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EduVa: Prototyping and testing AI-powered interactive LMS with adaptive modules and assessments

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Abstract. The rapid integration of artificial intelligence (AI) in higher education has increased the demand for adaptive Learning Management Systems (LMS) capable of delivering personalized learning at scale. However, empirical studies covering the full lifecycle of designing, prototyping, and testing AI-powered LMS remain limited, particularly in developing regions. This study aimed to design, prototype, and test EduVa LMS (Education Virtual Assistant), an AI-powered interactive LMS with adaptive modules and AI-driven assessments, implemented across ten private universities in East Nusa Tenggara, Indonesia. A Design Science Research (DSR) approach integrated with the ADDIE model guided the development process. A total of 360 participants were involved, including experts, students, and lecturers. Validation results showed a Content Validity Index (CVI) of 0.80, confirming content validity. Usability testing using the System Usability Scale (SUS) yielded mean scores of 82.4 (students) and 85.8 (lecturers). Adaptive performance analysis indicated 82.1% assessment accuracy, 3.7 content adjustments per session, and an 87.9% completion rate. A strong correlation ($r = 0.81$, $p < .01$) was found between AI assessments and learning objectives. The findings demonstrate that the EduVa LMS is valid, usable, and effective for implementing adaptive learning.

Introduction

The rapid advancement of digital technologies has fundamentally transformed the landscape of higher education, prompting institutions worldwide to reconsider how teaching and learning are designed and delivered. Learning Management Systems (LMS) have emerged as one of the most critical infrastructures supporting this transformation, providing centralized platforms for course delivery, student interaction, and academic assessment (Prahani et al., 2021). Over the past three decades, LMS adoption has grown exponentially, evolving from basic content repositories into sophisticated environments capable of supporting diverse pedagogical strategies (Furqon et al., 2023). Despite widespread adoption, conventional LMS platforms often fall short in addressing students' individual learning needs, relying instead on uniform content delivery and static assessment structures that fail to accommodate variation in learners' pace, prior knowledge, and cognitive style (Akour & Alenezi, 2022).

The integration of Artificial Intelligence into educational technology enables personalized learning by analyzing student data to adapt content, pacing, and assessments according to individual needs. Adaptive learning systems use machine learning to provide real-time customized learning pathways, which have been shown to improve academic performance, engagement, and self-regulated learning (Gupta et al., 2022). Research has demonstrated that such systems not only improve academic outcomes but also enhance student motivation, engagement, and self-regulated learning behaviors (Huang et al., 2020; Widana, 2022).

The convergence of AI and LMS has attracted significant scholarly attention in recent years. Studies have examined how AI-enabled recommendation systems, learning analytics, and intelligent agents can be embedded within LMS environments to support personalized learning (Sajja et al., 2024). Systematic reviews have confirmed a growing body of evidence suggesting that AI-integrated e-learning systems outperform traditional approaches in terms of learner engagement and academic performance (Tang et al., 2021; Susanto et al., 2026). Despite this, the majority of existing implementations remain at the theoretical or conceptual stage, with limited empirical studies examining the practical development, prototyping, and testing of fully integrated AI-powered LMS platforms in real-world higher education settings (Dogan & Dogan, 2023; Suwardika et al., 2026).

Adaptive learning systems rely on several core AI mechanisms, including learning-style detection, cognitive-state prediction, and reinforcement-learning-based path recommendations. These technologies enable the system to infer learner preferences and dynamically reconfigure the learning sequence accordingly (Amin et al., 2023). Furthermore, AI-based assessments have moved beyond static quizzes toward formative, adaptive, and competency-based evaluation formats, which have been identified as key components in supporting deeper learning and timely feedback. The role of pedagogical agents and intelligent assistants in guiding learners through these adaptive pathways has also been recognized as an important dimension of effective AI-powered LMS design (Apoki et al., 2022).

Higher education institutions face growing pressure to adopt digital transformation strategies that not only improve instructional quality but also ensure equity, accessibility, and scalability (Naveed et al., 2023). The increasing prevalence of online and blended learning modalities has further accelerated the demand for robust, intelligent LMS platforms capable of sustaining learner engagement across diverse contexts (Anoir et al., 2024). Studies have highlighted that the adoption of e-learning technologies in higher education is shaped by factors such as usability, perceived usefulness, institutional support, and technical infrastructure, all of which must be carefully considered during system design and prototyping (Lin, 2022).

The intersection of generative AI, large language models (LLMs), and educational technology represents a particularly promising frontier. Tools such as ChatGPT and other LLM-based assistants have demonstrated potential to support personalized academic advising, provide intelligent feedback, and augment instructors' capabilities (Adiguzel et al., 2023). However, the ethical, pedagogical, and technical implications of integrating such systems into formal LMS environments remain underexplored (Chiu, 2024). A comprehensive and structured approach to prototyping and empirically testing such systems is therefore essential to ensure they are both educationally sound and technically robust (Olatunbosun, O., 2026).

Scoping reviews on adaptive learning in higher education have identified key characteristics that distinguish effective systems, including real-time feedback mechanisms, data-driven personalization, and seamless integration with existing institutional platforms (du Plooy et al., 2024). These reviews also underscore the importance of measuring impact not only on academic performance but also on engagement, satisfaction, and self-regulation (Contrino et al., 2024). Despite these insights, few studies have moved from theoretical frameworks to actionable system prototypes tested under real-world conditions, particularly in developing economies, where infrastructure constraints add layers of complexity (Tudorache, 2023).

