents (via OCR where necessary), Microsoft Word documents, PowerPoint presentations, and web-based content.

Step 4 - Text Cleansing and Preprocessing

The extracted raw text undergoes systematic cleaning to remove irrelevant elements including formatting artifacts (extra whitespace, line breaks, special characters), document metadata and headers/footers that do not contribute to semantic content, inconsistent encoding that could cause processing errors, and redundant or non-informative text. The cleaned text is normalized to ensure consistency across documents from different sources, preparing high-quality input for subsequent embedding generation.

Step 5 - Data Chunking (Critical for Context Window Management)

This stage directly addresses the reviewer's concern about contextual data length limitations. Since entire learning resources which may be lengthy textbooks, comprehensive lecture slide decks, or extensive course materials are too large to be processed as a single context within LLM token limits, they must be strategically segmented into smaller, semantically coherent chunks. This chunking strategy prevented the loss of crucial information that would occur if large documents were simply truncated to fit context windows, thereby mitigating the risk of generating incomplete or non-comprehensive responses

Step 6 - Data Embedding

Each text chunk is converted into a high-dimensional numerical vector (embedding). These embeddings capture the semantic meaning of the text in vector space, where semantically similar content is represented by vectors that are geometrically close to each other. This mathematical representation enables efficient semantic similarity search: when a user query is embedded using the same model, the system can rapidly identify which document chunks are most semantically relevant by calculating vector distances

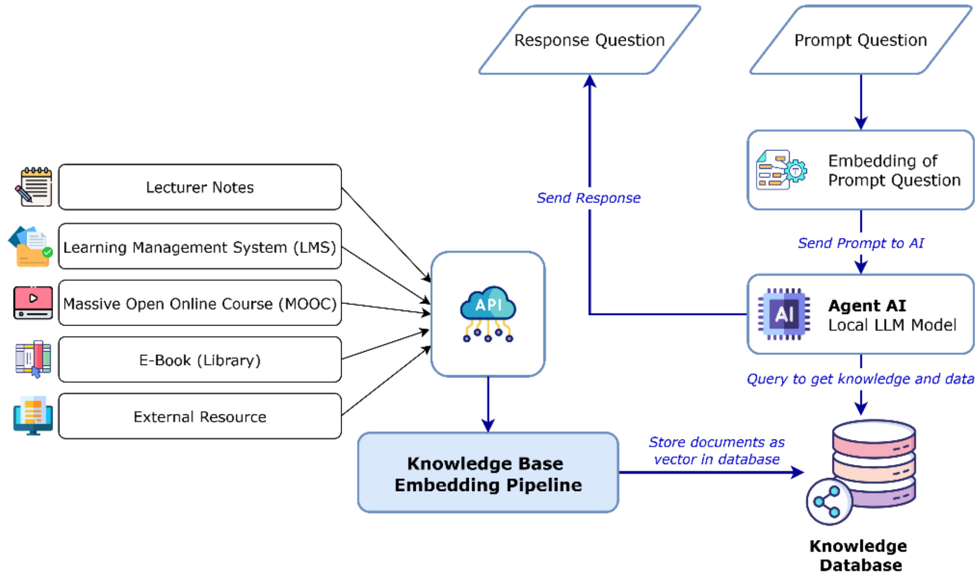

Figure 4. Query Processing and Response Generation Mechanism

Figure 4 provides the detailed technical architecture that operationalizes the conceptual workflow presented in Figure 2. This architecture illustrates the Query Processing and Response Generation mechanism (utilizing the constructed knowledge database). The knowledge database is populated through a multi-stage embedding pipeline that transforms raw query processing and response generation. The mechanism is explained below:

a. When a user submits a question (Figure 2, Steps 1-2) detailed in Figure 4, the query is forwarded to the Agent AI (LLM), which performs semantic search against the populated knowledge database. The user's query is embedded using the same model employed for document chunks, ensuring semantic compatibility. The system retrieves most similar document chunks from the vector database.
b. These retrieved chunks become the "contextual data" referenced in Figure 2 (Step 4). This selective retrieval addresses context window limitations: instead of attempting to pass all institutional learning resources (which would far exceed any LLM's capacity), the system passes only the most relevant excerpts tailored to the specific query. The LLM receives these retrieved chunks along with the original query and generates a contextualized, grounded response that synthesizes information from the institutional sources.
c. The formatted response (Figure 2, Step 5) is then delivered to the user via the chatbot interface (Step 6), typically including citations or references to the specific source documents from which information was retrieved, enabling transparency and allowing users to verify information or explore topics more deeply by accessing original sources.

This technical architecture forms the foundation of the RAG-based chatbot system evaluated in this study. The evaluation stage involved multiple testing phases designed to validate the effectiveness of the developed RAG-based system, identify technical issues and system optimization needs, assess pedagogical relevance and instructional integration capabilities, and conduct user testing to evaluate system acceptance. To measure user acceptance as a critical component of system viability assessment, we incorporated the Technology Acceptance Model (TAM), a well-established theoretical framework originally developed by Davis (1989) in Ramayani et al. (2023) for predicting and explaining user acceptance of information technology. TAM has been extensively validated in educational contexts, particularly for e-learning systems adoption (Rahmawati & Narsa, 2019), making it appropriate for evaluating user perceptions and adoption intentions toward the developed RAG-based chatbot system. The model focuses on three core constructs that determine technology acceptance and usage behavior, providing a framework to assess whether users will embrace and potentially continue using the educational chatbot beyond initial exposure.

