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Leveraging Artificial Intelligence in Learning Management Systems: A Systematic Review of Applications and Impacts in Higher Education

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Abstract

Objectives: This review examines global research published between 2020 - 2024 on integrating artificial intelligence (AI) into Learning Management Systems (LMS) in higher education. It identifies dominant platforms and applications, evaluates methodological practices, and highlights unresolved challenges. **Methods:** Following the PRISMA guidelines, 44 peer-reviewed articles were retrieved from Scopus, Web of Science, and IEEE Xplore. Each study was coded according to platform, AI application, dataset, algorithm, feature selection, interpretability approach, and outcomes. Bibliometric mapping was performed using VOSviewer. **Findings:** Research activity increased sharply during the pandemic (2020-2022) and stabilised after 2023. Most contributions came from Saudi Arabia, India, and China, while Africa and Latin America were rarely represented. Moodle accounted for about one-quarter of the reviewed studies. Predictive analytics was the most frequent application, with models such as kNN, Random Forest (RF), and PCA showing strong performance. However, few studies employed explainable AI (XAI) methods such as SHAP and LIME appeared in less than 5% of studies and dataset dependence, particularly on OULAD, limited cross-institutional replication. **Novelty:** Unlike earlier descriptive reviews, this study provides the first cross-platform quantitative synthesis of AI-enabled LMS research. It benchmarks predictive accuracy across algorithms, identifies methodological bottlenecks, and highlights neglected areas, including dataset diversity, XAI, inclusivity, and pedagogical validation.

Keywords: Artificial Intelligence; Learning Management Systems; Higher Education; Predictive Analytics; Explainable AI

1 Introduction

Digital transformation in higher education aims to improve efficiency, broaden access, and enhance the quality of teaching and learning. Learning Management System (LMS) is a platform for organising and delivering educational content online[(1,2)]. The transition from traditional to hybrid digital environments has established LMS as foundational in contemporary higher education. Recent advancements integrate artificial intelligence (AI), expanding LMS functionalities into adaptive learning, interactive content delivery, advanced course management, and comprehensive learning analytics[3–7]. Given this evolution, it is timely to systematically examine how AI is being integrated into LMS platforms in higher education identifying which applications are most prevalent, what impacts they have on student learning and institutional decision-making, and where critical gaps remain. Unlike earlier descriptive reviews[8–12], this study provides a cross-platform, quantitative synthesis highlighting achievements and persistent challenges in AI-enabled LMS research.

1.1 Limitations of Existing Reviews

Although LMS and AI adoption are expanding rapidly, prior reviews provide only partial insights. Studies highlight general impacts[1], system enhancement[2], application trends[3], institutional challenges[4], teaching paradigms[5], curriculum and pedagogy[6], and personalization[7]. Reviews of intelligent tutoring systems (ITS) also highlight relevance for adaptive pathways, although focused on K-12 contexts[9]. However, these reviews remain largely descriptive, failing to quantify platform dominance, application distribution, or algorithmic performance, and rarely addressing bottlenecks such as dataset imbalance, feature selection, or interpretability[10–12].

1.2 How the Proposed Review Addresses These Limitations

This review directly responds to these shortcomings by systematically analysing 44 peer-reviewed studies (2020-2024) from Scopus, Web of Science, and IEEE Xplore. Unlike prior descriptive work, it provides a cross-platform quantitative synthesis, mapping applications, algorithms, datasets, and methodological practices. It also highlights neglected but critical issues such as the limited use of feature engineering, explainable AI (XAI) methods like SHAP and LIME, and the absence of qualitative validation.

1.3 Problems Addressed by the Proposed Review

The study addresses several pressing challenges. First, it maps the global distribution of AI-enabled LMS research, showing concentrated contributions from Saudi Arabia, India, and China (>40% of studies), while regions like Africa and Latin America remain underrepresented. Second, it evaluates methodological practices such as predictive accuracy kNN up to 98.5%, Random Forest (RF) up to 92%, feature selection techniques, and interpretability, thereby identifying both strengths and weaknesses. Third, it critiques dataset diversity, heavily relying on OULAD and smaller institution-specific datasets that limit scalability and generalizability. Finally, it pinpoints underexplored domains such as personalisation, inclusivity, and pedagogy, proposing a roadmap for AI-LMS research.

1.4 Novelty of the Proposed Review

This review makes four novel contributions. First, it visually maps LMS platforms, AI applications, and geographic regions, revealing global trends. Second, it offers quantitative benchmarking, reporting distributions, counts, a list of existing AI-enabled LMS with their key features and thematic outcomes with AI in education. Third, it systematically documents LMS datasets, feature selection techniques, their accuracy and interpretability practices, highlighting the urgent need for XAI in education[13–15]. Finally, it explores emerging directions such as ITS[9], and AI-powered assistants, providing actionable insights for policymakers and educators. Table 1 contrasts prior reviews with the present study, underscoring how this review advances the field by offering the first cross-platform, quantitative synthesis of AI-enabled LMS research.

