INTEGRATING AI WITH EXISTING LEARNING MANAGEMENT SYSTEMS: A SYSTEMATIC LITERATURE REVIEW ON STUDENT SUCCESS

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Integrating AI with existing learning management systems: A Systematic Literature Review on Student Success

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Abstract

The integration of Artificial Intelligence (AI) into Learning Management Systems (LMS) provides transformative potential in modernizing higher education by enabling advanced data analytics and personalized learning experiences. Current LMS platforms often lack the adaptive capabilities necessary for fostering student success, and empirical research regarding the impact of AI-LMS integration remains fragmented and underexplored. To address the gap in research, this systematic literature review examines how AI-driven student success platforms influence student outcomes and institutional effectiveness. By synthesizing peer-reviewed articles published between 2019 and 2025, the study proposes an integrated framework utilizing the DeLone and McLean Information Systems Success Model to evaluate system quality and the Technology Acceptance Model (TAM) to analyze user adoption factors. The research aims to identify best practices for evaluating AI tools, such as predictive analytics and intelligent tutoring systems, to enhance engagement, retention, and graduation. In addition, it explores critical implementation challenges, including data governance and algorithmic bias, particularly within resource-constrained environments. Ultimately, this study seeks to develop an actionable strategic framework to guide administrators and policymakers in navigating data interoperability and ethical deployment, enabling institutions to optimize operational efficiency, close equity gaps, and improve long-term graduation rates in an increasingly data-driven academic landscape.

Keywords: e-learning technologies and tools, learning management systems, instructional design models, virtual learning environments, AI adoption

Introduction

The integration of AI and existing LMS transforms many academic practices, enhances the experiences of students and increases student success. These system integrations allow for advanced data analytics and real-time decision-making (Melnyk et al., 2024). AI tools and platforms significantly enhance support, personalize communication, improve engagement strategies, and streamline operations by automating routine tasks (Melnyk et al., 2024). AI technologies enhance engagement for students and instructors with existing LMS by using deep learning algorithms to allow for early identification of at-risk students, help predict academic success, and personalize instruction, fostering better student outcomes (Chu et al., 2022). Higher education is undergoing a significant transition, post-covid, in facilitating digital engagement and connecting data repositories across student information systems. Student success goals of colleges and universities worldwide have changed due to a number of factors, including rapid technological improvements, changing student demographics, an increase in the need for additional modalities, and a growing need for individualized learning experiences (Crompton & Burke, 2023).

The expansion and effectiveness of AI-driven student success platform technologies have been studied extensively in recent years. This paper explores the impact of integrating AI-driven platforms with existing learning management systems to meet students' complex and evolving needs by bringing together the power of artificial intelligence, academic technology resources, and the human-centered support strategies of student success initiatives. Artificial Intelligence is both a driver of innovation and a tool for automation and operational efficiencies. AI's role in reshaping historical academic practices and how LMS impact student success is evident across the adoption of AI driven student success platforms, as highlighted by Bates et al. (2020), Chu et al. (2022), and Melnyk et al. (2024). By aligning these technological innovations with individualized learning environments and personalized support systems, institutions can not only respond to today's challenges but also help shape the future of higher education (Crompton & Burke, 2023). Exploring how AI offers unique capabilities for enhancing the higher education experience and how it frees up staff time, uncovers hidden patterns, and enables timely, tailored interventions is an area of significant need (Crompton & Burke, 2023). This study can assist with developing an actionable AI integration strategy framework for existing learning management systems to enhance student success and improve operational efficiencies for institutions. To achieve this objective, a systematic review of articles collected from the ProQuest database, ACM digital library and Google Scholar databases will be conducted. The review of the selected articles will examine the impact of these integrations on student success and the development of a strategic framework for the deployment and adoption of AI tools in learning environments.

Problem statement

Although AI technologies have shown transformative potential in personalizing learning environments, enhancing student success platforms and broadening institutional effectiveness, the impact of the integration of AI with LMS on student success in higher education remains fragmented and underexplored. Current LMS platforms, while central to instructional delivery and administration, often lack adaptive and predictive intelligence capabilities necessary for fostering student success and personalized learning environments (Abid et al., 2024; Yamani et al., 2022). Studies have emphasized that while AI can enhance the student experience, institutions still face challenges related to data interoperability, algorithmic bias, adoption and implementation scalability (Alotaibi, 2024; Vergara et al., 2024).

In addition, research emphasizes the need for frameworks that measure system effectiveness and quality, such as the updated DeLone and McLean IS Success Model, to evaluate how integrated AI–LMS environments impact student performance, satisfaction, and institutional efficiency (Rulinawaty et al., 2024). Despite the expansion of AI-driven learning analytics and conversational agents, there remains a lack of empirical studies that evaluate how these AI tools, when integrated within LMS environments, influence student engagement, retention, and learning outcomes (Ayotunde et al., 2023; Ngulube & Ncube, 2025). The governance frameworks and data infrastructure required to properly use AI integrations for LMS, and enterprise systems are frequently absent from smaller and resource-constrained institutions in particular (Weil & Forrester, 2024).