Our evaluation approach employed demonstration-based assessment rather than extended hands-on usage. This represents a methodological constraint that affects the interpretation of our findings, as discussed in detail in the Limitations section. Participants evaluated the system based on observed demonstrations rather than direct experience using it for their actual academic work over an extended period. Our TAM measurements reflect anticipated usefulness and intended adoption rather than experienced usefulness and actual usage behavior. The model focuses on three core constructs as explained below:

a. Perceived Usefulness (PU) was defined as the degree to which a person believes that using a particular technology will enhance their job performance (Alnagrat et al., 2023; Rahmawati & Narsa, 2019). In the context of educational chatbots, perceived usefulness measures users' belief that the RAG-based system will improve their academic performance and provide valuable support for educational tasks such as information retrieval, assignment completion, and understanding course materials.
b. Perceived Ease of Use (PEU) refers to the extent to which users believe that using a particular technology will be free from effort (Alnagrat et al., 2023; Rahmawati & Narsa, 2019). In educational chatbot contexts, perceived ease of use evaluates how effortless users find the system to learn, navigate, and interact with, including clarity of system responses and intuitiveness of the conversational interface.
c. Intention to Use (ITU) represents users' behavioral intention regarding continued technology usage (Rahmawati & Narsa, 2019). This construct is theoretically influenced by both perceived usefulness and ease of use. For RAG-based educational chatbots, intention to use captures users' willingness to continue using the system if made available, integrate it into their regular academic activities, and recommend it to peers. However, users may express willingness to use a system based on demonstrations but may or may not actually adopt it when faced with real-world implementation.

To measure these TAM constructs empirically, questionnaires were distributed to a sample of 267 undergraduate students at Telkom University and three others institutions who participated in the demonstration of the RAG-based academic chatbot system and provided their responses regarding PU, PEU, and ITU. The participants were selected through convenience sampling from various undergraduate programs. During the demonstration phase, students observed the chatbot system's capabilities through live presentations showcasing its functionality for academic-related queries, including how it retrieved information from educational sources, generates contextually relevant responses, and assists with learning tasks. Following the demonstration session, participants completed the evaluation questionnaire based on their observations and understanding of the system's potential benefits and usability for their academic needs, ensuring that their responses reflected informed perceptions of the chatbot's applicability to their educational context.

The questionnaire items were adapted from Weng et al. (2018), who conducted a TAM-based study on multimedia technology acceptance among schoolteachers. The original instrument was modified to reflect the educational chatbot context, transforming teacher-oriented multimedia statements into student-focused academic chatbot perceptions. The adaptation process involved contextualizing the original multimedia teaching items to academic chatbot usage scenarios. All questionnaire items utilized a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The final questionnaire comprised 10 items distributed across the three TAM constructs as shown in Table 1.

Table 1. Questionnaire Items

Code	English Statement	Indonesian Statement
PU1	I find the Academic Chatbot application beneficial in helping me complete assignments and understand course materials.	Saya merasa aplikasi Chatbots Akademik ini bermanfaat dalam membantu saya mengerjakan tugas dan memahami materi perkuliahan.
PU2	I feel that the Academic Chatbot application can meet my needs in the learning process and completing academic tasks.	Saya merasa aplikasi Chatbots Akademik dapat memenuhi kebutuhan saya dalam proses belajar dan mengerjakan tugas akademik.
PU3	I feel that the Academic Chatbot application helps me find academic information quickly.	Saya merasa aplikasi Chatbots Akademik membantu saya menemukan informasi akademik dengan cepat.
PEU1	I feel that the Academic Chatbot application is easy to use in the learning process and helps complete academic tasks.	Saya merasa aplikasi Chatbots Akademik mudah digunakan dalam proses belajar dan membantu menyelesaikan tugas akademik.
PEU2	I feel that the Academic Chatbot application is easy to use in the learning process and helps complete academic tasks.	Saya merasa aplikasi Chatbots Akademik mudah digunakan dalam proses belajar dan membantu menyelesaikan tugas akademik.

Code	English Statement	Indonesian Statement
PEU3	I feel that the interaction with the Academic Chatbot application is clear and easy to understand.	Saya merasa interaksi dengan aplikasi Chatbots Akademik jelas dan mudah dimengerti.
ITU1	I intend to use the Academic Chatbot application to help with my learning process and academic tasks in the future.	Saya berniat untuk menggunakan aplikasi Chatbots Akademik untuk membantu proses belajar dan mengerjakan tugas akademik di masa depan.
ITU2	I feel that I will continue to use the Academic Chatbot application to help with my learning process and academic tasks in the future.	Saya merasa bahwa saya akan terus menggunakan aplikasi Chatbots Akademik untuk membantu proses belajar dan mengerjakan tugas akademik di masa depan.
ITU3	I plan to regularly use the Academic Chatbot application in my learning process and completing academic tasks in the future.	Saya berencana untuk secara teratur menggunakan aplikasi Chatbots Akademik dalam proses belajar dan menyelesaikan tugas akademik di masa depan.
ITU4	I will recommend the Academic Chatbot application to friends or colleagues to help with academic tasks.	Saya akan merekomendasikan aplikasi Chatbots Akademik kepada teman atau kolega untuk membantu dalam pengerjaan tugas akademik.