1.5 Research Questions

These gaps highlight the need for a comprehensive, cross-platform, and data-driven synthesis of AI in LMS. Accordingly, this review is guided by three key questions:

1. What are the dominant platforms, applications, and geographic regions of AI-enabled LMS research?
2. What methodological practices prevail, including datasets, feature selection, algorithms, and interpretability, and where are the bottlenecks?
3. How can these insights guide equitable, effective, and pedagogically meaningful AI adoption in higher education?

Table 1. Comparison of Previous Reviews and the Present Review

Review Study	Scope	Methodology	Coverage	Key Focus	Limitations	Novelty of Present Review
Altinpulluk & Kesim (2021) [1]	LMS adoption trends	Descriptive	2010-2020	Institutional adoption of LMS	No AI perspective; no cross-platform benchmarking	Integrates AI-enabled LMS and benchmarks across platforms
Imran et al. (2024) [2]	AI in higher education (general)	Narrative	2015-2023	System enhancement, pedagogical paradigms	Too broad; lacks LMS-specific synthesis	Focuses on LMS-specific AI applications with methodological rigor
Matos et al. (2025) [3]	AI in education broadly	Systematic review	2010-2024	Trends and challenges in AI for education	Does not quantify accuracy, datasets, or interpretability	Benchmarks algorithms, datasets, and explainability practices
Ocen et al. (2025) [4]	AI in HE institutions	Descriptive / systematic	2015-2024	Innovations and opportunities in HE	Limited technical detail; no platform-level analysis	Maps cross-platform LMS integration and predictive performance
Other reviews (2019–2023)	Scattered topics (analytics, engagement, e-learning)	Mostly descriptive	Varies	Single platform or narrow focus	Largely descriptive; no benchmarking, no interpretability analysis	Provides cross-platform, global, quantitative synthesis of 44 studies (2020-2024)
Present Review (2025)	AI-enabled LMS in higher education	Systematic (PRISMA)	2020-2024; Scopus, WoS, IEEE Xplore	Platforms, applications, datasets, algorithms, interpretability	-	First review to map global distribution, benchmark predictive accuracy, document feature selection & interpretability, and highlight inclusivity /pedagogy gaps

2 Review Methodology

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [5] to ensure transparency and methodological rigor. A targeted search was conducted using Boolean combinations of the terms: “AI” OR “Artificial Intelligence” AND “Prediction” OR “Predictive” AND “LMS” OR “Learning Management System” AND “Higher Education” OR “Higher Education Institutes”. Searches were performed across Scopus, Web of Science (WoS), and IEEE Xplore for 2020-2024. Bibliometric mapping was performed using VOSviewer [16].

2.1 Inclusion and Exclusion Criteria

Inclusion criteria were: (i) peer-reviewed articles published between 2020 and 2024, (ii) written in English, (iii) focused on higher education, and (iv) addressing AI-enabled LMS. Studies were excluded if published before 2020, not related to higher education, not focused on AI in LMS, or if the full text was unavailable.

2.2 Selection Process

The screening process proceeded in three stages: (i) title and keywords screening to remove irrelevant works, (ii) abstract review against inclusion criteria, and (iii) full-text review to confirm eligibility. References were managed and screened using Zotero [12]. This process initially identified 343 records, of which 299 were excluded at various stages, yielding a final dataset of

44 eligible studies. References were managed using Zotero [6], while bibliometric and co-occurrence analyses were performed with VOSviewer [7].