Addressing this research gap brings significant value for stakeholders across higher education, as AI-LMS integrations affect not only instructional delivery but also institutional sustainability, student equity, and long-term strategic planning (Chu et al., 2022; Crompton & Burke, 2023). Evidence based insights into how AI-enhanced LMS environments influence learning and operational outcomes can help administrators make informed decisions about technology procurement, resource allocation, and workflow redesign to maximize return on investment and support institutional student success initiatives (Bates et al., 2020; Weil & Forrester, 2024). By understanding which AI-driven features most effectively improve student retention, administrators can prioritize high impact capabilities, such as predictive analytics or adaptive content, and develop staffing models that streamline advising, enhance early alert systems, and improve intervention techniques (Chu et al., 2022; Melnyk et al., 2024).

These findings will also benefit faculty, who play a central role in orchestrating the student learning experience. Clearer guidance on how AI-LMS capabilities can personalize instruction, provide real-time feedback, and identify struggling learners enables faculty to tailor instruction more efficiently while reducing administrative burden (Al-Mamary et al., 2024; Geddam et al., 2024). Enhanced insight into student learning patterns can strengthen course design, empower faculty to incorporate evidence-based teaching strategies, and improve outreach to students who need individualized support. Such knowledge may also shape faculty development programs focused on equitable AI use, instructional innovation, and data-driven teaching (Zawacki-Richter et al., 2019).

For policymakers and institutional leaders, the outcomes of this research can inform the development of robust governance frameworks that address data interoperability, privacy, algorithmic transparency, and ethical AI deployment (Alotaibi, 2024; Sevate & Hofisi, 2024). These insights can help create policies that ensure responsible and equitable implementation across diverse institutional contexts, particularly benefiting smaller or resource-constrained colleges that may lack established IT governance infrastructures (Weil & Forrester, 2024). Additionally, these findings can establish the foundation and guidance to support the creation of statewide or system-level policy frameworks that promote shared services, strengthen data standards, and reduce the operational burden on individual institutions (Crompton & Song, 2021; Vergara et al., 2024).

This research can guide the development of scalable implementation strategies and evaluation models that support continuous improvement. Such knowledge will position institutions to enhance instruction, expand learning equity, optimize operational efficiency, and improve student retention and graduation rates (Rulinawaty et al., 2024; Ngulube & Ncube, 2025). In doing so, the study will contribute not only to academic discourse but also to actionable, real-world practices that advance institutional effectiveness and student success in an increasingly data-driven higher-education landscape (Chu et al., 2022; Melnyk et al., 2024).

Purpose of the study

This systematic literature review investigates the impact of integrating AI technology into current LMS on student success, and institutional effectiveness in higher education. This study also examines the DeLone and McLean Information Systems Success Model to assess how factors like system quality, information quality, service quality, system use, user satisfaction, and performance interact in AI-enhanced learning management system environments to create measurable learning outcomes. This research aims to identify patterns, gaps, and best practices from prior studies related to AI–LMS integrations (Abid et al., 2024; Alotaibi, 2024; Vergara et al., 2024), focusing on how higher education institutions implement AI-driven tools, such as adaptive learning algorithms, chatbots, predictive analytics, and personalized feedback systems, to improve student learning engagement and academic performance (Chu et al., 2022; Crompton & Burke, 2023; Melnyk et al., 2024). It also seeks to explore implementation challenges related to strategic integration, data governance, insistutional readiness, ethical use of AI, and platform data interoperability in AI-enhanced learning environments (Ngulube & Ncube, 2025; Weil & Forrester, 2024). The study's ultimate goal is to compile the most recent data in order to create an executable evaluation framework that would enable universities to strategically incorporate AI capabilities into their current LMS.

RQ1: What themes emerged from the systematic literature review on AI-enhanced LMS?

RQ2: How does the integration of AI technologies influence institutional effectiveness?

RQ3: To what extent do system quality, information quality, and service quality (as defined by the DeLone and McLean IS Success Model) combined with the perceived usefulness and perceived ease of use (as defined by TAM) predict successful implementations of AI-enhanced LMS environments?

Literature Review

The integration of AI and learning management platforms has become a critical focus in enhancing e-learning systems. These AI-enhanced student success platforms, offer flexible, adaptive, and personalized learning opportunities for students (Geddam et al., 2024). The global adoption of student success platforms has increased dramatically in recent years, and this growth has included innovative AI tools designed to meet the evolving needs of students across educational and professional settings (Ahmad, 2024). E-learning, defined as the use of computer and internet technologies to deliver educational content, has been increasingly adopted for corporate training, higher education, and skill development. It was estimated in 2019 that approximately 77% of U.S. institutions offered AI driven LMS and student success platforms to create personalized learning environments, (Kavitha & Lohani, 2019). The market for advanced LMS has also expanded rapidly, by 2023 it was projected that the industry grew to $240 billion, reflecting the demand for more efficient, accessible education technologies (Kavitha & Lohani, 2019).