After collecting the questionnaire responses, we mapped the results descriptively to assess potential users' responses toward the chatbot.

Recognizing that successful educational technology implementation depends on student acceptance and also on faculty perspectives, as instructors play essential roles in managing knowledge bases, ensuring information accuracy, and integrating tools into curriculum, we incorporated qualitative inquiry with faculty members to complement the quantitative student evaluation. This addition directly addresses the identified limitation that focusing solely on student end-users provides an incomplete picture of real-world implementation viability. Semi-structured interviews were conducted with five faculty members from three different universities, purposively selected to represent diverse disciplinary perspectives including both technical fields (engineering, computer science) and social sciences (management, business). The interview protocol explored four key themes: (1) pedagogical value and appropriate role of RAG chatbots in academic contexts, (2) integration strategies and concerns for incorporating the tool into teaching practice, (3) quality assurance perspectives regarding information accuracy and validation responsibilities, and (4) faculty role and positioning relative to AI-assisted learning tools.

Each interview lasted approximately 30-45 minutes and was conducted either in-person or via video conferencing, following demonstration of the RAG chatbot system's capabilities. Faculty participants were shown the same demonstration materials presented to students, including examples of how the system retrieved information from institutional sources, synthesizes responses across multiple documents, and provides source attribution. Following the demonstration, open-ended questions elicited faculty perspectives on benefits, concerns, appropriate usage boundaries, and implementation considerations. Interviews were recorded (with participant consent), transcribed, and analyzed thematically to identify convergent themes and divergent perspectives across participants. We acknowledge this qualitative component as exploratory and limited in scope. The small sample (n=5) from a limited number of institutions and the brief, single-session interview format constrain the depth and generalizability of insights.

C. Results and Discussion

1. Results

1.1. RAG-Based Chatbot System Implementation

The research successfully developed and implemented a functional RAG-based chatbot system specifically designed for higher education environments, operationalizing the technical architecture detailed in Figure 3. The system addresses the identified challenges of information fragmentation and cognitive overload in contemporary educational settings through seamless integration with existing Learning Management Systems and other institutional learning platforms. The implemented chatbot system enables intelligent information retrieval and contextually grounded response generation by processing diverse educational sources including lecturer notes, LMS content, MOOCs, e-books, and external academic resources. Through the embedding pipeline described in Section B (Steps 1-6), these learning materials are converted into searchable vector representations and stored in a comprehensive knowledge database, ensuring that student queries receive accurate, institutionally relevant responses grounded in approved educational materials rather than generic AI-generated content that may hallucinate information.

Figure 4 demonstrates the chatbot's operational interface in a real-world usage scenario. The interface presents a conversational layout familiar to students from consumer messaging applications, reducing the learning curve for adoption. The left sidebar shows a conversation history panel labeled "Chats," allowing users to maintain and return to multiple topic-based conversations including "*BOK prodi akuntansi S-1*", "*Marketing plan untuk agensi*", "*Artikel tentang sqlmap*", and "*Hitung x×2 dan p-value*", demonstrating the system's capability to handle diverse academic queries across different subjects and course contexts.

The main conversation panel shows a practical student interaction about microeconomics theory, specifically supply and demand curves (titled "*Teori Permintaan dan Penawaran dalam Ekonomi Mikro*" dated "*09 Agustus 2025*"). The student's initial query (shown in purple message bubble): "*Halo, saya sedang belajar tentang teori permintaan dan penawaran dalam Ekonomi Mikro. Bisa jelaskan apa itu kurva permintaan dan penawaran?*" translates to: "Hello, I'm learning about supply and demand theory in Microeconomics. Can you explain what supply and demand curves are?" The system's response shows several critical capabilities addressing reviewer concerns about completeness and multi-source integration:

a. Content Synthesis

The chatbot provides a detailed explanation spanning multiple paragraphs that defines supply curves (showing the relationship between price and quantity demanded by consumers, with inverse relationship higher prices lead to lower quantity demanded) and demand curves (showing the relationship between price and quantity supplied by producers, with positive relationship higher prices lead to higher quantity supplied). The response explains that both curves together determine market equilibrium price and quantity. This answer demonstrates the system's ability to synthesize conceptual understanding rather than merely retrieving fragmented facts.

b. Multi-Source Information Retrieval

Critically, the response includes explicit citations to three distinct institutional sources, presented as clickable links (shown in purple text at the bottom of the response): "*LMS Mata Kuliah Pengantar Ekonomi Mikro (DDK1KAB4) - PB3 Pertemuan Week 3*" (LMS course materials from Introduction to Microeconomics, Week 3 lecture), "*Video Pembelajaran - Pengantar Ekonomi Mikro - Bidang Studi Ilmu Ekonomi (1)*" (Educational video on Introduction to Microeconomics from Economics discipline), and "*Buku Perpustakaan - Pengantar Ekonomi Mikro (e7) - N. Gregory Mankiw*" (Library e-book: Introduction to Microeconomics 7th edition by N. Gregory Mankiw). The system retrieved and synthesized information from multiple document types simultaneously including LMS lecture materials, textbook resources, etc. The retrieval of several distinct sources for a single query validates the multi-document retrieval capability described in the technical architecture.