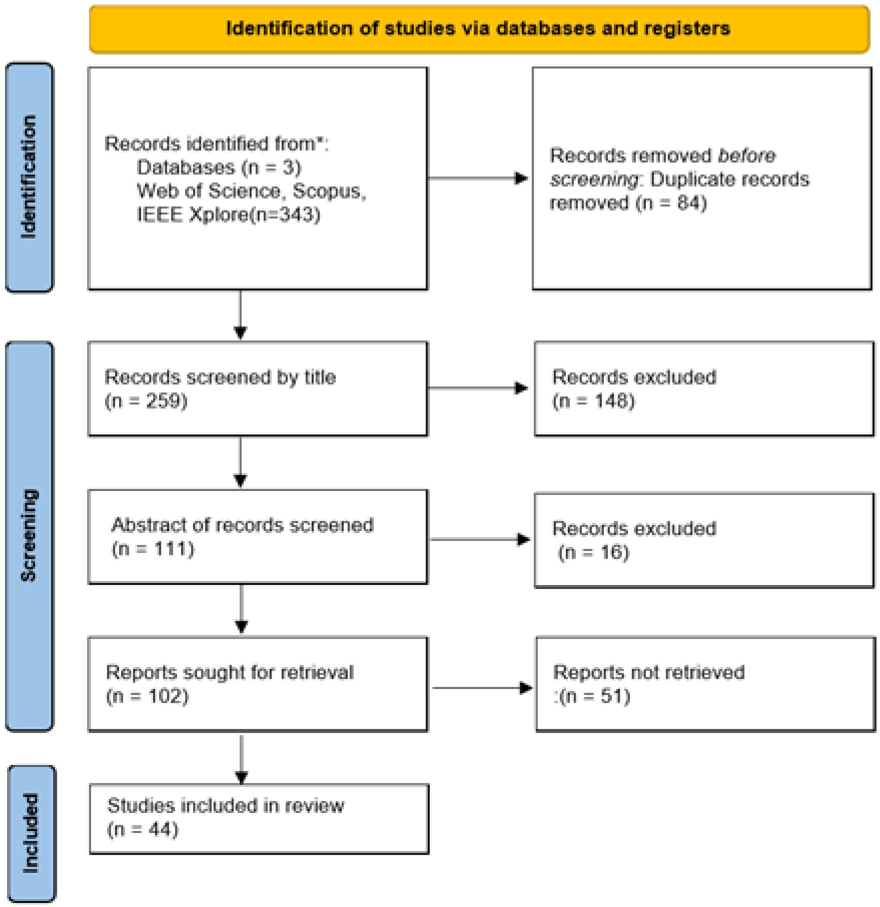

Fig 1. PRISMA model [5] A systematic approach was used for the search and selection process

For conceptual synthesis, each study was systematically coded along multiple dimensions: year of publication, geographic region, LMS platform, AI application domain, dataset characteristics, algorithms employed, feature selection techniques, and reported outcomes. Coding was independently verified by both authors to ensure reliability. This multi-dimensional approach enabled bibliometric mapping, content-level synthesis, and quantitative comparison, capturing where and how AI is applied in LMS and the associated strengths, limitations, and research gaps. Figure 1. PRISMA flow diagram [5] illustrating the identification, screening, eligibility, and final inclusion of studies.

3 Overview

This section presents a consolidated overview of the review's outcomes, providing a structured snapshot of how AI has been integrated into LMS in higher education. The overview is organised to capture the breadth of research themes and the depth of methodological practices while also identifying recurring bottlenecks and emerging opportunities.

The analysis begins with publication trends, which show a sharp increase during the COVID-19 pandemic (2020–2022) and stabilisation thereafter, reflecting institutional consolidation of digital practices. Term co-occurrence mapping highlights dominant themes such as predictive analytics and student engagement, while also pointing to emerging areas like recommendation systems and dropout detection. In terms of global contributions, the review reveals strong concentration in regions such as Saudi Arabia, India, and China (together >40% of studies), with limited representation from Africa and Latin America. Research methods are predominantly quantitative, with minimal qualitative or mixed-method validation, suggesting an emphasis on performance benchmarking over pedagogical evaluation. The review then examines LMS platforms, showing a heavy skew toward Moodle (25.6% of studies) compared with Blackboard, Canvas, and smaller proprietary systems. This is followed by an analysis of AI applications and outcomes, where predictive analytics dominates (46.4%), while personalisation and inclusivity remain underexplored. Datasets are another critical dimension: while OULAD provides a benchmark for comparability, most studies rely on smaller, institution-specific datasets, limiting scalability. Feature selection and interpretability practices are inconsistently applied, although algorithms such as kNN and RF achieve high accuracy (>90%), XAI techniques such as SHAP and LIME appear in fewer than 5% of studies. Finally, the review synthesises recurring bottlenecks and emerging directions, including dataset imbalance, methodological homogeneity, and lack of cross-institutional validation. Promising opportunities are identified in ITS, AI-powered virtual assistants, and the incorporation of explainable AI (XAI) to improve transparency and adoption.

This structured overview thus serves as a roadmap for the key findings section, which provides detailed quantitative evidence, tables, and figures to critically interpret these trends and gaps.

3.1 Results and Findings

3.1.1. Publication Trends

Figure 2(a) shows a sharp increase in AI-enabled LMS research during the COVID-19 pandemic. Publications rose steadily from 2020, peaking in 2022 with 18 studies (41.8% of total), before stabilising in 2023–2024. This surge reflects the urgency of digital adoption during pandemic-related campus closures, followed by a consolidation phase as institutions normalised hybrid education.

3.1.2. Term Co-occurrence

A term co-occurrence analysis was conducted using VOSviewer[16] to examine the conceptual structure of the reviewed literature. Figure 2(b) presents the co-word network, where nodes represent keywords and edges indicate their co-occurrence in abstracts. The visualisation reveals three dominant thematic clusters: a red cluster centred on predictive analytics for student performance and dropout risks, a green cluster highlighting adaptive and personalised learning approaches, and a blue cluster associated with recommendation systems and student engagement strategies. The keyword “Artificial Intelligence” strongly links prediction, performance, and recommendation, underscoring its central role in shaping research.

