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ARTIFICIAL INTELLIGENCE (AI)-BASED ONLINE ASSISTANT INTEGRATED INTO LEARNING MANAGEMENT SYSTEMS (LMS) FOR ASYNCHRONOUS LEARNING SUPPORT

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Abstract

The increasing adoption of asynchronous online learning has intensified the need for intelligent and responsive learning support within learning management systems (LMS). However, most existing LMS platforms remain limited to content management and administrative functions, providing minimal real-time and contextual assistance for learners. This study presents the design, integration, and technical evaluation of an artificial intelligence (AI)–based online assistant integrated directly into an LMS to support asynchronous learning activities. The proposed system, named ANSIA, was developed using a systems engineering approach that enables seamless integration without modifying the core LMS architecture. ANSIA utilizes learning context data from the LMS to generate relevant and context-aware responses to learners' queries. The system was implemented as a web-based module and evaluated through technical performance testing focusing on response accuracy, response time, and system reliability under realistic asynchronous learning scenarios. The results demonstrate that the AI assistant achieves high response accuracy, acceptable response times under varying loads, and stable operation during continuous use. These findings indicate that integrating an AI assistant into an LMS can enhance learning support while maintaining system stability and scalability. This study contributes a practical and technically validated approach for developing adaptive, modular, and sustainable AI-assisted online learning systems.

Keywords: AI Assistant, Design, Online learning, Higher education, Web.

1. Introduction

The rapid expansion of asynchronous online learning has increased the role of learning management systems (LMS) as the primary infrastructure for delivering instructional content, managing learning activities, and facilitating academic interactions in higher education. LMS platforms provide flexible access to learning resources and support independent study across diverse learning contexts [1, 2]. Despite continuous development, most LMS implementations remain primarily oriented toward content management and administrative processes, offering limited real-time and adaptive support for learners during asynchronous learning activities [3, 4].

In asynchronous learning environments, students frequently encounter challenges when seeking timely clarification, feedback, or guidance while working independently. The absence of immediate instructional support often disrupts learning continuity, reduces engagement, and increases learner frustration [5, 6]. Although communication tools such as forums and messaging systems are available within LMS platforms, these tools largely depend on delayed instructor responses and lack intelligent mechanisms for contextualized assistance. Consequently, existing LMS architectures remain insufficient in addressing learners' dynamic support needs in self-directed learning scenarios.

Recent advances in artificial intelligence (AI), particularly in natural language processing, have enabled the development of AI-based assistants to support online learning. Prior studies indicate that AI assistants can enhance learner engagement, motivation, and self-regulated learning by providing continuous and accessible support [7, 8]. However, most existing AI assistants are developed as standalone systems or loosely connected to LMS platforms, limiting their ability to utilize learning context data such as course structure, learning materials, and student activity records. Moreover, existing research predominantly focuses on user perceptions and pedagogical outcomes, while system architecture design, integration mechanisms, and technical performance evaluation remain underexplored [9, 10].

To address these limitations, this study aims to design, integrate, and evaluate an artificial intelligence–based online assistant embedded directly into an LMS to support asynchronous learning. The novelty of this study lies in (i) integrating an AI assistant into an LMS without modifying its core architecture, (ii) leveraging LMS learning context to generate relevant and context-aware responses, and (iii) conducting a technical performance evaluation based on response accuracy, response time, and system reliability. Through a systems engineering approach, this study contributes a modular, scalable, and technically validated solution for enhancing LMS-based asynchronous learning support.

2. Literature Review

2.1. Learning management systems in asynchronous online learning

LMS serves as the core infrastructure for asynchronous online learning in higher education, enabling the organization of learning content, management of learning activities, and facilitation of academic communication between instructors and students [1, 2]. LMS platforms support flexible and self-paced learning, allowing students to access materials and complete activities independently across time and

location constraints. Empirical studies have shown that effective LMS adoption contributes positively to learner engagement and learning outcomes when system usability and content quality are adequately addressed [3, 4].