c. Transparency and Source Validation

The prominent display of source citations addresses the critical faculty concern identified in qualitative interviews about compelling students to consult original sources rather than treating chatbot responses as definitive answers. Students can click these links to access full original materials, enabling the verification and deeper engagement that faculty emphasized as pedagogically essential. This design feature operationalizes the faculty recommendation that the system should promote, not replace, engagement with primary sources.

d. Follow-up Query Capability

The interface shows a subsequent student question (purple bubble at 10:10 AM): "*Jadi, apa yang dimaksud dengan harga keseimbangan?*" ("So, what is meant by equilibrium price?"), demonstrating the system's conversational capability to handle follow-up questions that build on previous context. The response explains equilibrium price concepts including supply-demand intersection and market dynamics (shortage and surplus), showing contextual understanding across multi-turn conversations.

e. User Experience Features

The interface includes standard interaction affordances such as copy, regenerate response, thumbs up/down feedback buttons, share, and report options (shown as icons below responses), enabling users to provide feedback on response quality.

f. Data Privacy

The technical architecture ensures institutional data privacy through local processing infrastructure. All query processing, semantic search, and response generation occur on institutional servers. The system's ability to reference specific institutional resources with precise citations (including course codes like DDK1KAB4, specific week numbers, and exact textbook editions) demonstrates successful integration with existing educational infrastructure metadata.

g. Scalability and Replication Across Disciplines

The conversation history sidebar showing queries across diverse topics shows that this implementation mechanism can be replicated across all academic courses within the institution. By adapting the knowledge base to include course-specific materials, syllabi, lecture notes, and relevant academic resources for each subject area, the RAG-based chatbot system can serve as an educational support tool that scales across disciplines from technical fields like engineering and computer science to social sciences, humanities, and professional programs.

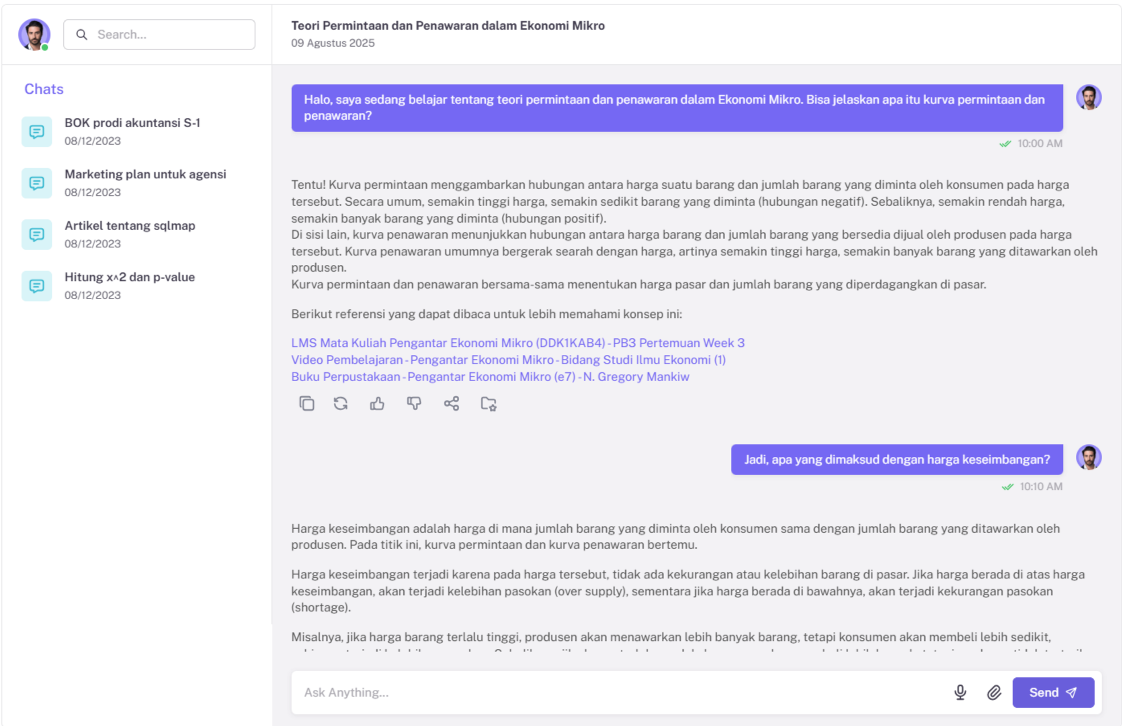

Figure 5. Interface of RAG-Based Chatbot

Figure 5 presents the Knowledge Source Management administrative interface, which serves as the operational backbone for maintaining and monitoring the knowledge base. The dashboard displays key system metrics including 24,983 total files, 11,338 subjects, and 37 study programs, showing the system's capability to handle substantial institutional content volumes. The main interface provides a tabular view of ingested learning resources with critical columns:

a. File Sources (showing document names, sizes, and page counts)
b. Apps Sources (identifying origin platforms like "LMS" or "Library" through color-coded tags, validating successful API integration)
c. Subjects (listing specific courses with codes like "Big Data dan Data Analitik DAK3AAB4")
d. Study Program (indicating which academic programs the materials serve)
e. Status Embedding (displaying real-time processing status "Done," "On Progress," or "Failed"),
f. Date Embedding (tracking when content was processed).