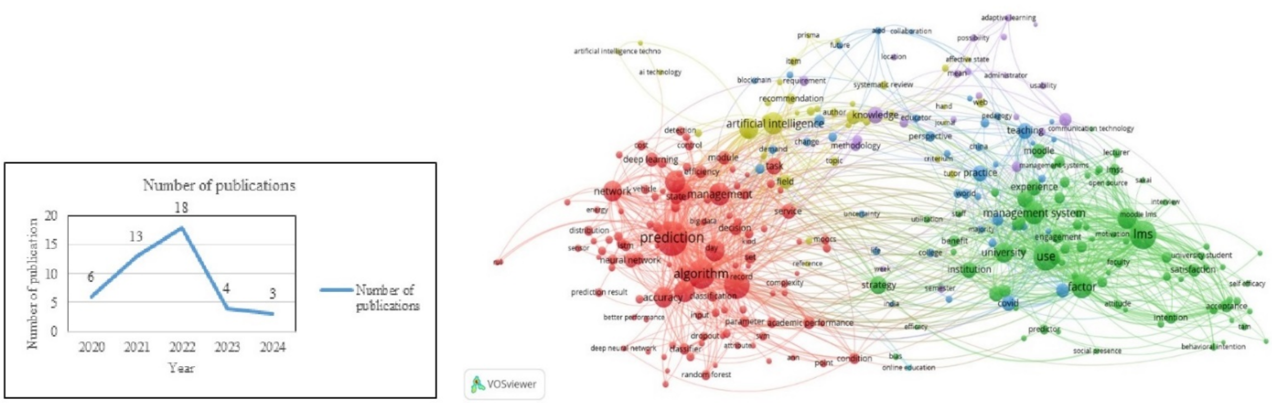

Fig 2. (a) Publications per year. (b) Term co-occurrence analysis in the abstract and title of reviewed articles

Figure 2(a) Publications per year showing a peak during the COVID-19 pandemic and stabilization thereafter. Figure 2 (b) term co-occurrence network generated using VOSviewer, illustrating thematic clusters including predictive analytics, personalized/adaptive learning, and recommendation systems. Together, these clusters reflect the thematic breadth of AI-enabled LMS research, while also highlighting their concentration on predictive performance rather than inclusivity, transparency, or cross-institutional scalability. This imbalance suggests that although predictive analytics is well established, emerging themes such as XAI, equity, and immersive technologies remain underdeveloped and present key opportunities for future research.

3.1.3. Global Contribution

Geographical analysis shown in Figure 3 indicates a strong concentration of research activity in Asia, particularly in Saudi Arabia, India, and China, which together account for more than 40% of the reviewed studies. Additional contributions were identified from European countries such as the UK, Spain, and Romania, and from emerging regions including Ecuador and South Africa. While this distribution reflects the growing global recognition of AI's role in enhancing LMS, the overall picture remains uneven.

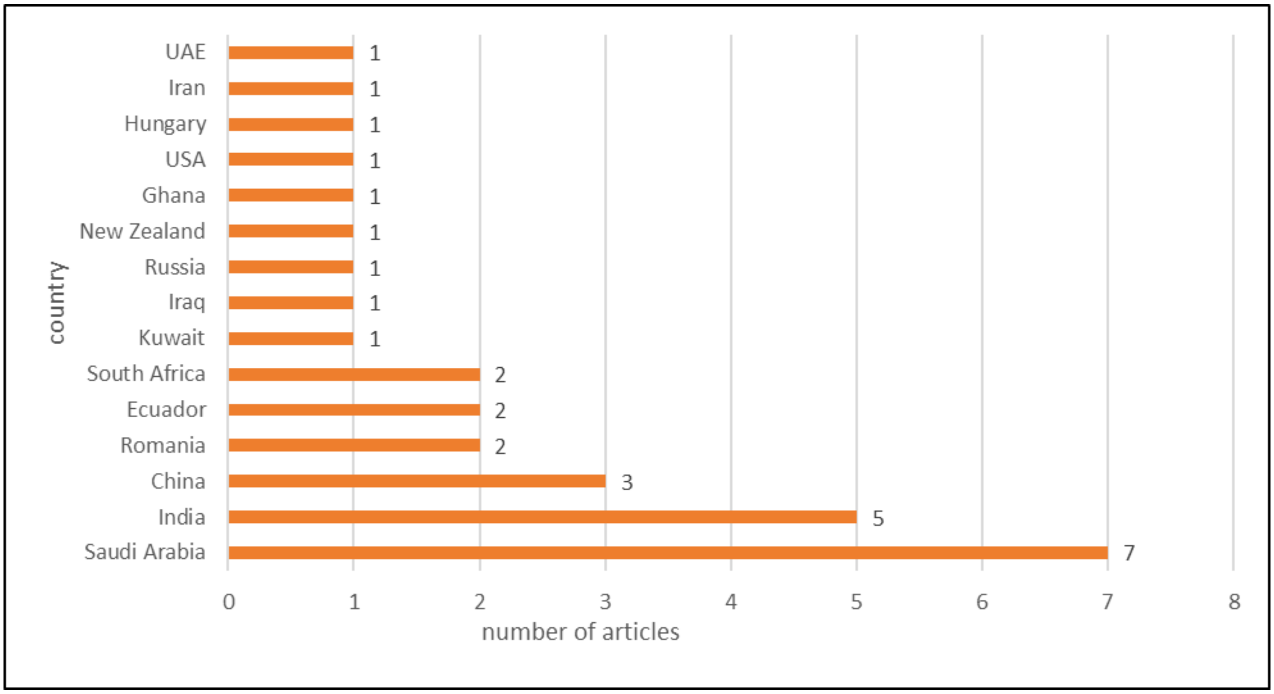

Fig 3. Publications country-wise

The dominance of Asia and Europe highlights regional leadership in AI-LMS integration, but the limited representation from Africa and Latin America (<5% of studies) raises concerns about inclusivity and the generalizability of current findings across diverse educational contexts. Expanding research participation from underrepresented regions is therefore essential to ensure that AI-driven LMS innovations are globally relevant and responsive to diverse institutional needs.