The concept of AI and LMS integration has been explored from multiple perspectives, including its impact on student outcomes, faculty workload, institutional strategy, and long-term sustainability (Alotaibi, 2024). Research emphasizes that successful implementation requires not only technological sophistication but also alignment with pedagogical goals, curriculum design, and learner-centered principles (Ayeni et al., 2024). When properly implemented, personalized adaptive learning has shown measurable positive effects on both academic performance and learner engagement, supporting its continued development and adoption in higher education settings (Hashim et al., 2022).

Despite the growing body of literature on AI in education, a significant gap remains in empirical studies that document the full lifecycle of designing, prototyping, and systematically testing an AI-powered interactive LMS with adaptive modules and intelligent assessments (Chiu et al., 2023). Many existing platforms lack integration between adaptive content delivery and AI-driven assessment, resulting in fragmented learning experiences that do not fully capitalize on the potential of intelligent systems (Nouman et al., 2024). Furthermore, studies examining learning technology models that support personalization within blended environments highlight the need for platforms that can accommodate diverse instructional contexts without sacrificing technical performance or educational effectiveness (Alauri et al., 2021).

Unlike previous studies that addressed adaptive content delivery and AI-based assessment separately or remained at conceptual stages (Dogan & Dogan, 2023), this study uniquely integrates both within a single fully prototyped LMS, empirically tested across ten institutions in a developing regional context rarely represented in the literature (du Plooy et al., 2024), thereby contributing original evidence on the full design-to-testing lifecycle of an AI-powered adaptive LMS in Indonesian higher education. This study aims to design, prototype, and empirically test an AI-powered interactive LMS with adaptive learning modules and intelligent assessments for higher education. The system integrates personalization, adaptive content sequencing, and formative assessment within a cloud-based platform to address the limitations of conventional LMS and strengthen the evidence base for adaptive learning (Naatonis et al., 2026). This research contributes to ongoing efforts to develop scalable, intelligent, and pedagogically grounded learning environments that dynamically respond to individual learners' needs (Azadi et al., 2021). This study investigates how valid, usable, and effective the EduVa LMS is as an AI-powered adaptive learning system for higher education in East Nusa Tenggara, Indonesia, hypothesizing that the system will demonstrate expert-confirmed content validity (CVI $\geq$ 0.70), acceptable usability for both students and lecturers (SUS $\geq$ 70), and adaptive assessment accuracy strongly aligned with learning objectives ($r \geq 0.70$).

Method

Research Design

This study applied a Design Science Research methodology, integrated with the ADDIE model, to guide the development and testing of an AI-powered LMS with adaptive modules for Indonesian higher education. DSR supported the creation and evaluation of the system, while ADDIE ensured alignment with instructional design principles (Atif et al., 2021; Meena & Richards, 2021; Deborah & Bilgin, 2021). The ADDIE model complemented DSR by ensuring that each development phase remained grounded in sound instructional design principles and maintained alignment between technological capabilities and pedagogical objectives throughout the process (Chiu et al., 2023). This study was conducted in 2025 across 10 private universities in East Nusa Tenggara Province, Indonesia, involving 360 participants in three roles: 10 expert validators who assessed content validity, 320 undergraduate students who participated in usability testing, and 30 lecturers who evaluated the pedagogical appropriateness of the EduVa LMS. The research followed six sequential and iterative phases: needs analysis, system design, prototyping, expert validation, usability testing, and revision and finalization, as shown in Image 1.

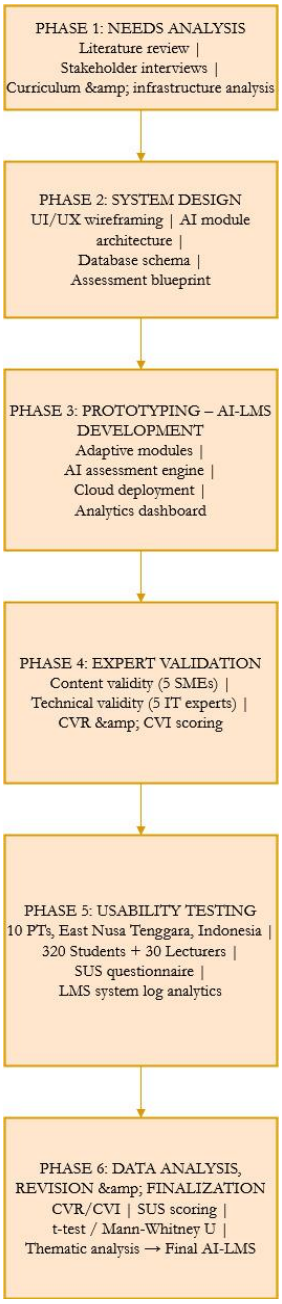

Image 1. Research Procedure for Development and Testing of the AI-Powered Interactive LMS

Participating Institutions
The usability testing phase was conducted across ten private universities in East Nusa Tenggara Province, Indonesia. Institutions were selected through purposive sampling based on three eligibility criteria: (1) active digital or blended learning programs at the undergraduate level; (2)

sufficient internet infrastructure to support cloud-based LMS access; and (3) formal institutional consent. The ten participating institutions represented major technology-related study programs in the province, including Information Technology, Computer Science, Informatics Engineering, and Information Systems, with each institution contributing between 28 and 36 student participants and 2 to 4 lecturer participants, ensuring proportional multi-site representation. All institutions held active BAN-PT accreditation at the time of the study, with ratings of Good or Very Good.