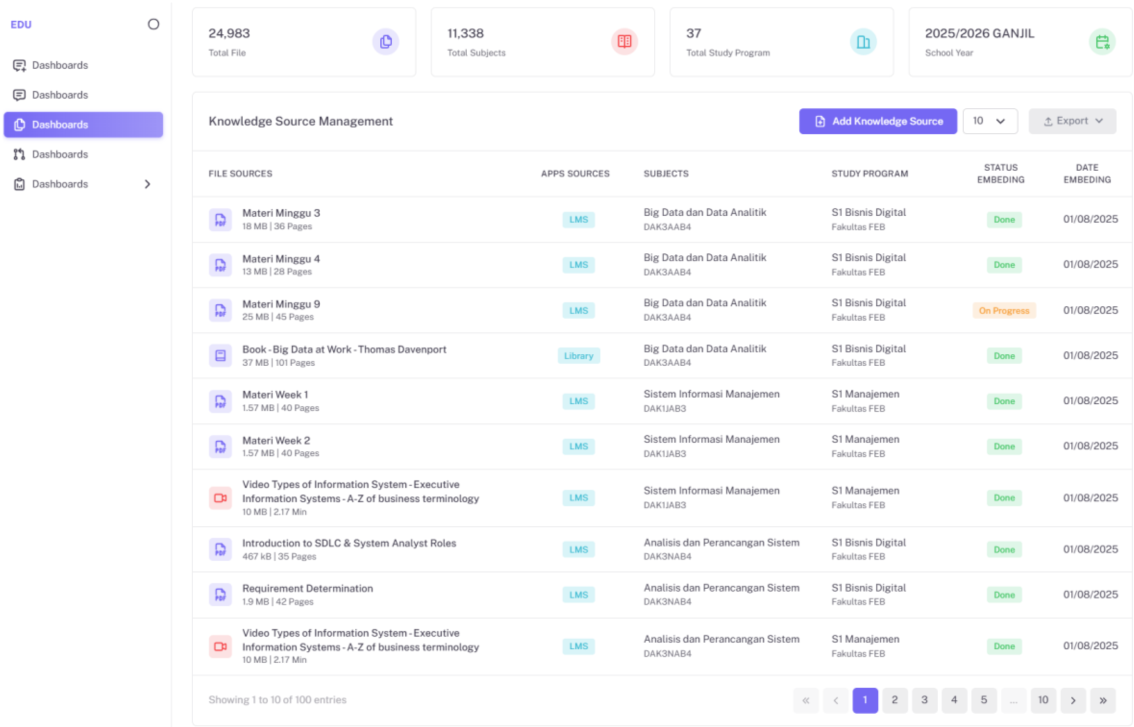

Figure 6. Knowledge Source Management

The most critical feature is the embedding status monitoring, which provides transparency into whether documents have been successfully processed through the extraction-chunking-embedding pipeline. Administrators can identify "Failed" documents and retry processing without re-uploading, ensuring system resilience and preventing knowledge gaps due to temporary technical glitches. The "Add Knowledge Source" button enables manual upload of specialized materials not available through automated API ingestion, complementing the automated synchronization capabilities. However, several constraints remain. The current implementation lacks systematic content validation, automated ingestion relies entirely on the quality of materials faculty upload to source platforms without detecting outdated content, contradictory information across sources, or extraction accuracy issues. This granular level of monitoring and control is essential for maintaining the integrity and reliability of the knowledge base, which is a direct prerequisite for the chatbot's performance in delivering accurate and contextually relevant responses.

1.2. Technology Acceptance Model (TAM) Evaluation

Following the implementation and validation of the RAG-based chatbot system's technical capabilities, the evaluation process proceeded to assess user acceptance and adoption potential. To measure user perceptions and behavioral intentions, we demonstrated to 267 undergraduate students from four higher education institutions through presentation sessions showcasing its functionality for academic-related queries and educational support capabilities. The Technology Acceptance Model evaluation reveals highly positive user acceptance across all measured constructs. The comprehensive assessment provides valuable insights into user perceptions and adoption intentions for the developed educational technology. The evaluation results are presented in Tables 2 and 3, which detail the statistics and acceptance categorization for each TAM construct and individual questionnaire item.

Table 2. TAM Summary

TAM Variable	Mean Score	Acceptance Category
Perceived Usefulness (PU)	4.138	High
Perceived Ease of Use (PEU)	4.023	High
Intention to Use (ITU)	4.129	High
Overall Average	**4.097**	**High**

Table 3. Individual Item Analysis

Code	Mean Score	Acceptance Category
PU1	4.068	High
PU2	4.133	High
PU3	4.213	High
PEU1	4.103	High
PEU2	4.072	High
PEU3	3.894	Moderately High
ITU1	4.027	High
ITU2	4.046	High
ITU3	4.194	High
ITU4	4.251	High

The Technology Acceptance Model evaluation demonstrates exceptional user acceptance of the RAG-based chatbot system, with an overall mean score of 4.097 indicating "High" acceptance across all constructs. This finding provides valuable preliminary evidence for the system's viability and potential for widespread adoption in educational environments.