3.1.4. Research Methods

As shown in Figure 4, the methodological landscape is heavily skewed toward quantitative approaches (n = 12, 65%), which typically involve predictive modelling, machine learning algorithms, and statistical evaluation. In contrast, qualitative approaches (n = 1, 2%) and mixed methods designs (n = 2, 5%) are rarely employed. This imbalance indicates that while technical benchmarking dominates the field, interpretive and user-centered perspectives remain underrepresented. Such a gap limits understanding of how AI-enabled LMS solutions are experienced by educators and learners, underscoring the need for more qualitative and mixed-methods studies to complement quantitative findings and ensure pedagogical relevance.

3.1.5. LMS Platforms

Figure 5 shows that Moodle is the most widely researched platform (n = 11, 25.6%), followed by Blackboard (n = 6, 14%). Moodle's dominance can be attributed to its open-source nature, adaptability, and strong community support, making it particularly attractive for testing AI-based features such as predictive analytics and adaptive learning [8,9]. Other platforms including Canvas (n = 2), Google Classroom, Sakai, NeoLMS, IntelliDaM, and Future Gate (together n = 8) appear far less frequently.

This concentration of studies on Moodle highlights both an opportunity and a limitation. On one hand, it has enabled rapid experimentation due to openness and accessibility. On the other hand, it risks narrowing the scope of AI-LMS research, as

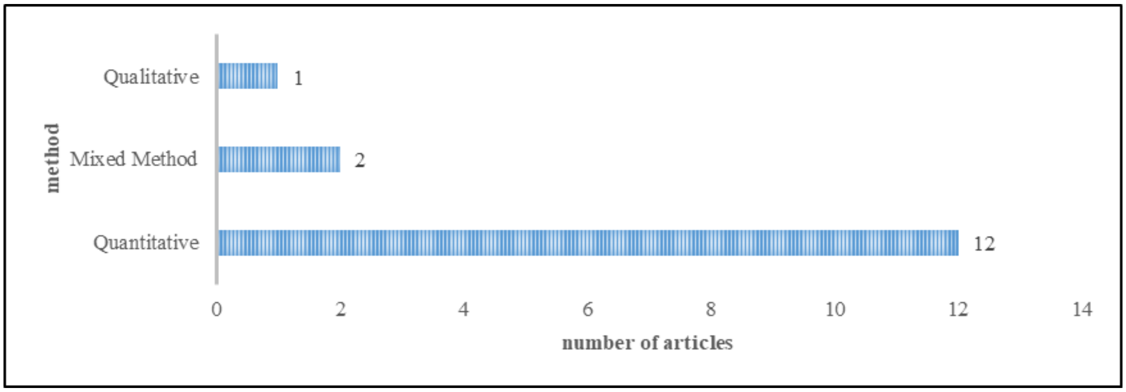

Fig 4. Distribution of research methods in reviewed studies (2020–2024)

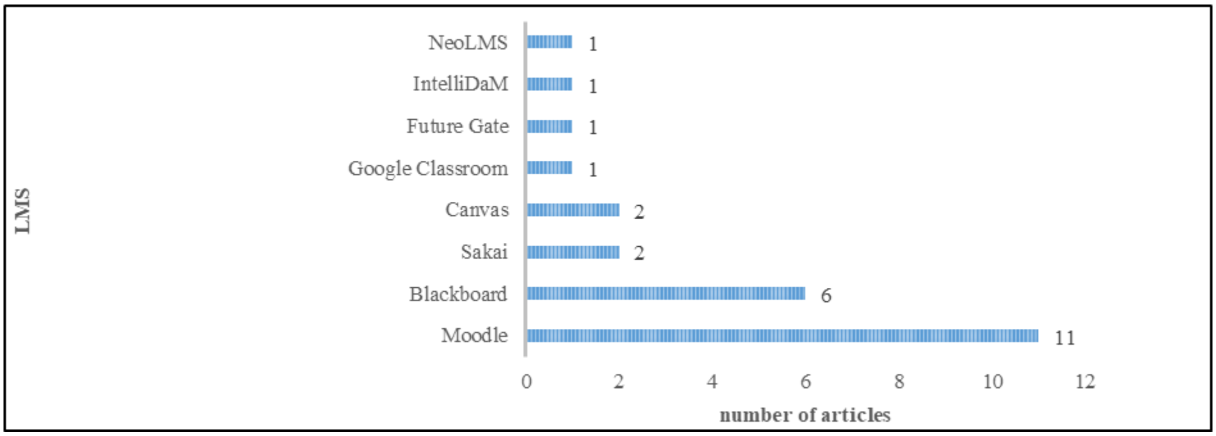

Fig 5. LMS platforms represented in reviewed studies (2020–2024)

findings may not generalize well to proprietary or less-studied platforms. Future work should expand beyond Moodle-centric studies to provide more balanced insights across diverse LMS ecosystems.