Research Participants

A total of 350 participants were involved across the usability testing and validation phases. The usability testing phase engaged 320 undergraduate students and 30 lecturers from the ten participating universities. For the expert validation phase, 10 validators were recruited separately, comprising five subject-matter experts (SMEs) in educational technology and instructional design, and five information technology and media experts in AI systems and LMS development (Tendulkar et al., 2023). All participants provided written informed consent, and data collection complied with applicable ethical standards for educational research in Indonesia. Student participants were undergraduate students in technology-related programs who were actively enrolled in courses that used digital platforms, while lecturers were selected for their involvement in technology-mediated teaching within the same programs. The demographic profile of both groups, including academic semester and prior LMS usage experience, is presented in Table 1 (Chan, 2023).

Table 1. Demographic Profile Of Research Participants Clustered By Semester and LMS Experience

Cluster	Category	Students (n)	Students (%)	Lecturers (n)	(%)
Cluster A — Academic Semester (Students) / Academic Rank (Lecturers)					
Semester (Students)	Semester 3	68	21.3		
	Semester 5	124	38.7		
	Semester 7	96	30.0		
	Semester 9+	32	10.0		
Academic Rank (Lecturers)	Asisten Ahli			9	30.0
	Lektor			13	43.3
	Lektor Kepala			6	20.0
	Profesor			2	6.7
Subtotal A		320	100.0	30	100.0
Cluster B — Prior LMS Usage Experience					
Students & Lecturers	Never used LMS	42	13.1	2	6.7
	< 2 years	96	30.0	8	26.7
	2–3 years	118	36.9	14	46.6
	> 3 years	64	20.0	6	20.0
Subtotal B		320	100.0	30	100.0
TOTAL	All Clusters	320	100.0	30	100.0

As shown in Table 1, Cluster A indicates that student participants were concentrated in Semester 5 (38.7%, n = 124) and Semester 7 (30.0%, n = 96), suggesting that the majority had intermediate to advanced levels of academic experience. Among lecturers, the Lektor rank was most prevalent (43.3%, n = 13), reflecting a predominantly mid-career teaching cohort. Cluster B shows that the largest proportion of students reported 2–3 years of prior LMS experience (36.9%, n = 118), while most lecturers similarly reported 2–3 years of usage (46.6%, n = 14), suggesting a moderate level of digital platform familiarity across both groups that is relevant to interpreting usability findings (Chan, 2023).

Data Collection Instruments

Four instruments were employed across the validation and testing phases. First, an expert validation questionnaire of 40 items organized across five dimensions, content accuracy, pedagogical alignment, adaptive mechanism quality, technical feasibility, and interface design, was administered to the ten expert validators using a five-point Likert scale. Content Validity Ratio (CVR) was computed per item using the Lawshe formula, with a minimum CVR threshold of 0.62 for a 10-member panel ($p < .05$). Retained items were aggregated into the Content Validity Index (CVI). System Usability Scale (SUS), a validated 10-item instrument yielding scores from 0 to 100, was administered to students (n = 320) and lecturers (n = 30) after structured interaction sessions with the LMS prototype, interpreted using standard benchmarks: above 85 (excellent), 71–84 (good), below 70 (marginal). Third, the LMS system analytics logs captured learner interaction data, including response accuracy, adaptive path trigger frequency, and average time on task. Fourth, open-ended questionnaire items collected qualitative user feedback on system experience, perceived benefits, and improvement suggestions (Chaudhry et al., 2023).

Data Analysis

A mixed-methods approach was used, where expert validation data were analyzed using CVR and CVI, while SUS scores were examined descriptively and compared between students and lecturers using appropriate statistical tests based on data normality, with effect sizes reported. System performance data from LMS logs were analyzed descriptively and correlated with learning objectives, and qualitative responses were examined using thematic analysis. All quantitative analyses were conducted using SPSS, Python, and R.

Table 2. Data Analysis Framework: Objectives, Techniques, And Tools

Research Objective	Data Source	Analysis Technique	Tool	Output
Content validity of AI-LMS	Expert questionnaire (n = 10)	Content Validity Ratio (CVR) & Content Validity Index (CVI)	MS Excel / SPSS	CVR per item; overall CVI score
System usability	SUS — Students (n=320) & Lecturers (n=30)	System Usability Scale (SUS) scoring & percentile benchmarking	SPSS v26	SUS score (0–100) & adjective rating
Group usability difference	SUS scores (both groups)	Independent t-test (normal) or Mann-Whitney U; Shapiro-Wilk normality test	SPSS v26	p-value; Cohen's d effect size