The Perceived Usefulness construct achieved the highest mean score of 4.138, proving that students strongly recognize the practical value of the RAG-based chatbot for their academic activities. Notably, PU3 (information retrieval efficiency) scored highest at 4.213, validating the system's core functionality in addressing information fragmentation challenges identified in the problem formulation phase. The consistently high scores across all usefulness items (PU1: 4.068, PU2: 4.133, PU3: 4.213) indicate that students perceive clear benefits in task completion, learning support, and rapid information access, aligning with the design objectives established during the DSRM development phase.

The Perceived Ease of Use construct scored 4.023, indicating that users find the system intuitive and accessible. While all items maintained high acceptance levels, PEU3 (interaction clarity) received the lowest score at 3.894, categorized as "Moderately High." Some users may experience minor challenges in understanding system responses or interface elements, though the score remains well within acceptable ranges for technology adoption. There exists room for improvement in how the chatbot presents information and guides user interactions. Users are occasionally needed additional time to interpret system responses, uncertainty about available commands or functions, or slight confusion regarding the chatbot's conversational flow. The impact of this finding is relatively limited given that the score approaches the "High" threshold, yet it represents a critical area for enhancement since interaction clarity directly affects user confidence and sustained engagement with the system. While the current interface design is functional, optimizing response formatting, providing clearer system prompts, or enhancing visual feedback mechanisms could further improve user experience. The strong PEU1 and PEU2 scores (4.103 and 4.072 respectively) demonstrate that the conversational interface design successfully provides effortless user interaction, supporting the natural language processing capabilities inherent in the RAG architecture.

The Intention to Use construct scored 4.129, with ITU4 (peer recommendation) achieving the highest score among all questionnaire items at 4.251. This score indicates strong confidence in peer recommendation, suggesting high perceived value and reliability. The consistently strong ITU scores (ranging from 4.027 to 4.251) providing compelling evidence for successful technology acceptance and future adoption potential. These strong acceptance scores must be interpreted carefully within the methodological constraint of demonstration-based evaluation acknowledged throughout this manuscript. Participants evaluated the system based on observed demonstrations showcasing capabilities rather than hands-on extended usage in authentic academic contexts. This approach may inflate scores due to several well-documented phenomena. Initial enthusiasm for innovative technology before experiencing real-world friction and limitations; evaluation of potential benefits without experiencing costs such as time spent formulating effective queries, occasional inaccurate or incomplete responses, or system failures under heavy load; absence of frustration from actual usage challenges that polished demonstrations do not reveal; and social desirability bias in evaluation contexts where participants may provide positive ratings to please researchers or appear technologically savvy. Therefore, while these TAM scores provide encouraging preliminary evidence of strong initial reception and adoption potential.

1.3. Faculty Qualitative Perspective

To complement student quantitative evaluation and address the limitation that successful implementation requires faculty buy-in, semi-structured interviews were conducted with five faculty members from three universities, representing both technical (engineering, computer science) and social science (management, business) disciplines. Following system demonstrations, interviews explored pedagogical value, integration strategies, quality assurance concerns, and faculty role positioning. We acknowledge this as exploratory with limited scope (n=5, single-session interviews, no structured thematic analysis), requiring validation through more systematic qualitative research with larger samples and longitudinal perspectives.

Faculty uniformly identified the RAG chatbot as an innovative breakthrough for supporting student learning outside classroom hours, praising its ability to provide rapid, integrated access to fragmented institutional resources through an intuitive conversational interface. The 24/7 availability was consistently highlighted as addressing a persistent challenge students encountering difficulties when faculty are unavailable. Faculty expressed willingness to endorse it as an official university-supported tool, positioning it as a legitimate "first-stop" resource for initial information retrieval before seeking direct instructor consultation for deeper conceptual discussion.

A crucial insight emerged. While the tool excels at information retrieval and summarization, its design must compel students to consult and validate information through original sources rather than treating responses as definitive answers. Faculty worried about student over-reliance on synthesized summaries without engaging primary materials, potentially undermining critical thinking and scholarly verification practices. Design implications include: prominent source citations (which Figure 4 demonstrates through clickable links), explicit prompts reminding students to verify information independently, and response formats encouraging original document consultation. Some faculty suggested assignments explicitly requiring cross-referencing chatbot information with sources, teaching appropriate AI tool usage while maintaining source engagement as a learning objective.

Faculty affirmed their expert role remains essential for ensuring information accuracy, validating tool outputs in disciplinary contexts, providing nuanced interpretation beyond factual retrieval, facilitating deep conceptual understanding through adaptive dialogue, and maintaining academic standards. Rather than perceiving the chatbot as threatening, they positioned it as handling routine queries, freeing time for higher-order teaching activities requiring human judgment and expertise. However, faculty emphasized critical concerns: "Who verifies accuracy? Who is liable if incorrect information misleads students?" These questions underscore that implementation requires clear governance structures, regular content auditing with faculty oversight, transparent communication about system limitations, and institutional policies addressing quality assurance and accountability.

Technical faculty focused on technical accuracy and content currency in rapidly-evolving fields, emphasizing retrieval of recent materials over outdated versions. Social science faculty emphasized interpretation concerns and theoretical complexity, worried about oversimplified summaries of nuanced debates. Despite differences, both converged on: need for source validation mechanisms, importance of faculty oversight in content validation and pedagogical integration, and positioning chatbots as supplementary tools supporting and not replacing expert instruction.