However, most LMS implementations remain primarily focused on content delivery and administrative management rather than providing adaptive and intelligent learning support. Interaction within LMS environments is often limited to one-directional communication, where students rely on delayed instructor responses for clarification or feedback, particularly in asynchronous settings [11]. Figure 1 illustrates the general position of LMS within online learning systems, highlighting its central role in managing learning processes while exposing limitations related to interaction and real-time support.

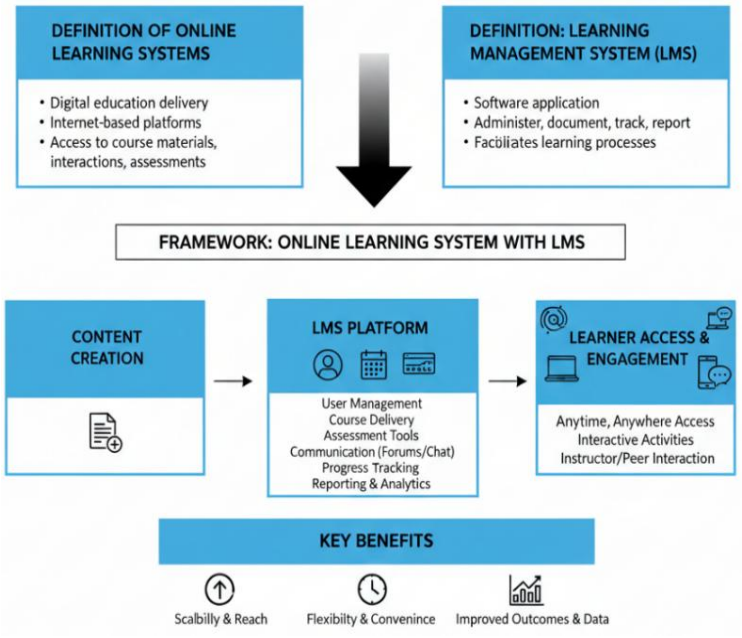

Fig. 1. Online learning systems and the role of LMS.

From a system perspective, these limitations indicate that LMS platforms lack built-in mechanisms for delivering timely, contextual, and personalized assistance to learners during independent study. Asynchronous learning environments, therefore, require complementary systems that can enhance LMS functionality without compromising system stability or scalability.

Table 1 summarizes the primary roles of LMS in online learning systems alongside the limitations identified in previous studies, emphasizing gaps in adaptive learning support and intelligent interaction.

2.2. AI-based online assistants for learning support

Recent advances in AI, particularly in natural language processing, have enabled the development of AI-based online assistants to support learning activities in digital environments. Prior research indicates that AI assistants can enhance learner

motivation, engagement, and self-regulated learning by providing continuous and accessible responses to learner inquiries [7, 8]. AI assistants are commonly used to answer content-related questions, provide explanations, and guide learners through learning tasks, thereby reducing instructor workload and supporting independent learning processes.

Table 1. The role of LMS in online learning systems.

No.	System Aspects	The Role of LMS in Online Learning	Limitations Found
1	Content Management	Providing and managing learning materials in a structured manner	Content is static and lacks interactive support
2	Learning Activities	Facilitating asynchronous assignments, forums, and quizzes	Limited interaction and not adaptive to user needs
3	Learning Support	Providing learning information and guidance	Does not provide real-time intelligent assistance
4	User Interaction	Connecting students and instructors through communication features	Dependence on manual responses from instructors

Figure 2 presents the general role of AI assistants and chatbots in online learning contexts, illustrating their function as interactive support tools that mediate learner-system interactions.

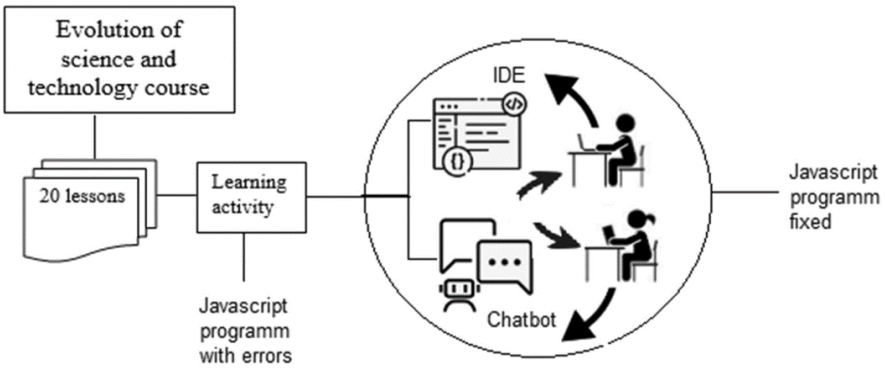

Fig. 2. Chatbots in the context of online learning.