Research Objective	Data Source	Analysis Technique	Tool	Output
Adaptive module performance	LMS system log data	Descriptive statistics (mean, SD); adaptive path trigger frequency; time-on-task	Python / R	Performance report per learner session
AI assessment accuracy	Student responses (n=320)	Percentage accuracy; Pearson correlation with learning objectives	SPSS v26	Accuracy %; correlation coefficient (r)
Qualitative user feedback	Open-ended questionnaire items	Thematic analysis — 6-phase Braun & Clarke framework	NVivo / manual	Thematic clusters & improvement recommendations

This study employed a structured six-phase design integrating expert validation, multi-site usability measurement across ten private universities in East Nusa Tenggara, system performance analytics, and qualitative thematic analysis. Together, these methods ensured a methodologically rigorous and contextually grounded evaluation of the EduVa LMS prototype, supporting valid conclusions regarding its readiness for broader deployment in Indonesian higher education.

EduVa LMS was developed as a cloud-based web application accessible via standard browsers on desktop and smartphone devices, requiring a minimum internet connection of 2 Mbps to ensure stable performance across diverse institutional settings. The system was built using a responsive frontend framework and a Python-based backend, integrated with a machine learning engine that supports real-time adaptive content sequencing and automated AI-driven assessment. The platform consists of five core functional modules: a learning dashboard, a three-level adaptive learning module, an AI-based adaptive assessment engine, an intelligent learning assistant, and a student learning analytics dashboard. All modules are accessible through a single integrated web interface that supports multi-institutional deployment, with personalized learner profiles, and requires no additional software installation on the end users' part beyond a compatible web browser.

Results and Discussion

Prototype of the AI-Powered Interactive LMS (EduVa LMS)

The developed system (EduVa LMS) is a cloud-based, AI-powered Learning Management System featuring five core functional modules, accessible through an integrated, responsive web interface. The system was designed and developed to deliver personalized, adaptive learning experiences by integrating artificial intelligence mechanisms for content sequencing, difficulty adjustment, formative assessment, and learning analytics. Images 2 through 6 present the key interface screens of the EduVa LMS prototype.

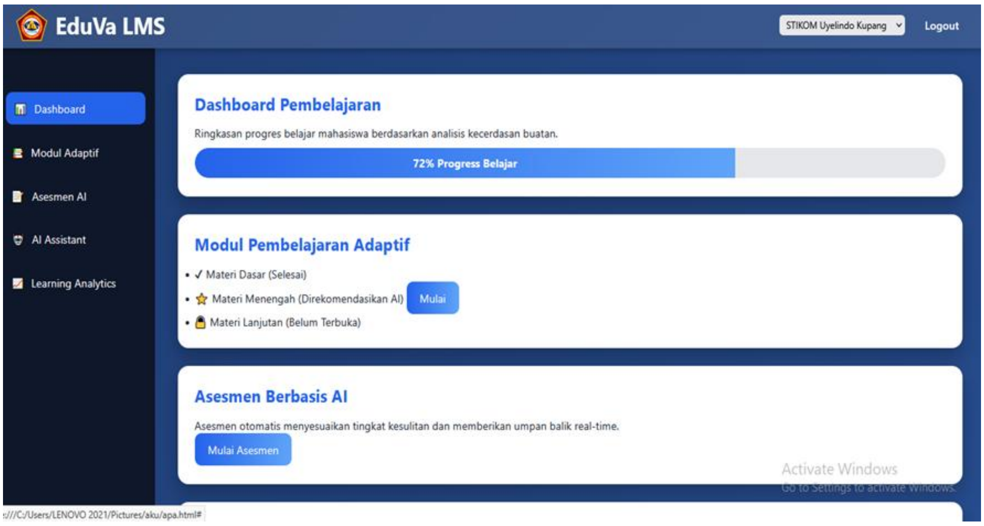

Image 2. Main Learning Dashboard of EduVa LMS

Image 2 shows the Dashboard Pembelajaran as the central interface of the EduVa LMS, which monitors student learning progress in real time by aggregating interaction data and displaying it in a simple, accessible format. The dashboard presents a progress bar indicating a 72% completion rate calculated by the AI based on completed modules, assessment results, and learning duration, while also providing quick access to key features such as the Adaptive Learning Module, AI-Based Assessment, AI Assistant, and Learning Analytics, thereby reducing navigation complexity and improving user experience, with the institution label indicating support for multi-institutional use with personalized learner profiles.