The rapid advancement of AI, particularly in the area of large language models (LLMs), has been researched and developed significantly in academic and industry circles. Generative AI tools, such as OpenAI's GPT models, are increasingly being integrated into e-learning tools to enhance student success (Bensah et al., 2023). This literature review examines the key studies and findings on the integration of LMS with AI-enhanced student success platforms and its impact on student success and institutional effectiveness. The increasing integration of AI technologies across academic domains has prompted extensive research into its implications, including student success impacts, graduation rates and higher education operational concerns (Shibiti & Mulaudzi, 2024).

AI-enhanced learning management systems and student success

AI-enhanced LMS facilitate digital communication, adaptive content distribution, and collaborative tools, all of which increase knowledge exchange within learning communities. In LMS ecosystems, AI facilitates both formal and informal learning interactions and helps organize information repositories, enhancing a collaborative educational experience. (Zamiri & Esmaeili, 2024). The integration of AI can help LMS develop personalized learning paths, adaptive feedback, and intelligent tutoring systems that impact student success in higher education institutions. It should also be noted that AI integration improves usability and interactivity through APIs and mobile compatibility. Traditional LMS frequently lack those adaptive and interactive capabilities (Arafat, 2024). Research has found that when LMS and AI tools (like ChatGPT) are well aligned with the type of learning assignments, students have a higher chance of academic success. These studies also show that students' behavioral intentions and academic performance improve when they believe that LMS is helpful, dependable, and appropriate for their learning needs (Al-Mamary et al., 2024). User acceptance is central to effective LMS implementation in higher education contexts. Student perceptions of an LMS's features and quality map closely to the TAM constructs like, perceived usefulness and perceived ease of use, which influence whether students will adopt and utilize the system meaningfully (Arafat, 2024). Extending this logic through the lens of the DeLone and McLean model, AI-enhanced LMS features that demonstrate high system quality, information quality, and service quality contribute to measurable net benefits. Features like predictive learning analytics, AI conversational agents, adaptive assessments, and personalized learning pathways improve engagement, early identification of at-risk students, enhanced academic performance, and stronger retention and completion outcomes (Alotaibi, 2024; Zamiri & Esmaeili, 2024).

Researchers contend that in order to fully realize the revolutionary potential of AI technology, a greater comprehension of institutional structures, power dynamics, and stakeholder participation is necessary (Sevate & Hofisi, 2024). This collaborative model enables a shared digital decision-making process among faculty, advisors, administrators, and students and is enhanced by real-time data analytics and transparency, helping institutions implement academic interventions more effectively, ultimately improving student success metrics (Crompton & Song, 2021). Alignment with institutional and pedagogical objectives is necessary to assess the return on investment, efficacy and usefulness of AI implementations. The deployment of AI needs to be backed by sufficient infrastructure, ethical guidelines, and training. Without these, institutions can spend a lot of money on AI and not get any significant benefits (Zawacki-Richter et al., 2019).

Institutional readiness and strategic integration

Collectively, the reviewed literature suggests that the association between AI-enhanced learning management systems and student success can be coherently explained by integrating the Technology Acceptance Model with the DeLone and McLean Information Systems Success Model, particularly the net benefits aspect related to student success. From a TAM perspective, students' and instructors' perceptions of perceived usefulness and perceived ease of use shape acceptance and behavioral intention to use AI-enabled LMS features, which in turn drives actual system use (Al-Mamary et al., 2024; Arafat, 2024). Institutions can effectively leverage the TAM to assess and enhance their readiness for adopting and integrating AI into their existing LMS. These concepts are critical when considering institutional readiness, faculty and student adoption, and the long-term success of AI integrations in higher education settings (Han & Sa, 2022).

For institutional readiness, TAM provides a structured framework to evaluate stakeholder perceptions (Han & Sa, 2022). Research shows that perceived usefulness significantly impacts both satisfaction and the intention to use AI-enhanced systems, while ease of use enhances perceived usefulness and satisfaction (Al-Mamary et al., 2024; Han & Sa, 2022). In terms of AI adoption, TAM enables institutions to identify behavioral and cognitive barriers that may hinder implementation. For example, institutions may invest in AI chatbots, intelligent tutoring systems, or predictive analytics tools, but their success largely depends on whether users believe these tools are reliable, user-friendly, and beneficial (Melnyk et al., 2024; Miraz et al., 2024). TAM-based evaluations allow leaders to tailor training and policy development to improve user experience and perceived effectiveness. Institutions that strategically use TAM to assess perceptions before and after implementation are better positioned to foster adoption, increase engagement, and improve educational outcomes (Chu et al., 2022; Crompton & Burke, 2023).