Despite these benefits, many AI assistants are developed as standalone systems or loosely connected tools operating outside institutional LMS platforms. Consequently, such systems lack access to structured learning context data, including course organization, learning materials, and learner activity records. Without contextual awareness, AI-generated responses often remain generic and insufficiently aligned with learners' actual academic needs [9]. Furthermore, most existing studies emphasize learner perceptions and pedagogical impacts, while technical considerations such as system architecture, integration strategies, and performance reliability are less frequently addressed.

2.3. Integration of AI assistants into learning management systems

Integrating AI assistants directly into LMS platforms has emerged as a promising approach to addressing the limitations of standalone AI systems. LMS-integrated AI assistants can leverage learning context data to deliver more relevant, contextual, and timely support, thereby improving the effectiveness of asynchronous learning environments [10]. Such integration enables AI assistants to function as part of the learning workflow rather than as external applications, reducing platform switching and improving system usability.

Figure 3 illustrates the potential benefits of AI integration within LMS platforms, including the use of natural language processing, data analysis, and content generation to enhance learning support.

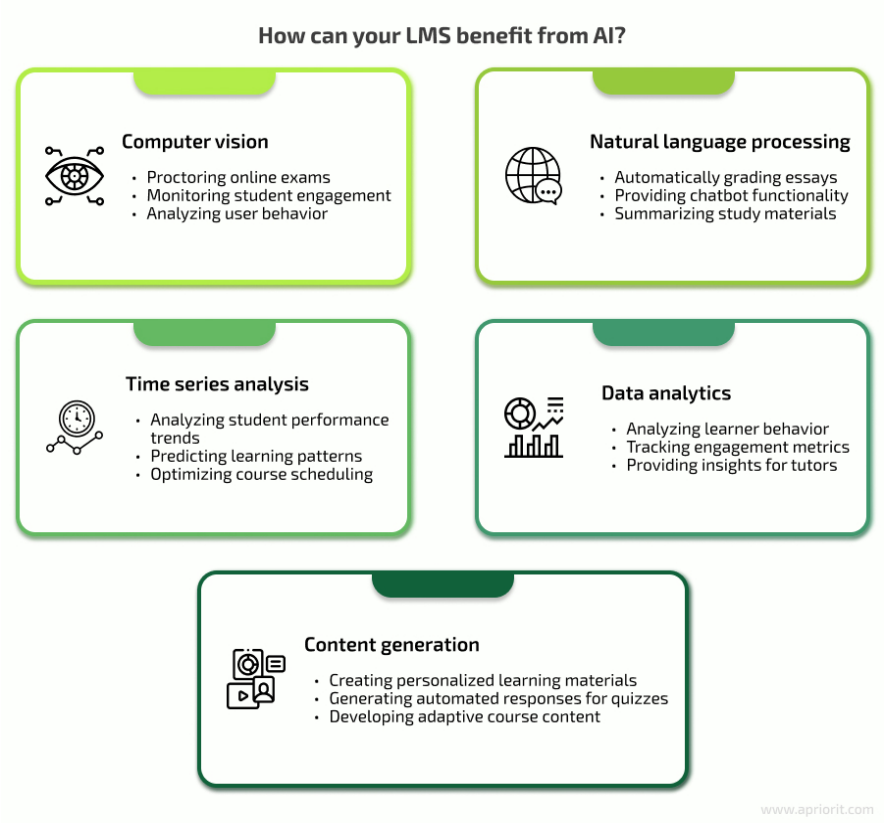

Fig. 3. How AI can benefit Learning Management Systems.