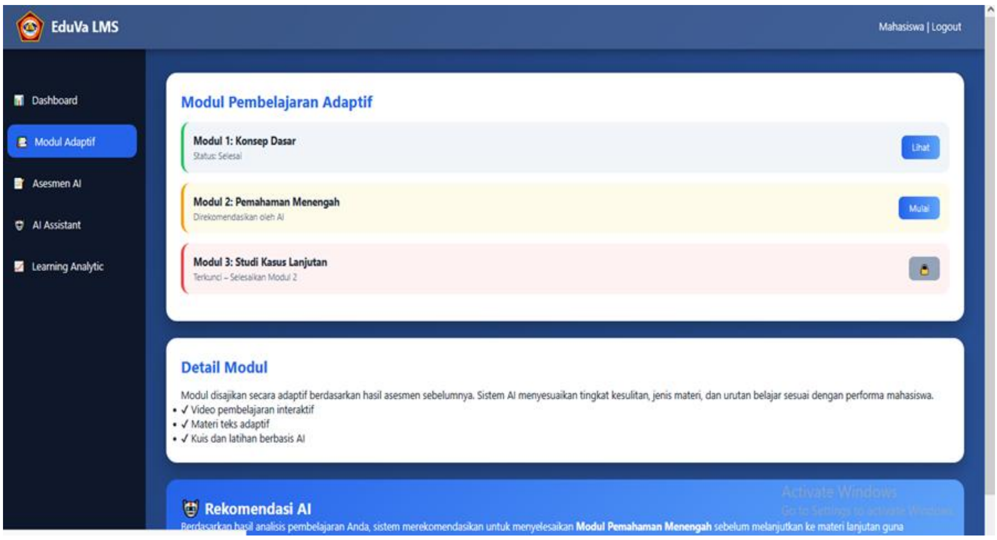

Image 3. Adaptive Learning Module Interface

Image 3 shows the Modul Pembelajaran Adaptif as the main instructional component of the EduVa LMS, where learning content is organized into three sequential modules, namely Basic Concepts, Intermediate Understanding, and Advanced Case Studies, which are unlocked progressively based on the learner's mastery. The system indicates that Module 1 is completed, Module 2 is recommended by the AI as the next step, and Module 3 remains locked until the previous module is finished, with the AI determining progression based on assessment results, response accuracy, and learning speed.

Image 4. AI-Based Adaptive Assessment Interface

Image 4 displays the Asesmen Adaptif Berbasis AI interface as the intelligent assessment component of the EduVa LMS, which dynamically adjusts question difficulty in real time based on learner responses. The system shows the current difficulty level as Menengah and indicates that adjustments are performed automatically by AI, ensuring transparency, while the questions presented are aligned with learning objectives and designed to measure conceptual understanding. After each answer is submitted, the system immediately evaluates the response and adapts the next question's difficulty, ensuring that the assessment remains appropriate and optimally challenging for each learner.

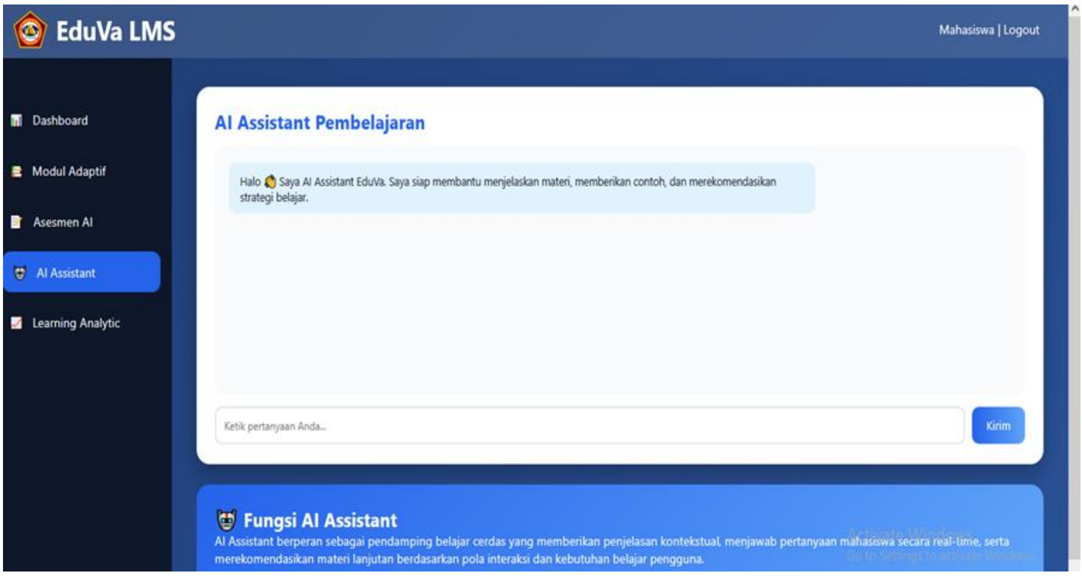

Image 5. Intelligent Learning Assistant Interface

Image 5 presents the AI Assistant Pembelajaran module as an embedded intelligent conversational agent within the EduVa LMS that provides immediate academic support without direct instructor involvement, allowing continuous guidance beyond scheduled learning sessions. The system introduces its main functions, including explaining course material in an accessible way, providing relevant examples, and recommending learning strategies tailored to the learner's performance and identified knowledge gaps.