3.1.6. AI Applications and Outcomes

3.1.6.1. AI-Enabled LMS . The development of AI-enabled LMS reflects continuous innovation and customization in higher education. Table 2 summarises platforms such as DeepLMS, SMILE, AISAR, RADIAL, and IntelliDaM, each extending standard LMS capabilities with predictive analytics, adaptive feedback, and domain-specific enhancements. Systems like DeepLMS and AISAR focus on predicting performance and providing recommendations, while RADIAL and SMILE address specialised contexts, such as radiology training or multidimensional learning environments. These examples demonstrate how AI integration enables more tailored, data-driven, and interactive educational experiences that enhance student engagement and institutional decision-making.

3.1.6.2. Learning Outcomes in AI-enabled LMS. The broader literature on AI-enabled LMS aligns with seven thematic outcomes: predictive analytics, student engagement, dropout risk identification, recommendation systems, personalization, technology acceptance, and teaching evaluation. As shown in Figure 6, predictive analytics dominates, representing 46.4% of studies, while engagement, recommendation, and technology acceptance each account for 12.5%. Teaching evaluation, personalization, and dropout risk detection appear in only 5.4% of cases.

Predictive studies consistently report high accuracy using deep learning ensembles, stacked generalisation, IoT-enhanced models, and RF (up to 98% accuracy)[17–20]. Engagement-focused research employs learning analytics and transmedia activities to monitor participation[21,22]. Dropout risk detection studies use divide-and-conquer and RF strategies for early-warning systems[23]. Recommendation systems leverage classifiers, collaborative filtering, and reinforcement learning, achieving F1 scores and accuracy between 74% and 97%[12,13,24]. Personalisation research highlights the role of ITS[9,14,24], while technology

Table 2. AI-Enabled LMS

Platform	Key Features	Articles
DeepLMS	Deep learning–based predictive model for personalized Quality of Instruction (QoI); supports learner motivation and participation monitoring	(10)
SMILE (Simple, Multidimensional, and Interactive Learning Ecosystem)	Multidimensional LMS designed to address diverse student learning needs	(11)
AISAR (AI-based Student Assessment and Recommendation system)	AI-enabled assessment & recommendation system; includes mark estimation, clustering, prediction, and personalized support	(17)
RADIAL	Domain-specific LMS for radiology education; robust analytics for user statistics and performance	(12)
IntelliDaM	Machine learning framework for decision-making support in higher education	(18)