From a systems engineering perspective, effective integration requires a modular and scalable architecture to ensure that AI components do not disrupt core LMS functionality. Prior research suggests that modular integration strategies can enhance LMS capabilities while maintaining system stability and sustainability [12]. Nevertheless, technical challenges remain, particularly regarding response latency, system reliability, data privacy, and ethical considerations. Moreover, empirical evaluations of LMS-integrated AI assistants often prioritize user satisfaction metrics, leaving technical performance indicators such as response accuracy and system reliability underexplored.

2.4. Research gap and positioning of the proposed system

Based on the reviewed literature, a clear research gap exists concerning the design and technical evaluation of AI-based online assistants integrated into LMS platforms for asynchronous learning support. Existing studies rarely provide detailed discussions of system architecture design, integration mechanisms, or quantitative performance evaluation under realistic learning conditions. This study addresses these gaps by proposing an AI-based online assistant integrated directly into an LMS using a systems engineering approach. The proposed system leverages the LMS learning context to generate relevant responses while maintaining system stability through modular integration. Furthermore, this study contributes empirical technical evaluation results based on response accuracy, response time, and system reliability, providing a comprehensive assessment of the feasibility and effectiveness of LMS-integrated AI assistants for asynchronous learning support.

3. Methodology

This study employed a systems engineering approach to design, integrate, and evaluate an artificial intelligence–based online assistant integrated into an LMS to support asynchronous learning. The methodological focus was placed on system development, integration strategy, and technical performance evaluation rather than on user perception analysis. The proposed system, named ANSIA, was developed as a web-based AI assistant module and embedded directly into the LMS environment without modifying the core LMS architecture.

The development process began with a requirement analysis to identify limitations of existing LMS platforms in providing timely and contextual learning support during asynchronous learning activities. Typical learner queries, learning contexts, and system constraints were analysed to inform architectural design decisions. Based on this analysis, a modular system architecture was designed, consisting of a user interface layer, an AI processing component, and a learning context management module that enables the assistant to access relevant course and activity information within the LMS. ANSIA was implemented as an integrated feature accessible through the LMS interface, ensuring that users could interact with the AI assistant without switching platforms or altering existing learning workflows. The system processes learner queries by first identifying the relevant learning context before generating responses, thereby improving response relevance and alignment with course content.

Technical performance evaluation was conducted to assess the feasibility and reliability of the proposed system in realistic asynchronous learning scenarios. The evaluation focused on three key metrics: response accuracy, response time, and system reliability. Response accuracy was measured by assessing the relevance of system responses to different types of learning-related questions, including conceptual, procedural, and clarification queries. Response time was evaluated under varying system load conditions to examine system efficiency, while reliability was assessed through continuous operation testing over an extended usage period to identify potential system failures or performance degradation.

4. Results and Discussion

4.1. System implementation results

The implementation of the artificial intelligence–based online assistant, ANSIA, focused on seamless integration into the existing LMS to support asynchronous learning activities. From a systems engineering perspective, the primary objective of the implementation phase was to embed the AI assistant as an additional functional module without modifying the core LMS architecture. This approach was adopted to ensure system stability, maintainability, and scalability while extending LMS functionality through intelligent support features.

The integration strategy enabled ANSIA to be accessed directly from the LMS interface via a dedicated menu, allowing learners to interact with the AI assistant within the same learning environment. This design minimizes platform switching and preserves existing user workflows, which is essential in asynchronous learning contexts where usability and simplicity strongly influence system adoption. Figure 4 illustrates the high-level interaction flow between users, the LMS, and the ANSIA module, showing how learner queries are processed and returned as contextualized responses.