The DeLone and McLean IS Success Model extends this understanding by linking system use to system quality, information quality, and service quality, which collectively determine net benefits. This includes student success factors like improved engagement, academic performance, retention, and graduation outcomes (Alotaibi, 2024). Collectively these studies emphasize that AI-enhanced LMS features such as learning analytics, predictive risk identification, AI conversational agents, intelligent tutoring systems, and personalized learning pathways contribute to student success only when they deliver high-quality, accurate, timely, and actionable information within reliable systems (Alotaibi, 2024; Zamiri & Esmaeili, 2024). By integrating the TAM and the DeLone and McLean model, institutions can create an AI–LMS integration evaluation framework in which user acceptance enables sustained use (TAM), and sustained use is supported by high system, information, and service quality that produces measurable net benefits for student success (DeLone & McLean). This integrated framework allows higher education leaders to evaluate AI initiatives holistically, ensuring that AI adoption strategies address not only usability and acceptance, but also instructional effectiveness, data quality, and institutional outcomes.

Student success and institutional effectiveness

Across the reviewed literature, AI-enhanced learning management systems are consistently shown to improve operational efficiency and reduce administrative workload by automating routine processes, enhancing data-driven decision-making, and streamlining academic and support services. AI adoption in higher education learning environments has enabled institutions to automate grading, assessment feedback, scheduling, and reporting functions, reducing the manual administrative effort required and allowing faculty and staff to redirect time toward higher-value instructional and student-support activities (Kamalov et al., 2023; Kavitha & Lohani, 2019). Kamalov et al. (2023) described AI's integrations into LMS as a catalyst for a "multifaceted transformation" in educational operations. The authors emphasized AI's role in improving scalability, optimizing resource allocation, and supporting sustainable institutional practices through automation and analytics. AI-enhanced learning analytics play a central role in improving operational efficiency at institutions by reducing the labor required for monitoring student progression and generating institutional reports. Learning analytics systems embedded within LMS platforms automate the collection, analysis, and visualization of learner data, which allows instructors and administrators to identify engagement trends and at-risk students without extensive manual data processing (Ngulube & Ncube, 2025).

Recent research studies highlight how institutional operations can gain efficiencies from the deployment of AI chatbots in handling repetitive tasks across business processes, such as recruitment, academic advising, and student service operations. More specifically, AI-driven chatbots and conversational agents embedded within LMS platforms consistently have shown to significantly reduce administrative burden by handling high-volume, repetitive inquiries related to course logistics, deadlines, enrollment, and academic policy enforcement. Research on chatbot-enabled business process management at institutions show that these tools streamline workflows, improve response times, and lower staff workload by automating front-line interactions and routine service processes. This not only cuts down operational costs but also improves response times and overall service quality (Melnyk et al., 2024). Those same studies show that AI chatbots improve communication effectiveness and trust in systems like LMS and student portals, which directly influence faculty, staff and student satisfaction. Increased satisfaction often correlates with improved performance and retention in both academic and administrative roles (Miraz et al., 2024).

The DeLone and McLean Information Systems Success Model provides a comprehensive framework for measuring AI's impact on both operational efficiencies and student outcomes with LMS in higher education by linking system characteristics to usage, satisfaction, and measurable net benefits. Its six interrelated components, system quality, information quality, service quality, system use, user satisfaction, and net benefits, offer a structured framework in which higher education institutions can evaluate and optimize the impact of AI-driven digital ecosystems, including LMS and student success platforms (DeLone & McLean, 2003; Rulinawaty et al., 2024). When applied strategically, the model helps institutions enhance operational efficiency, improve student outcomes, and enable data-informed decision-making, ultimately strengthening institutional effectiveness. This collection of research shows that high-quality AI systems reduce administrative friction, automate routine tasks, and support scalable service delivery, thereby improving operational efficiency and lowering staff workload (Kamalov et al., 2023; Melnyk et al., 2024). Information quality further explains AI's impact on LMS by emphasizing the accuracy, timeliness, and relevance of AI-generated insights. These studies indicate that AI-driven learning analytics and predictive models enhance the early identification of at-risk students which improves decision-making and intervention timelines by faculty, advisors, and administrators. This directly supports institutional goals for retention and academic performance outcomes (Alotaibi, 2024; Ngulube & Ncube, 2025).

Methodology

This study adopts a systematic, thematic literature review methodology to synthesize peer-reviewed evidence on how the integration of AI into LMS influences student success and institutional effectiveness in higher education (Alotaibi, 2024; Zamiri & Esmaeili, 2024). A thematic synthesis approach enabled the identification of key ideas, recurring patterns, implementation challenges, and academic relationships across studies (Kamalov et al., 2023). AI integration with LMS research spans system design, behavioral intention, organizational impact, and student outcomes. Thematic synthesis allows for the integration of constructs drawn from models such as the Technology Acceptance Model and the DeLone and McLean IS Success Model (Arafat, 2024; Rulinawaty et al., 2024). This approach supports the conceptual integration of acceptance factors like perceived usefulness, system quality dimensions, and net benefits related to student success and operational efficiency (Al-Mamary et al., 2024; Rulinawaty et al., 2024).