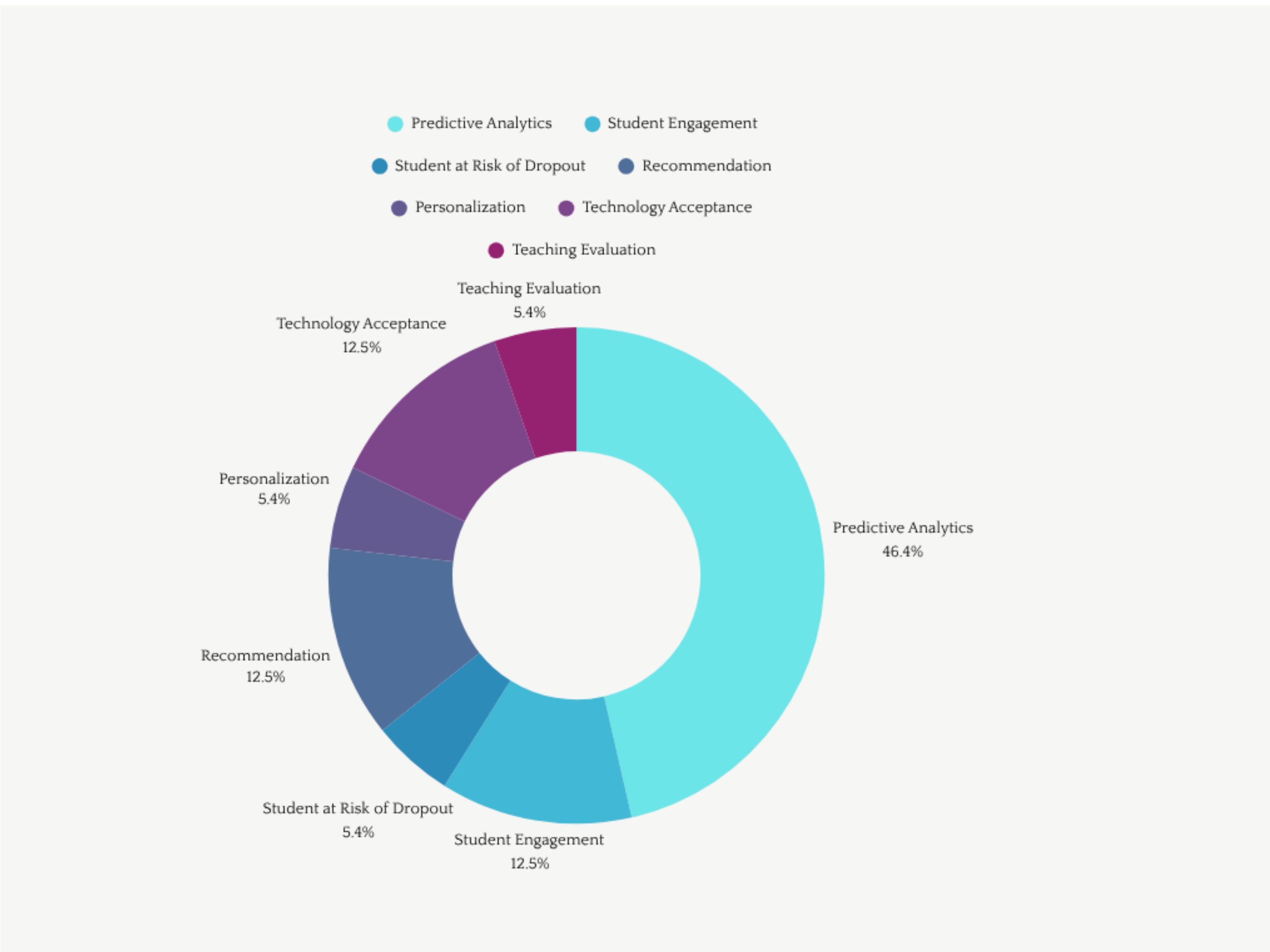

Fig 6. Categories of Predicted Outcomes

acceptance studies using TAM and SEM frameworks emphasise usability and professional alignment [11]. Teaching evaluation research employs AI to analyse feedback and outcomes [6]. While these applications demonstrate technological strength, they reveal a significant imbalance: nearly half of the research focuses narrowly on prediction, while inclusivity, personalisation, and evaluation remain marginal. This concentration suggests a gap between performance optimization and pedagogical impact, underscoring the need for broader exploration.

3.1.7. Datasets

Table 3 summarises the datasets used across the reviewed studies. OULAD [21] remains the most prominent benchmark (>10 million records). Other institutional datasets include AISAR [17], IntelliDaM [18], dropout studies with small datasets (<10k) [15,22], and Australasian Moodle [9]. Several recommender system studies also used institution-specific datasets [13,23,24]. While large-scale datasets enable replicability, the dominance of small, siloed sources limits generalizability. In contrast, most studies rely on small, institution-specific datasets, often fewer than 10,000 records, such as those from universities in India, Hungary, Malaysia, and Saudi Arabia [15,17,18,22]. These datasets provide localised insights but limit scalability and cross-institutional comparability. Few studies used synthetic datasets, reducing opportunities for controlled experimentation. Overall, dataset diversity illustrates both strength and weakness: while large-scale benchmarks such as OULAD [21] enable replicability, over-reliance on single institutions constrains the development of globally generalizable AI models. Expanding collaborative, cross-institutional datasets should be a priority for future research.

3.1.8. Feature Selection and Interpretability

Despite strong predictive modeling, systematic feature selection and interpretability remain underdeveloped. RF classifiers consistently reported accuracies between 84% and 92% [15,19–21]. PCA achieved 94% accuracy when applied for dimensionality reduction [24], while kNN produced the highest result at 98.5% [21]. Linear SVC also showed competitive performance with an F1 score of 80.3% [22]. Additional strategies such as Z-score normalisation [22], feature ranking [18], and hybrid models combining CatBoost, neural networks, and logistic regression attained 81% precision [23]. However, interpretability methods such as SHAP and LIME appeared in fewer than 5% of studies [14], highlighting a persistent lack of XAI in LMS research. Table 4 summarises the algorithms, feature selection, and interpretability techniques applied in AI-enabled LMS studies.

However, interpretability methods such as SHAP and LIME appeared in fewer than 5% of studies [14]. This lack of explainable AI represents a major bottleneck, as models remain “black boxes” despite high accuracy. Without transparency, institutional trust and ethical adoption are compromised. Addressing this gap is crucial for ensuring that AI-driven decision support systems are not only effective but also accepted and responsibly implemented.

3.1.9. Bottlenecks and Emerging Directions

The reviewed literature reveals recurring bottlenecks: over reliance on Moodle [19,20], dominance of quantitative methods, heavy use of small datasets [17,18,21,22], and limited adoption of explainability tools [13–15]. These trends reinforce methodological homogeneity and restrict generalizability. At the same time, promising directions are emerging. ITS can provide adaptive, personalized learning pathways [9]. AR/VR technologies offer immersive, experiential learning potential, while AI-powered virtual assistants can deliver real-time, individualized support to students and instructors. Most critically, integrating XAI into LMS platforms will enhance transparency, trust, and ethical use [13].

Compared to earlier reviews that remained descriptive and often limited to single-platform or regional analysis [1–12], the present study advances the field in three distinct ways: (i) it provides the first cross-platform, quantitative benchmarking of AI-enabled LMS research across 44 global studies, (ii) it systematically documents feature selection and explainability practices areas largely overlooked in prior work [13–15], and (iii) it identifies underexplored but critical domains such as personalization, inclusivity, and pedagogical impact [6,7,10,11]. These contributions position this review as a methodological and conceptual bridge, moving beyond descriptive mapping toward actionable synthesis for equitable and transparent AI integration in higher education.