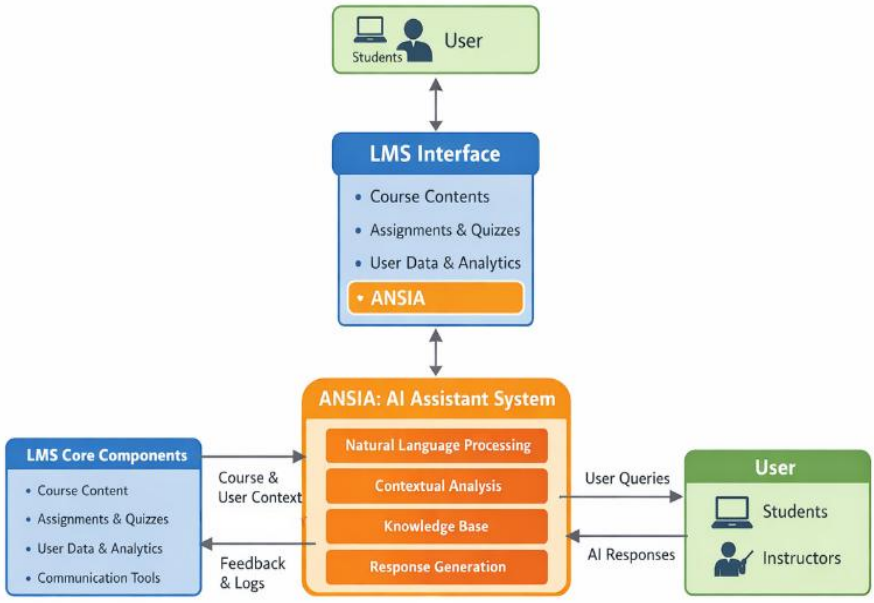

Fig. 4. Flowchart of ANSIA system access within the LMS.

At the architectural level, ANSIA was implemented using a modular design consisting of three main components: a user interface layer embedded in the LMS, an AI processing module responsible for natural language understanding and response generation, and a learning context management component that retrieves relevant course and activity information from the LMS. This modular separation ensures that updates or improvements to the AI component can be implemented independently without disrupting LMS core operations.

The system interface was designed to be lightweight and intuitive to accommodate learners with varying levels of digital literacy. Figure 5 presents the ANSIA interface as accessed through the LMS, demonstrating its integration as an internal support feature rather than an external application. From a functional standpoint, ANSIA successfully receives text-based learner queries and generates responses within the LMS environment, confirming that the integration does not interfere with standard LMS operations such as content access, assignment submission, or communication tools.

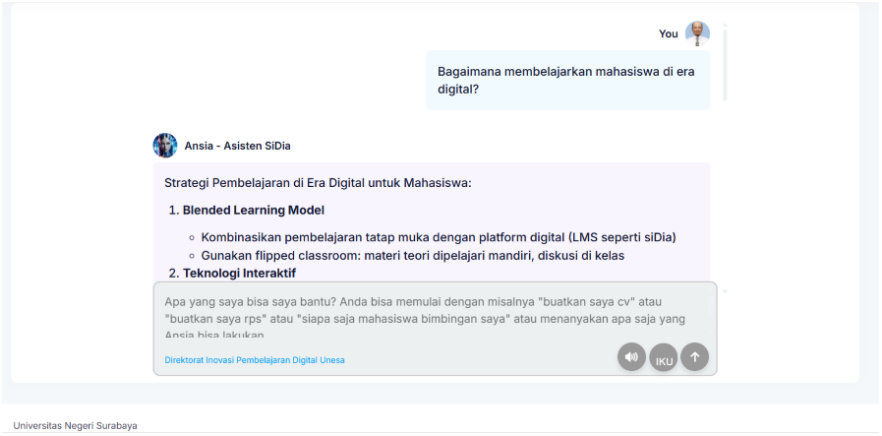

Fig. 5. ANSIA system interface embedded in the LMS.

The successful implementation confirms that AI-based online assistants can be integrated into LMS platforms using a non-intrusive approach. This finding supports prior assertions that modular system integration is essential for sustaining LMS stability while enabling intelligent extensions [12]. Unlike standalone AI assistants, ANSIA operates within the same learning ecosystem as its users, enabling direct access to learning context data and reinforcing its role as a system-level support component for asynchronous learning.