A comprehensive search was conducted across major academic databases to ensure coverage of both educational technology and information systems research. These databases were selected to capture interdisciplinary perspectives spanning AI adoption, LMS implementation, business process automation, learning analytics, and chatbot-enabled systems (Melnyk et al., 2024; Miraz et al., 2024; Ngulube & Ncube, 2025).

These databases include:

- ProQuest
- ACM Digital Library
- Google Scholar
- Scopus
- Web of Science

The search terms were constructed using Boolean operators to capture a full range of published work. These terms reflect recurring identifiers in prior AI in higher education research, including AI-driven analytics, adaptive systems, chatbot automation, and LMS learning technologies (Alotaibi, 2024; Kamalov et al., 2023; Kavitha & Lohani, 2019).

Example query strings include:

- “AI OR “artificial intelligence” AND “learning management system OR LMS” AND “higher education”
- “AI-driven” OR “AI-enhanced” OR “AI-powered” AND “LMS integration”
- “student success” AND (AI OR “AI-platforms”)
- “institutional effectiveness” AND “educational data analytics”

Filters limited results to peer-reviewed sources published between 2019–2025 to capture recent AI advancements and the post-pandemic LMS evolution. This time frame was targeted because of the accelerated adoption of AI tools, particularly conversational agents, generative AI, and predictive analytics tools within higher education learning environments during and after COVID-19 (Al-Mamary et al., 2024; Kamalov et al., 2023).

The inclusion and exclusion criteria used are as follows:

<u>Inclusion Criteria</u>

- In1- Empirical or conceptual research
- In2- Peer-reviewed journal articles, conference proceedings, dissertations

- In3- Focus on AI tools integrated into LMS
- In4- Studies involving higher education settings
- In5- Research reporting outcomes related to student success, or institutional effectiveness

These inclusion criteria align with prior systematic reviews examining AI integration and learning analytics impacts on institutional performance and user outcomes (Alotaibi, 2024; Zamiri & Esmaeili, 2024).

Exclusion Criteria

- Ex1- K–12-only studies
- Ex2- Articles without AI–LMS integration focus
- Ex3- Commentary pieces without evidence
- Ex4- Non-English publications
- Ex5- Studies lacking methodological transparency

Excluding non-empirical or non-transparent studies strengthens the rigor and credibility of the synthesis, consistent with systematic review standards used in AI and information systems research (Alotaibi, 2024; Rulinawaty et al., 2024).

The selection process identified a total of 1,119 records as potentially eligible for inclusion. Each record was subjected to the inclusion and exclusion criteria by evaluating titles and abstracts to determine their relevance to the study's inclusion criteria, which led to the exclusion of 995 records that did not meet the specified research scope and objectives as per the inclusion criteria. Consequently, 124 publications were selected for retrieval and further evaluation. In the eligibility assessment phase, the full texts of these studies were carefully examined to determine their suitability for inclusion in the review. During this phase, articles were excluded based on the predefined exclusion criteria, predominantly for not having an AI-LMS focus or lacking methodological transparency. This resulted in the exclusion of an additional 99 articles. The culmination of this rigorous selection process was the inclusion of 25 studies in the final review. These studies were considered to be aligned closely with the research objectives and met all the criteria set forth for the systematic review. No additional reports included studies were identified, confirming the completeness of the search and selection strategy. The transparent and systematic approach to study selection, as evidenced by the PRISMA flow diagram (see Fig. 1), aims to give a high level of confidence in the comprehensiveness and relevance of the studies included in this review.