2. Discussion

This research was motivated by the persistent challenges of information fragmentation and cognitive overload in contemporary higher education environments, where students struggle to access relevant learning materials scattered across multiple digital platforms (Kaklij et al., 2019).Traditional educational technologies often fail to provide integrated, contextually-aware support that addresses individual learning needs while maintaining institutional data privacy. The exponential growth of digital information and finite cognitive processing capabilities fundamentally impairs decision-making accuracy, with the phenomenon of information overload emerging when individuals fail to synthesize available information into coherent decisions (Shahrzadi et al., 2024). Educational stakeholders express profound concern regarding digital overload's impact on psychological well-being and academic performance (Lauri et al., 2020; Upadhyaya & Vrinda, 2021).

To address these challenges, we developed a Retrieval Augmented Generation (RAG)-based chatbot system that integrates seamlessly with existing Learning Management Systems, providing students with unified access to diverse educational resources through natural language interaction. This approach directly addresses the identified limitations of current LLM applications in educational settings, particularly the hallucination phenomenon where models generate factually incorrect information (Ji et al., 2023; Klesel & Wittmann, 2025), and static knowledge bases unable to incorporate current curricular updates (Li et al., 2025), making it suitable for educational applications requiring precise and verifiable information.

The higher Perceived Usefulness score compared to Perceived Ease of Use (4.138 vs 4.023) indicates that while students find the system user-friendly, they place greater emphasis on the practical benefits offered. This finding aligns with TAM theoretical predictions that usefulness often serves as the primary driver of technology adoption in educational contexts. The system's ability to provide real-time explanations and respond to student queries addresses the fundamental challenge that many students face when unable to engage in meaningful conversations with instructors due to large class sizes or limited faculty availability outside regular hours (Swacha & Gracel, 2025). The exceptional peer recommendation score (ITU4: 4.251) show organic adoption potential, which could facilitate the widespread implementation of AI-powered conversational agents that represent significant improvement over traditional search systems (Klesel & Wittmann, 2025).

Student TAM scores (4.097) reflect enthusiasm for convenience, efficiency, and 24/7 access. For faculty, while recognizing benefits, tempered their enthusiasm with concerns about educational soundness, sustainability, and quality assurance. This divergence reflects typical stakeholder priorities: students value practical benefits while faculty weigh educational soundness and institutional alignment. Successful implementation must address both perspectives, leveraging student enthusiasm as adoption motivation while addressing faculty concerns through robust governance frameworks, quality assurance protocols, explicit usage guidelines promoting appropriate use, student training teaching effective chatbot use alongside source validation, faculty involvement in content management decisions, and institutional support for sustainable operation. Strong student acceptance provides evidence of adoption potential; faculty concerns identify the organizational and pedagogical infrastructure necessary to realize that potential responsibly.

2.1. Implications

This research carries implications for multiple stakeholders in higher education. For educational institutions, the RAG-based chatbot demonstrates a viable pathway for modernizing learning support infrastructure while maintaining data privacy through local deployment. The system's ability to integrate fragmented resources addresses persistent accessibility challenges without requiring complete platform overhauls. For students, the 24/7 conversational interface provides immediate access to institutional knowledge, potentially reducing frustration from information seeking and enabling more efficient learning processes. For faculty, the technology offers potential to reduce routine informational queries, allowing greater focus on higher-order pedagogical activities requiring expert judgment. However, successful implementation demands robust governance frameworks including phased deployment with pilot courses, governance committees with IT and academic affairs representation, dedicated resources for knowledge base maintenance, source authority weighting and temporal prioritization mechanisms, clear policies for data privacy and ethical AI use, faculty training on pedagogical integration, and quality assurance protocols with regular content audits. Success requires addressing both technical functionality and organizational infrastructure supporting sustainable operation, positioning AI tools as supplementary rather than replacement mechanisms for expert instruction.

2.2. Research Contributions

This exploratory study contributes to understanding RAG architecture deployment in educational contexts across theoretical, methodological, and practical dimensions. Theoretically, we demonstrate that retrieval-based knowledge augmentation can address information fragmentation challenges while maintaining institutional data privacy through local infrastructure, extending AI-in-education literature by showing how RAG architecture addresses well-documented LLM limitations including hallucination and static knowledge bases. Methodologically, we provide a replicable Design Science Research framework for developing and evaluating educational AI systems, integrating quantitative Technology Acceptance Model assessment with qualitative faculty perspectives for multi-stakeholder evaluation. Practically, we deliver a functional proof-of-concept with detailed technical architecture validating technical feasibility and establishing baseline user acceptance, providing foundation for future validation studies. The adapted TAM instrument for educational chatbot contexts contributes measurement tools for subsequent adoption research, while the integration of student acceptance and faculty perspectives offers essential insights for implementation planning.