4.2. Response accuracy performance

Following system implementation, a technical performance evaluation was conducted to assess the effectiveness of ANSIA in providing relevant and accurate responses to learner queries. Response accuracy was selected as a primary evaluation metric because it directly reflects the system's ability to interpret learner intent and deliver meaningful assistance aligned with course content. In asynchronous learning environments, inaccurate or irrelevant responses may disrupt learning continuity and reduce user trust in AI-supported systems.

Response accuracy testing involved a structured set of learning-related questions designed to simulate realistic asynchronous learning scenarios. The questions were categorized into three main types: learning material concept questions, task instruction queries, and term clarification requests. Each response generated by ANSIA was evaluated for relevance and correctness based on alignment with the intended learning context.

Table 2 presents the results of the response accuracy evaluation, showing the proportion of relevant responses generated for each question category. The results indicate that ANSIA achieved a high average response accuracy of 87.6%, demonstrating its capability to provide contextually appropriate support across different types of learner inquiries. The highest accuracy was observed for task instruction queries, suggesting that structured learning context data retrieved from the LMS effectively supports procedural guidance. In contrast, slightly lower accuracy was observed for term clarification questions, which often require nuanced interpretation or broader conceptual explanations.

Table 2. ANSIA system response accuracy test results.

Question Type	Number of Questions	Relevant Responses (%)
Learning Material Concepts	40	87.5
Task Instructions	35	91.4
Term Clarification	25	84.0
Average	100	87.6

These findings align with previous research indicating that LMS-integrated AI assistants benefit from access to structured learning data, enabling more relevant responses compared to standalone systems [10]. The use of learning context as a filtering mechanism before response generation appears to play a critical role in enhancing accuracy. From a systems engineering perspective, this result validates the architectural decision to include a learning context management component within ANSIA.

4.3. Response time performance

In addition to accuracy, response time was evaluated to assess system efficiency under varying usage conditions. In asynchronous learning environments, timely responses are essential to maintain learning flow, particularly when learners engage in self-directed study without immediate instructor support. Excessive response delays may negatively affect user experience and diminish the perceived usefulness of AI-based support systems.

Response time testing was conducted under three simulated system load scenarios: low, medium, and high usage levels. Each scenario involved a predefined number of user requests submitted within a controlled testing period. The average response time for each scenario is presented in Table 3.

Table 3. ANSIA system response time test results.

Usage Scenario	Number of Requests	Average Response Time (ms)
Low Load	30	820
Medium Load	40	1,140
High Load	30	1,560

The results show that ANSIA maintains acceptable response times across all tested load conditions, with average response times remaining below two seconds even under high load. This performance level is consistent with prior studies on

LMS-integrated AI assistants, which report that response times within this range are sufficient to support effective asynchronous learning interactions [13].

The gradual increase in response time under higher load conditions reflects expected system behaviour and indicates that the system architecture scales proportionally with usage demand. Importantly, no system crashes or timeouts were observed during testing, suggesting that the AI processing and LMS integration layers are adequately optimized for sustained operation. These findings support the feasibility of deploying ANSIA as a reliable support system in real-world asynchronous learning environments.

4.4. System reliability performance

System reliability is a critical requirement for AI-based support systems embedded in LMS, particularly in asynchronous learning environments where learners depend on continuous system availability. Reliability testing was therefore conducted to evaluate ANSIA's ability to operate stably over an extended period under repeated usage conditions. From a systems engineering perspective, reliability reflects not only system robustness but also the effectiveness of the chosen integration strategy.

The reliability test simulated real asynchronous learning conditions by allowing repeated user interactions with ANSIA over a seven-day continuous operation period. During this phase, the system processed a total of 1,250 learner interactions involving various types of queries related to course materials, task instructions, and clarifications. The primary indicators observed included system uptime, interaction success rate, and the occurrence of functional failures or interruptions. Table 4 summarizes the system reliability test results.

Table 4. ANSIA system reliability test results.

Test Parameter	Test Results
Test Duration	7 days
Number of Interactions	1,250
System Failures	0
Success Rate (%)	100%
Operational Status	Stable

The results indicate that ANSIA maintained stable operation throughout the testing period, with no recorded system failures or interruptions. All user requests were processed successfully, and no degradation in response accuracy or response time was observed during continuous use. This outcome demonstrates that the modular integration of the AI assistant into the LMS did not introduce instability or performance bottlenecks within the system.