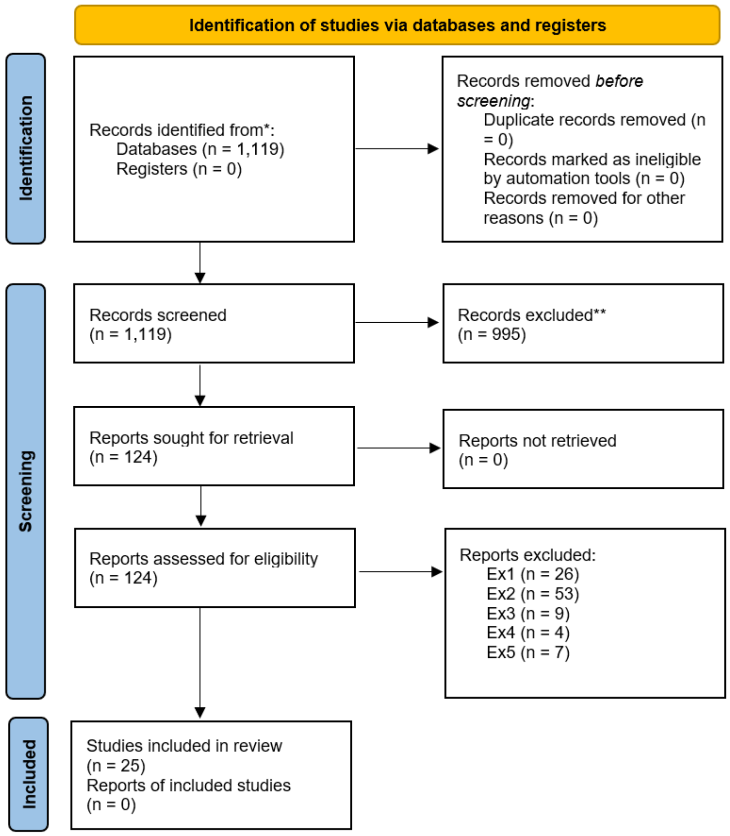

Figure. 1 Flowchart depicting the retrieval and selection of retrieved publications, following the PRISMA Approach.

Results

The thematic synthesis of the reviewed research articles identified several recurring patterns regarding the integration of AI within LMS and its relationship to student outcomes and institutional effectiveness. The results are organized around six core themes: (1) personalized and adaptive learning, (2) student engagement and conversational AI, (3) learning analytics and early identification of at-risk students, (4) system and information quality influences on LMS effectiveness, (5) operational efficiencies and workflow automation, (6) structured evaluation frameworks for AI–LMS integration.

Table 1: Core Themes

Theme	Key findings	Challenges / Constraints	Sources
Personalized & adaptive learning for improved student performance	Adaptive and personalized learning is repeatedly linked to more effective learning environments	Personalization depends on high-quality data, interoperable systems, and careful design choices.	(Alotaibi, 2024; Kamalov et al., 2023).
Student engagement & “always-on” learner support via conversational tools	AI-enabled conversational agents and AI-supported discussion/interaction	Effective use requires sustained faculty adoption, integration into course design, and safeguards for student autonomy/consent.	(Alotaibi, 2024; Melnyk et al., 2024;

Theme	Key findings	Challenges / Constraints	Sources
	tools can increase participation and engagement, with downstream benefits.		Miraz et al., 2024).
Learning analytics for early identification of at-risk students & targeted intervention	Learning analytics is a key AI capability for improving LMS impact by monitoring behavioral indicators to generate insights that can support engagement, satisfaction, and academic outcomes.	Adoption is impeded by implementation complexity, difficulty translating data into actionable insights, limited model transferability/generalizability, the need to balance personalization with constraints, and persistent data privacy/ethical concerns.	(Alotaibi, 2024; Kamalov et al., 2023; Ngulube & Ncube, 2025).
System quality, information quality, and service quality impact satisfaction, and perceived usefulness	System, information, and service quality positively influence perceived usefulness and user satisfaction. These factors map clearly DeLone & McLean's logic.	Quality-driven outcomes depend on reliability/adaptability, secure and relevant information, and responsive services. When quality is weak, it undermines satisfaction/usefulness, reduces adoption, and limits impact on learning outcomes.	(DeLone & McLean, 2003; Rulinawaty et al., 2024).
Operational and instructional efficiency gains (automation, streamlined workflows, scalable delivery)	AI–LMS integration enables more scalable, data-driven teaching/learning delivery. Supporting operations through more efficient resource use and improved delivery models.	Efficiency gains can be offset by up-front implementation costs, integration burdens, and the need for training and new competencies to operationalize AI responsibly at scale.	(Alotaibi, 2024; Kamalov et al., 2023; Melnyk et al., 2024).
Need for structured evaluation frameworks to select/assess LMS capabilities that include AI integrations	Feature-based, rubric/scoring method to compare systems more thoroughly than ad hoc comparisons, enabling more justifiable choices regarding platform fit and capability coverage.	Evaluation framework must account for "current and future" academic/administrative requirements, usability/satisfaction differences, and feature completeness; weak evaluation approaches can lead to misalignment with institutional needs and hinder consistent student experience.	(Abid et al., 2024; Alotaibi, 2024; Vergara et al., 2024)

Personalized & adaptive learning for improved student performance

Research question 1 was answered by theme 1. AI-enhanced LMS environments are consistently associated with personalized and adaptive learning capabilities designed to improve student success. AI-driven systems leverage learner behavioral data to generate personalized learning pathways, adaptive assessments, and targeted instructional support (Alotaibi, 2024). These personalized learning environments are key contributors to improved engagement and academic performance, particularly when AI tools are aligned with course objectives and learner needs. Similarly, studies examining AI integration in higher educational environments emphasize that adaptive systems enhance learning effectiveness by dynamically adjusting content and pacing to individual performance patterns (Kamalov et al., 2023). Collectively, the reviewed literature suggests that AI-enabled personalization strengthens the instructional responsiveness of LMS platforms, Driving increased academic performance.