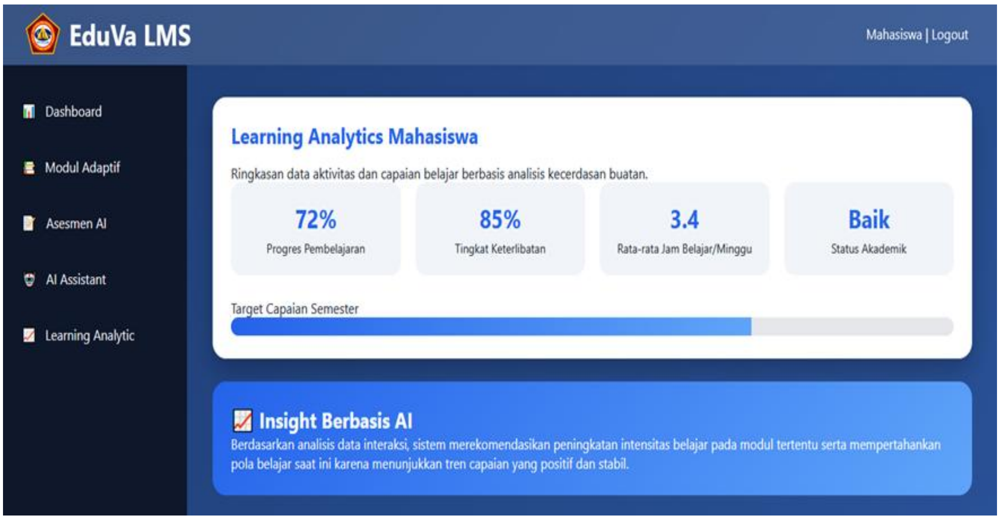

Image 6. Student Learning Analytics Dashboard

Image 6 displays the Learning Analytics Mahasiswa module as the data visualization and AI-driven insight component of the EduVa LMS, which presents a comprehensive summary of student learning activities, behavior, and performance in a clear dashboard format. The system highlights key indicators such as learning progress at 72%, engagement level at 85%, average study time of 3.4 hours per week, and academic status categorized as good, all of which are generated dynamically by the AI based on module completion, assessment results, learning duration, and interaction frequency.

Expert Validation Results

Prior to usability testing, the EduVa LMS prototype was subjected to expert validation involving five subject matter experts and five information technology and media experts. Validation was conducted across five dimensions: content accuracy, pedagogical alignment, adaptive mechanism quality, technical feasibility, and interface design. Content Validity Ratio (CVR) was computed per item and aggregated into a Content Validity Index (CVI) for each dimension. Table I presents the validation results across all dimensions.

Table 3. Expert Validation Results By Dimension (N = 10 Experts, 40 Items)

Validation Dimension	Items (n)	Mean Score (1–5)	CVR	CVI	Status
Content Accuracy	8	4.62	0.80	0.81	Valid
Pedagogical Alignment	8	4.55	0.80	0.79	Valid
Adaptive Mechanism Quality	8	4.48	0.80	0.77	Valid
Technical Feasibility	8	4.70	1.00	0.84	Valid
Interface Design	8	4.53	0.80	0.78	Valid
Overall	40	4.58	0.84	0.80	Valid

As shown in Table 3, all five validation dimensions achieved CVR values of at least 0.80, exceeding the minimum threshold of 0.62, while the overall CVI of 0.80 confirms the instrument and system validity. Technical Feasibility obtained the highest CVR and mean score, indicating strong expert agreement, whereas Adaptive Mechanism Quality showed the lowest CVI, suggesting the need for minor improvements in AI-based content sequencing before usability testing. After revisions were made, the system was deemed suitable for the usability testing phase.

System Usability Scale (SUS) Results

Following expert validation, the EduVa LMS prototype was deployed across ten private universities in East Nusa Tenggara, Indonesia, for usability testing involving 320 undergraduate students and 30 lecturers. All participants completed structured interaction sessions with the system followed by the System Usability Scale (SUS) questionnaire. Table II presents the SUS score results by participant group.

Table 4. System Usability Scale (SUS) Results By Participant Group

Group	n	Mean SUS Score	Std. Dev.	Min to Max	Category
Students	320	82.4	6.31	67.5 to 97.5	Good
Lecturers	30	85.8	5.72	72.5 to 97.5	Excellent
Combined	350	82.7	6.18	67.5 to 97.5	Good to Excellent

As presented in Table 4, the overall mean SUS score for student participants was 82.4 (SD = 6.31), falling within the Good usability category, while lecturer participants achieved a mean SUS score of 85.8 (SD = 5.72), categorized as Excellent. The combined mean SUS score of 82.7 across all 350 participants confirms that the EduVa LMS prototype achieved acceptable to excellent usability levels from the perspective of both student and lecturer end-users. The higher usability scores among lecturers may reflect their greater familiarity with digital learning platforms and more structured interaction patterns during testing sessions. Image 7 shows a dimension-level breakdown of SUS scores for both student and lecturer participant groups, providing a more granular view of usability perceptions across the ten SUS questionnaire items.