2.3. Limitations

Several critical limitations affect interpretation of findings. First, the demonstration-based evaluation means participants assessed anticipated rather than experienced usefulness, potentially inflating acceptance scores due to novelty effects without experiencing real-world friction. TAM scores reflect intended rather than sustained adoption patterns, requiring longitudinal field studies with actual usage over semester-long periods to validate effectiveness. Second, sample constraints (n=267 from four Indonesian universities) limit generalizability to different educational contexts, cultures, or student populations with varying technological readiness. TAM scores and acceptance patterns may differ across institutions with different resource levels, governance cultures, or learning value emphases. Third, absence of statistical validation (Cronbach's alpha, validity testing) means TAM construct measurements may contain unknown error, making findings indicative rather than psychometrically validated. Fourth, the exploratory faculty component (n=5, single-session interviews) requires validation through systematic qualitative research with larger samples, structured thematic analysis, and longitudinal perspectives tracking attitude changes through implementation phases. The small sample may not capture variations based on career stage, teaching philosophy, or institutional culture. Fifth, current implementation lacks systematic quality assurance mechanisms automated ingestion occurs without content validation, authority weighting, or temporal prioritization, with response accuracy depending entirely on faculty upload quality. Sixth, this study evaluated one solution without systematic comparison to alternatives like unified search portals or enhanced FAQ systems, demonstrating RAG viability but not definitively optimal approach.

2.4. Suggestions

Future research should prioritize five directions to validate and extend these preliminary findings. First, longitudinal field studies (12-18 months) tracking actual usage patterns, sustained adoption rates, and learning outcome impacts through semester-long deployments with real coursework usage are essential to move beyond proof-of-concept demonstrations. Second, comparative effectiveness research should empirically evaluate RAG chatbots against alternative solutions on information retrieval speed, task completion, user satisfaction, and learning outcomes to inform design decisions. Third, comprehensive faculty acceptance studies employing larger samples across diverse disciplines and institutions, structured thematic analysis with multiple coders, and longitudinal perspectives examining pedagogical integration challenges, workload impacts, and quality assurance practices are needed. Fourth, statistical validation through reliability testing and structural equation modeling would validate TAM constructs and theoretical relationships, strengthening measurement rigor. Fifth, cross-institutional replication studies across diverse institution types, countries, and educational contexts are necessary to test generalizability and identify boundary conditions.

Institutions considering adoption should employ phased deployment starting with pilot courses and faculty champions, establish governance committees with IT, academic affairs, and faculty representation, allocate dedicated resources for knowledge base maintenance, implement source authority weighting and temporal prioritization mechanisms, develop clear policies for data privacy and ethical AI use, provide faculty training on pedagogical integration and content management, and establish quality assurance protocols with regular content audits. Success requires addressing both technical functionality and organizational infrastructure supporting sustainable operation.

Despite acknowledged limitations, this research provides valuable preliminary evidence that RAG-based chatbots represent a promising technological approach for addressing information fragmentation and supporting student learning in higher education. The strong initial user acceptance combined with faculty recognition of pedagogical value, suggests the concept warrants continued investigation and cautious institutional experimentation through well-governed pilot implementations. We emphasize that our contribution lies in demonstrating technical feasibility and establishing baseline acceptance rather than validating effectiveness or sustained adoption. The path forward requires moving beyond proof-of-concept demonstrations to rigorous validation through longitudinal field studies measuring actual usage, learning outcomes, and sustained adoption in authentic educational contexts. We position this work as foundational exploratory research establishing that RAG technology can be successfully deployed in educational settings and resonates positively with potential users.

D. Conclusion

This research successfully developed and evaluated a RAG-based chatbot system that addresses information fragmentation and cognitive overload in higher education. The system demonstrated functional capabilities including multi-source information retrieval, content synthesis, transparent source citations, and scalability across academic disciplines. Student evaluation reveals strong initial acceptance (TAM score 4.097), with students prioritizing perceived usefulness (4.138) over ease of use (4.023) and showing high usage intentions (4.129) and recommendation willingness (4.251). Faculty interviews recognize the pedagogical value for 24/7 learning support while emphasizing critical needs for quality assurance mechanisms, source validation protocols, governance frameworks, and design features that compel students to consult original sources rather than over-rely on synthesized summaries.

This study delivers a functional proof-of-concept demonstrating technical feasibility and baseline user acceptance for RAG-based chatbots in educational contexts. However, critical limitations affect interpretation: demonstration-based evaluation rather than extended usage, sample constraints limiting generalizability beyond Indonesian undergraduate contexts, absence of statistical validation for TAM constructs, exploratory faculty inquiry with small sample, lack of systematic quality assurance in current implementation, and no comparative evaluation against alternatives. We position this as foundational exploratory research showing the RAG technology can be feasibly deployed in education and resonates positively with users, not validated evidence of sustained adoption or learning effectiveness.

Future research should prioritize longitudinal field studies tracking actual usage and learning outcomes, comprehensive faculty acceptance studies, statistical TAM validation, cross-institutional replication, and comparative effectiveness evaluation. Institutions considering adoption need phased deployment, robust governance committees, dedicated maintenance resources, quality assurance protocols, clear policies on data privacy and ethical AI use, faculty training, and mechanisms for source validation. Success requires addressing both technical functionality and organizational infrastructure aligned with educational values and pedagogical soundness.

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F. Author Contribution Statement

YM designed the research methodology, developed and implemented the RAG-based chatbot system, conducted system demonstrations and testing, distributed TAM questionnaires. HI, and DR analyzed the evaluation results. YM, DR, and HI wrote the manuscript and handled formatting.

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