From a technical standpoint, these findings validate the architectural decision to integrate ANSIA without modifying the LMS core architecture. By isolating AI functionalities within a modular layer, the system minimizes the risk of cascading failures that could compromise LMS operations. This approach aligns with prior research emphasizing modular and service-oriented architectures as key enablers of sustainable LMS enhancement [12]. The reliability results further suggest that ANSIA can be deployed as a long-term support component within asynchronous learning environments.

4.5. Discussion: Technical implications and system-level contribution

The results of this study provide important insights into the feasibility and effectiveness of integrating an AI-based online assistant into an LMS to support asynchronous learning. From a systems engineering perspective, the successful implementation and evaluation of ANSIA demonstrate that intelligent learning support can be added to existing LMS platforms without compromising system stability, scalability, or performance [13-15].

First, the system implementation results confirm that non-intrusive integration is achievable through a modular architectural design. Unlike approaches that require modifications to LMS core components, the integration strategy adopted in this study allows the AI assistant to function as an extension of the LMS rather than a replacement or parallel system. This is particularly significant for higher education institutions that rely on stable LMS infrastructures and are often reluctant to adopt solutions that may disrupt existing systems. The findings reinforce the notion that LMS enhancement should prioritize compatibility and maintainability to ensure long-term sustainability.

Second, the response accuracy results highlight the importance of contextual awareness in AI-based learning support systems. By leveraging learning context data available within the LMS, ANSIA was able to generate relevant responses across different categories of learner queries. This supports previous findings that context-aware AI assistants outperform generic or standalone systems in educational settings [10]. From a technical design standpoint, the inclusion of a learning context management component proved to be a key factor in improving response relevance and system effectiveness.

Third, response time performance indicates that ANSIA meets efficiency requirements for asynchronous learning support. Maintaining response times below two seconds under varying load conditions suggests that the system can support realistic usage scenarios without introducing delays that could disrupt learning flow. These results are consistent with prior studies reporting acceptable performance thresholds for LMS-integrated AI assistants [16]. The scalability observed in response time behaviour further demonstrates that the system architecture can accommodate increased usage demand [17-21].

System reliability results further strengthen the technical contribution of this study. Continuous operation without failures over an extended testing period indicates that the integration approach is robust and suitable for sustained deployment. Reliability is a fundamental prerequisite for user trust and system adoption, particularly in educational contexts where system failures can negatively impact learning outcomes. The observed stability suggests that AI-based online assistants can be integrated into LMS platforms as dependable support systems rather than experimental add-ons [22-24].

Beyond individual performance metrics, the overall findings contribute to addressing a key research gap identified in the literature. While previous studies have largely focused on user perceptions and pedagogical impacts of AI assistants, this study provides empirical evidence from a technical and system-level evaluation [25-29]. By examining response accuracy, response time, and reliability within a real LMS environment, this work offers a comprehensive assessment of the feasibility of LMS-integrated AI assistants from an engineering perspective [30].

The implications of this study extend to future development of intelligent online learning systems. The results suggest that higher education institutions can enhance asynchronous learning support by adopting modular AI solutions that operate within existing LMS infrastructures. Such an approach enables gradual system evolution, reduces implementation risks, and supports scalability across courses or institutional contexts. Nevertheless, future work should address additional technical considerations, including data privacy, ethical use of AI, and integration with advanced learning analytics to further enhance system functionality.

5. Conclusions

This study demonstrates that an artificial intelligence–based online assistant can be effectively integrated into an LMS to support asynchronous learning without modifying the core system architecture. Using a systems engineering approach, the proposed ANSIA system achieved satisfactory technical performance in terms of response accuracy, response time, and system reliability under realistic usage conditions. The results confirm that leveraging LMS learning context enhances the relevance of AI-generated responses while maintaining system stability and scalability. This study contributes a practical and technically validated integration model for AI-assisted learning support within LMS environments, offering a sustainable pathway for enhancing asynchronous online learning systems in higher education.

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