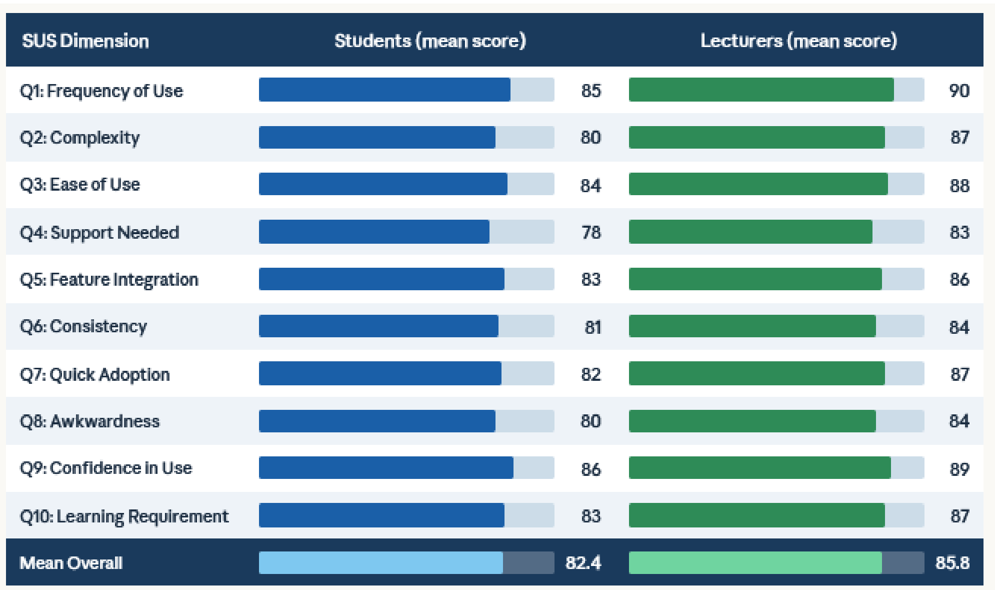

Image 7. SUS Score Breakdown by Dimension: Students vs. Lecturers

As shown in Image 7, lecturer participants consistently rated the system higher than student participants across all ten SUS dimensions. The most notable differences were observed in Q1 (Frequency of Use: 85 vs. 90), Q2 (Complexity: 80 vs. 87), and Q7 (Quick Adoption: 82 vs. 87), suggesting that lecturers found the system more intuitive and less complex relative to students. Both groups rated Q9 (Confidence in Use) and Q1 (Frequency of Use) among the highest dimensions, indicating strong user confidence in the system's functionality and perceived value for regular academic use.

Adaptive Module and AI Assessment Performance

In addition to usability measurements, the EduVa LMS system logs were analyzed to assess the performance of the adaptive learning modules and AI assessment engine across student interaction sessions. Table 5 presents the system performance metrics for each of the three adaptive learning modules.

Table 5. Adaptive Module Performance Metrics (n = 320 Students)

Module	Mean Accuracy (%)	Adaptive Triggers (avg/session)	Avg. Time-on-Task (min)	Completion Rate (%)
Module 1: Basic Concepts	88.4	2.1	18.3	96.2
Module 2: Intermediate Understanding	81.7	3.8	24.6	89.4
Module 3: Advanced Case Studies	76.3	5.2	31.2	78.1
Overall Average	82.1	3.7	24.7	87.9

As presented in Table 5, Module 1 achieved the highest accuracy and completion rates, indicating its accessibility as a foundational level, while Module 2 showed moderate accuracy with increased adaptive adjustments by the AI, reflecting variability in student performance at the intermediate stage. Module 3 recorded the lowest accuracy and completion rates but the highest adaptive activity, confirming more intensive personalization at the advanced level. Overall, the system demonstrated strong performance, with an average accuracy of 82.1%, a completion rate of 87.9%, and a strong positive correlation between AI assessment accuracy and learning objective alignment.

Inferential Statistical Analysis: Group Comparison

To examine whether statistically significant differences existed between student and lecturer usability perceptions, the Shapiro-Wilk normality test was first applied to the SUS scores of both groups. Results indicated that the student group's SUS scores were not normally distributed ($W = 0.961$, $p = .021$), while the lecturer group's scores approximated normality ($W = 0.942$, $p = .096$). Given the violation of normality in the student group, the Mann-Whitney U non-parametric test was applied for group comparisons. Table 6 presents the results of the Mann-Whitney U test across key SUS dimensions.

Table 6. Mann-Whitney U Test Results: Students Vs. Lecturers' SUS Scores

Variable	Students Mean Rank	Lecturers Mean Rank	U Statistic	p-value	Interpretation
Overall SUS Score	174.8	196.3	4128.0	.043	Significant ($p < .05$)

Variable	Students Mean Rank	Lecturers Mean Rank	U Statistic	p-value	Interpretation
Learnability	172.4	199.1	3982.5	.031	Significant ($p < .05$)
Interface Satisfaction	176.2	193.8	4276.0	.118	Not Significant
Adaptive Feature Perception	173.6	197.4	4053.0	.037	Significant ($p < .05$)

As shown in Table 6, significant differences were found between student and lecturer SUS scores for overall usability, learnability, and perception of adaptive features, with lecturers consistently giving higher ratings than students. However, no significant difference was observed in interface satisfaction, indicating both groups had similar positive perceptions of the system's design. Overall, the results suggest that while all users rated usability positively, lecturers showed greater appreciation for the system's adaptive capabilities and learning support features, possibly due to differences in digital literacy and pedagogical perspectives.

System Validity and Expert-Confirmed Design Quality

The expert validation results, with an overall CVI of 0.80 and CVR values above the 0.62 threshold, confirm that the EduVa LMS meets standards for content accuracy, pedagogical alignment, and technical feasibility. This is important in the context of AI integration in education, which requires alignment with learning objectives and ethical principles (Chan, 2023). The perfect CVR score for Technical Feasibility also indicates that the system is technically robust and ready for real-world institutional implementation.