3.2 Overall Synthesis and Comparative Insights

The analysis shows several recurring patterns. First, research output is strongly clustered around Moodle [19,20], creating a narrow base for cross-platform generalisation. Second, methodological homogeneity is evident: most studies apply quantitative machine learning models, while qualitative and mixed approaches remain rare. Third, dataset size and diversity continue to pose limitations, as many studies rely on institution-specific data with fewer than 10,000 records [17,18,21,22]. Despite strong predictive results, RF up to 92%, PCA 94%, kNN 98.5% [21–24], interpretability tools such as SHAP and LIME are almost absent

Table 3. Dataset used in reviewed articles

Sr. no	Dataset	Number of Records	Duration	Reference
1	AISAR institutional dataset (Wollo University & Kombolcha Institute of Technology)	32,582	2017-2022	[17]
2	IntelliDaM dataset (Romanian/Hungarian universities)	331-570	2019-2020	[18]
3	Federal Institute of Education, Science, and Technology of Ceara (IFCE), Brazil	1,549	2008-2019	[17]
4	Malaysia Polytechnic (JTMK) dataset	1,282	2016-2019	[22]
5	Mehralborz University (MAU), Iran	153	-	[22]
6	Chinese university (Chaoxing Xuexitong system)	3,976	-	[22]
7	Blackboard dataset – Umm al-Qura University, Saudi Arabia	500-1,000	2019-2021	[15]
8	French higher education institution	4,424	-	[23]
9	Kalboard 360 synthetic dataset	481	2016	[24]
10	King Saud University dataset	471	2020-2021	[15]
11	Open University Learning Analytics Dataset (OULAD)	10,655,28	2013-2014	[21]
12	Australasian HEI Moodle dataset	7,108	2018-2022	[9]
13	Dropout prediction datasets (Jouf University & Finland)	<10,000	2018-2019	[15,22]
14	Recommender system datasets (institution-specific)	Vary	-	[13,23,24]

Table 4. Feature selection and interpretability techniques

Sr. no	Algorithm / Technique	Result	Reference
1	RF classifier	Accuracy = 92.02%	[21]
2	Z-score standardization (feature scaling)	–	[22]
3	Linear SVC classifier	F1 = 80.33%	[22]
4	Principal Component Analysis (PCA)	Accuracy = 94%	[21]
5	RF classifier	Accuracy = 85%	[15]
6	k-Nearest Neighbors (kNN)	Accuracy = 98.5%	[21]
7	RF classifier	Accuracy = 90%	[19]
8	RF classifier	Accuracy ≈ 84–85%	[20]
9	RF classifier	–	[15]
10	Feature Ranking	–	[18]
11	CatBoost (CAT), Neural Networks (NN), Logistic Regression (LR)	Precision = 81%	[22]
12	SHAP (Explainability)	–	[14]

(<5% of studies)[13–15]. This lack of transparency undermines trust and limits adopting AI-driven decision support in higher education. At the same time, several promising directions are emerging. ITS demonstrates how adaptive pathways can support personalisation[9]. Augmented and virtual reality are increasingly being considered for immersive learning environments. AI-enabled assistants provide real-time guidance to both instructors and students. Most importantly, the integration of Explainable AI into LMS could address the ethical and transparency concerns raised in current practice[13].

Compared with earlier reviews that were primarily descriptive and often restricted to a single platform[1–12],, the present study contributes three distinct advances: (i) offers the first quantitative benchmarking of AI-enabled LMS research across 44 global studies, (ii) systematically documents feature selection and explainability practices. Dimensions rarely examined in earlier work [13–15], and (iii) it draws attention to underexplored areas such as personalisation, inclusivity, and pedagogical outcomes [6,7,10,11].

These contributions position this review as a methodological benchmark and a conceptual reference point for future AI integration in higher education.

4 Conclusion

This systematic review synthesises 44 peer-reviewed studies published between 2020 and 2024 that explore the integration of AI into LMS within higher education. By applying the PRISMA framework and conducting a multi-dimensional, cross-platform analysis, the study provides the first comprehensive quantitative synthesis of AI-enabled LMS research.

The findings reveal several clear trends. Publication output peaked during the COVID-19 pandemic and later stabilized as digital practices became institutionalized. Research is geographically concentrated, with over 40% of studies emerging from Saudi Arabia, India, and China, while Africa and Latin America remain underrepresented. Quantitative methodologies dominate, indicating a focus on algorithmic performance rather than pedagogical validation. Moodle is the most widely studied platform, and predictive analytics remains the most common application. Although models such as kNN, Random Forest, and PCA demonstrate strong performance, the lack of interpretability through XAI approaches remains a critical gap. Dataset usage also shows imbalance, with a heavy reliance on OULAD and small, institution-specific sources, which limits scalability and cross-context replication.

This review advances the field by benchmarking predictive accuracy across algorithms, documenting feature selection and explainability practices, and identifying underexplored yet essential domains such as inclusivity, personalization, and pedagogical integration. The findings underscore the need for future AI-LMS research to prioritize transparency, equity, and scalability. Incorporating explainable AI, expanding dataset diversity, and integrating mixed-method evaluations will be crucial for ensuring that AI-driven learning systems in higher education are both effective and ethically grounded.

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