Student engagement and conversational AI

Research question 1 was also answered by theme 2. The use of AI-powered conversational agents and chatbots emerged as a recurring theme in improving student engagement and providing scalable academic support. AI-enabled chatbots embedded within LMS platforms facilitate real-time responses to frequently asked questions, enhance accessibility to course information, and support continuous interaction outside traditional instructional hours (Alotaibi, 2024). In addition, research on conversational agents and chatbot-supported LMS demonstrated that conversational AI improves efficiency and user responsiveness while reducing administrative burden (Melnyk et al., 2024; Miraz et al., 2024). These findings indicate that conversational AI contribute not only to improved engagement and perceived support but also to institutional operational efficiency.

Learning Analytics and Early Identification of At-Risk Students

Research question 1 was also answered by theme 3. One of the main ways that AI-enhanced LMS platforms affect student outcomes is through learning analytics. Learning analytics systems offer insightful data that enables early intervention efforts by examining student behaviors such login frequency, time on task, involvement in conversations, and assessment performance (Ngulube & Ncube, 2025). When universities successfully convert analytics into tailored academic support, these prediction and monitoring capabilities are associated with better academic progression and retention outcomes (Alotaibi, 2024). In addition, the literature also emphasizes the challenges of transforming big data sets into timely, effective interventions and the complexity of execution (Ngulube & Ncube, 2025).

System, Information, and Service Quality Influences

Research questions 1 and 2 were answered by theme 4. Research supporting the DeLone and McLean Information Systems Success Model, indicates that system quality, information quality, and service quality significantly influence perceived usefulness, user satisfaction, and effective LMS implementation (Rulinawaty et al., 2024). Secure information architecture, flexible design, and high system reliability all favor user happiness and perceived usefulness, which impacts sustained use and improved educational effectiveness. In contrast, weaknesses in system performance or information accuracy undermine adoption and limit measurable benefits (Rulinawaty et al., 2024). These research findings highlight the significance of evaluating AI–LMS integration beyond adoption rates to include system performance and quality metrics.

Operational Efficiencies and Workflow Automation

Research questions 1 and 2 were also answered by theme 5. AI-enhanced LMS solutions provide quantifiable gains in operational efficiencies in addition to instructional benefits. AI integration facilitates the automation of routine administrative activities, data-driven resource allocation methods, and enhanced workflow management (Kamalov et al., 2023; Melnyk et al., 2024). Institutions using AI tools report better service responsiveness and fewer demands for manual processing, which enhances institutional sustainability and agility (Alotaibi, 2024). These practical benefits expand AI's influence beyond academic results to include increased institutional effectiveness and operational performance.

Structured Evaluation Frameworks for AI–LMS Integration

Research questions 1 and 3 were answered by theme 6. Studies emphasize how crucial it is to use systematic evaluation frameworks when choosing and evaluating the integration of AI tools and capabilities with existing LMS systems. Compared to ad-hoc comparisons, feature-based scoring models and formal evaluation rubrics give institutions a more structured view for making integration decisions (Abid et al., 2024). These frameworks facilitate the alignment of academic, administrative and operational goals with technology capabilities, guaranteeing that AI-enabled solutions satisfy present and future institutional demands.

Discussion of Findings

The findings from this study answer the primary research question, what themes emerged from the systematic literature review on AI-enhanced LMS? The integration of AI with LMS significantly enhances both student success and institutional operational efficiency in higher education. Across the reviewed literature, several of the AI capabilities, including adaptive learning systems, learning analytics, and conversational agents, were consistently associated with improved student engagement, personalized instruction development, and early identification of at-risk students (Alotaibi, 2024; Ngulube & Ncube, 2025). These AI tools allow institutions to leverage student performance and behavioral data to generate predictive insights, and tailor instructional support, which contributes to improved academic performance, retention, and progression outcomes. In addition to instructional benefits, the findings also answered the second research question, how does the integration of AI technologies influence institutional effectiveness? The result of this study shows that AI-LMS integrations streamline administrative processes by automating routine tasks, improving workflow management, and enabling scalable student support services (Kamalov et al., 2023; Melnyk et al., 2024).

While these results highlight the transformative potential of student outcomes with AI-enhanced LMS platforms, the literature also emphasizes that technological capabilities alone do not guarantee improved outcomes. The findings also suggest that system success depends on the interaction between technology design, user adoption, and institutional support structures. This finding aligns with the Technology Acceptance Model, which theorizes that users' perceptions of "perceived usefulness" and "perceived ease of use" influence their willingness to adopt and utilize technology (Arafat, 2024). When AI-enabled LMS features are intuitive, reliable, and clearly beneficial to the teaching and learning processes, students and faculty are more likely to engage with these tools consistently.

In addition, the DeLone and McLean Information Systems Success Model provides a broader framework for evaluating how AI-enabled LMS technologies generate measurable institutional value. The reviewed studies showed that system quality, information quality, and service quality also play a critical role in shaping user satisfaction and effective system utilization (Rulinawaty et al., 2024). High-quality data analytics, reliable performance, and institutional support contribute to sustained system use, which leads to measurable net benefits, including improved learning outcomes, enhanced decision-making, and increased operational efficiency (Alotaibi, 2024; Rulinawaty et al., 2024).