Usability Findings and Learner-Centered Design

The mean SUS scores of 82.4 for students and 85.8 for lecturers indicate that the EduVa LMS falls within the good to excellent usability range, showing that the system is accessible and easy to use for both groups. These findings are consistent with previous studies on AI-based personalized learning systems that report high usability when designed with learner-centered approaches and real-time feedback (Dai et al., 2023). The significant differences in perceptions between students and lecturers also align with research showing that users with higher digital literacy tend to evaluate AI systems more positively (Farazouli et al., 2024). highlighting the need for better onboarding and digital literacy support for students.

Adaptive Module and AI Assessment Performance

The adaptive module performance results, with an overall accuracy of 82.1%, an average of 3.7 adaptive triggers per session, and a completion rate of 87.9%, demonstrate that the EduVa LMS effectively implements AI-driven content sequencing and dynamic difficulty adjustment across students. The gradual decrease in accuracy and completion from Module 1 to Module 3 reflects increasing learning complexity and indicates that the adaptive mechanism is functioning appropriately. The strong correlation between AI assessment accuracy and learning objective alignment ($r = 0.81$, $p < .01$) further confirms that the system maintains consistency with educational goals, addressing concerns about potential misalignment in AI-based assessments (Elsayed, 2023; Widana et al., 2021).

Implications for Higher Education in Indonesia

The successful deployment of the EduVa LMS across ten private universities in East Nusa Tenggara highlights its potential for broader adoption in Indonesian higher education, especially in regions with varying infrastructure and digital readiness. The dominance of smartphone-based learning among students was effectively supported by the system's responsive design, indicating that mobile-compatible cloud-based LMS platforms are a practical solution for resource-constrained environments (Cross et al., 2023). Additionally, consistent usability outcomes across institutions with varying accreditation levels demonstrate that the system is flexible and adaptable, reinforcing its value as a scalable, AI-powered learning solution for diverse educational contexts.

The findings of this study are consistent with previous research confirming that AI-integrated learning systems outperform conventional LMS platforms in terms of learner engagement and academic performance (Tang et al., 2021). However, unlike most existing studies that remain at conceptual or theoretical stages (Dogan & Dogan, 2023), this study presents a fully developed, empirically tested prototype deployed across ten real higher education institutions, representing a significant methodological advancement. Furthermore, while previous studies have examined AI in LMS from single-institution perspectives, this study contributes a multi-site validation framework across private universities in a developing region, addressing a gap identified in the literature regarding infrastructure-constrained educational contexts. The integration of adaptive content sequencing, AI-driven assessment, and intelligent learning assistance within a single unified platform further distinguishes EduVa LMS from fragmented implementations reported in prior work.

Despite its contributions, this study has several limitations that should be acknowledged. First, the study was conducted exclusively across private universities in East Nusa Tenggara, which may limit the generalizability of the findings to other regional or institutional contexts. Second, the testing period was relatively short, preventing longitudinal assessment of the system's impact on student learning outcomes over time. Third, the study did not examine the long-term sustainability of AI-driven adaptive mechanisms under varying internet infrastructure conditions. Future research is therefore recommended to conduct longitudinal studies examining the impact of EduVa LMS on academic performance and learning behavior across extended periods, to replicate the study in public universities and other provinces, and to explore the integration of generative AI features such as large language models to further enhance the personalization capabilities of the platform.

Theoretical and Practical Implications

Theoretically, this study contributes to the growing body of literature on AI-based adaptive learning systems in higher education by providing empirical evidence that a Design Science Research approach integrated with the ADDIE model serves as an effective framework for systematically designing and testing AI-powered LMS platforms. The findings reinforce the argument that AI-driven personalization in learning is not merely a theoretical concept but can be implemented meaningfully and measurably even within institutional contexts characterized by infrastructure limitations. Practically, the successful deployment of EduVa LMS across ten private universities in East Nusa Tenggara demonstrates that the system holds strong potential for broader adoption by other higher education institutions in Indonesia, particularly in regions that require flexible, adaptive, and mobile-accessible learning solutions. For policymakers and institutional leaders, these findings provide a strong empirical basis for encouraging investment in AI-powered LMS development as part of a sustainable digital transformation strategy in higher education, ultimately supporting more personalized, equitable, and effective learning experiences for diverse student populations.

Conclusion

This study successfully designed, prototyped, and tested an AI-powered interactive Learning Management System, EduVa LMS, which integrates adaptive learning modules and intelligent assessment features, and was deployed across 10 private higher education institutions in East Nusa Tenggara, Indonesia. The results show strong content validity based on expert evaluation and positive usability ratings from both students and lecturers, while the system also demonstrated high performance in terms of accuracy, completion rate, and alignment between AI assessment outputs and learning objectives, indicating that it is technically sound, pedagogically appropriate, and well accepted by users for broader implementation. In addition, this study contributes to the growing evidence on the effectiveness of AI driven adaptive learning in higher education, especially in developing regions where flexible and personalized learning solutions are needed, and offers a scalable framework that can be adopted by other institutions, Future research is recommended to conduct longitudinal studies of at least one full academic semester to measure specific impacts on student GPA, assignment completion rates, and self-regulated learning behaviors using LMS analytics logs, and to replicate the study across public universities in other Indonesian provinces using validated instruments such as TAM or the ARCS Motivation Model

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