The findings from this study also answered the last research question, to what extent do system quality, information quality, and service quality (as defined by the DeLone and McLean IS Success Model) combined with the perceived usefulness and perceived ease of use (as defined by TAM) predict successful implementations of AI-enhanced LMS environments? The reviewed literature suggests that integrating the TAM with the DeLone and McLean IS Success Model provides a foundation for developing an AI–LMS evaluation framework. TAM can be used to assess user acceptance and behavioral intention, while the

DeLone and McLean model can measure system quality, satisfaction, and resulting net benefits. Together, these models allow higher education institutions to evaluate not only whether AI technologies are adopted, but also whether they deliver meaningful improvements in student success and institutional effectiveness.

Implications of Findings

The findings of this study highlight several important implications for higher education institutions seeking to integrate AI into LMS platforms to improve student success and institutional effectiveness. The results show that AI tools add capabilities such as learning analytics, adaptive learning environments, and conversational agents, to enhance student retention and engagement, personalize learning environments, and enable early identification of at-risk students (Alotaibi, 2024; Ngulube & Ncube, 2025). These technologies allow institutions to move toward more data-driven educational environments in which instructional strategies and student support services can be implemented. At the same time, AI-supported automation can improve institutional operational efficiency by streamlining administrative processes, reducing repetitive service workloads, and enabling scalable academic support systems (Kamalov et al., 2023; Melnyk et al., 2024; Miraz et al., 2024).

Despite these opportunities, the study also identifies several implementation challenges, including concerns related to data privacy, institutional readiness, technological complexity, and faculty readiness (Alotaibi, 2024; Kamalov et al., 2023). The findings emphasize that institutions must adopt structured evaluation frameworks to guide AI integration and ensure that technological innovation translates into measurable academic and operational outcomes. Integrating the TAM with the DeLone and McLean Information Systems (IS) Success Model offers a promising approach for developing such an evaluation framework. TAM provides insight into user adoption dynamics by examining how perceived usefulness and perceived ease of use influence behavioral intention to use AI-enabled systems (Arafat, 2024; Al-Mamary et al., 2024). The DeLone and McLean model enables institutions to evaluate system effectiveness through dimensions such as system quality, information quality, service quality, user satisfaction, and net benefits (Rulinawaty et al., 2024). By combining these models, institutions can assess both the human and technological dimensions of AI–LMS implementation, providing a more comprehensive understanding of system success and impact.

Conclusion

This systematic literature review explored how the integration of AI technologies within LMS platforms has transformed higher education by enhancing student learning experiences while simultaneously improving institutional operational efficiency. The reviewed literature consistently indicates that AI-driven learning analytics, adaptive learning systems, and conversational support tools can improve engagement, personalize instruction, and facilitate timely academic interventions that support student success (Alotaibi, 2024; Ngulube & Ncube, 2025). Additionally, AI-supported automation and chatbot technologies can streamline administrative processes, improve service responsiveness, and reduce institutional workload by automating repetitive tasks and providing scalable student support (Kamalov et al., 2023; Melnyk et al., 2024; Miraz et al., 2024).

However, the review also reveals that successful AI integration depends not only on technological capability but also on effective system design, user acceptance, and institutional governance. The integration of TAM and the DeLone and McLean IS Success Model provides a comprehensive framework for evaluating AI-enhanced LMS systems by linking user acceptance with system performance and measurable institutional outcomes (Arafat, 2024; Rulinawaty et al., 2024). This integrated evaluation framework enables higher education leaders to assess whether AI technologies are not only adopted but also delivering measurable results in student success, engagement, and operational efficiency. As AI technologies continue to evolve, applying a structured evaluation framework model is essential for guiding successful implementations that align with institutional goals for teaching, learning, and organizational effectiveness.

Limitations of the study

Several limitations should be acknowledged when interpreting the results of this review. First, the study relied exclusively on published peer-reviewed literature, which can introduce publication. Second, the review focused primarily on higher education, which can limit representation of findings to other educational settings such as K–12 or corporate learning environments. Lastly, the rapid pace of AI innovation means that emerging technologies, particularly with generative AI tools, may not be fully represented in the existing literature.

Recommendations for future research

Future research should continue to examine the long-term impact of AI-LMS platforms on student success and institutional effectiveness. Studies that incorporate quantitative measures of retention, graduation rates, and academic performance could provide stronger evidence of AI's educational impact. Additionally, future research should explore faculty adoption and instructional design practices since instructor engagement remains a key factor influencing the effective use of AI-supported learning technologies. Researchers should also investigate ethical considerations, including algorithmic bias and data privacy considerations, to ensure responsible implementation of AI in higher educational environments. Lastly, additional research is needed to refine and validate the proposed integrated evaluation framework that combines TAM and the DeLone and McLean IS Success Model to systematically assess AI adoption, system performance, and measurable institutional benefits in higher education.

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