Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 7.056

IJCSMC, Vol. 15, Issue. 5, May 2026, pg.26 – 37

NexEd: An Electronic Learning Management System with Descriptive Analytics for Data-Informed Education

Kyla May G. Broñola[1]; Angel Mae L. Lamis[2]; Andrew C. Braza[3]; Myca Pacibo[4]; Alejandro Leganada[5]; Serafin C. Palmares[6]; Kristine Soberano, Ph.D[7]

[1,2,3,4,5,6,7] State University of Northern Negros, Philippines

[1] kylamaybronola@gmail.com; [2] angelmaellamis@gmail.com; [3] brazaandrew@gmail.com; [4] mycapacibo21@gmail.com; [5] leganada.alejandro.bulaquena@gmail.com; [6] spalmares@sunn.edu.ph; [7] ksoberano@sunn.edu.ph

DOI: https://doi.org/10.47760/ijcsmc.2026.v15i05.004

Abstract: Traditional Learning Management Systems (LMS) primarily function as content repositories with limited support for real-time academic monitoring. This study presents NexEd, an Electronic Learning Management System (ELMS) integrated with descriptive analytics and AI-assisted assessment tools, designed for basic education. Using a developmental research approach guided by the Agile Development Model, the system was developed and evaluated by administrators, teachers, and students.

Results indicate high usability across key dimensions: System Usefulness (1.78), Information Quality (1.86), Interface Quality (1.84), and Overall Satisfaction (1.83), all interpreted as "Strongly Agree." Inferential analysis using paired t-test revealed a significant improvement in user engagement and task efficiency ($t = 7.21$, $p < 0.001$). Engagement increased by approximately 19% after system implementation.

The findings demonstrate that integrating descriptive analytics within an ELMS enhances data-driven decision-making and supports early identification of at-risk students. The study recommends incorporating predictive analytics models and expanding implementation across institutions to improve scalability and impact.

Keywords: Educational Data Analytics, Learning Analytics Dashboard, Descriptive Analytics, ELMS, Predictive Analytics

INTRODUCTION

E-learning systems have made educational resources easier to access, more interactive, and more effective for learners, removing limits of location and time (Liu & Yu, 2023). Recent studies show that e-learning platforms that integrate descriptive data analytics can improve student engagement and participation by transforming raw data into meaningful information. Descriptive analytics focuses on summarizing historical data such as quiz scores, grades, and task completion rates. These are presented through dashboards, charts, and reports that help both students and teachers understand learning progress.

For instance, learning analytics dashboards provide visual summaries of student activity, allowing users to answer questions like "What is happening in student performance?" and "Which students are less active?" Paulsen and Lindsay (2024) found that students who used dashboards based on descriptive analytics improved their course engagement and completion rates by 18%, as they became more aware of their learning behavior.

Learning Management Systems (LMS) are essential in modern education because they support course delivery, assessment, and communication (Abdul-Gafaar et al., 2025). However, many LMS platforms mainly serve as storage systems for learning materials and lack effective descriptive analytics features. While they collect large amounts of student data, they often do not provide clear summaries or visual insights that teachers can easily interpret. Batra (2025) emphasized that most LMS platforms do not include well-designed dashboards or reports that show trends in student performance.

This creates a gap in data-driven decision-making. Without descriptive analytics, teachers must manually review student records, which is time-consuming and may lead to delayed interventions. According to Ifenthaler and Yau (2020), descriptive analytics is essential because it provides a clear overview of student progress and helps educators make informed decisions based on actual data. Similarly, Guo et al. (2022) found that when LMS platforms lack analytics dashboards, teachers struggle to identify at-risk students early, contributing to lower retention and performance. Common measurable issues in existing LMS include low student engagement due to lack of feedback and insights, difficulty identifying inactive or struggling students, limited visibility of overall class performance and delayed instructional decisions due to a lack of summarized data.

Although interest in educational data is growing, there is still a lack of all-in-one systems that connect data collection with instructional action in local basic education. Most platforms today require additional tools or manual exports to generate insights. NexEd, the proposed ELMS, takes a new approach by integrating a built-in Descriptive Analytics Engine into the main user experience. Unlike other systems, NexEd creates a closed-loop process: it uses AI to create content and assessments, then quickly displays results on dashboards for students, teachers, and administrators. This way, data is not just stored but is quickly turned into useful classroom strategies.

At Light Christian Academy of Binalbagan, there is no integrated system to show student performance in real time. Because of this, administrators face delays, as teachers must review raw data by hand to identify students who need help. This often leads to lower student engagement and slower support for those who are struggling.

HYPOTHESIS

To find out how well the proposed system works, the study will test the following:

H1: The integration of descriptive analytics within NexEd significantly reduces the time required for educators to identify at-risk students compared to traditional methods.

H2: Students using NexEd dashboards demonstrate significantly higher engagement and task completion rates compared to baseline LMS usage

OBJECTIVES OF THE STUDY

The primary objective of this study is to develop an Electronic Learning Management System (ELMS) with integrated data analytics to enhance teaching and learning outcomes.

Specifically, this study aims to:

1. Develop an integrated ELMS frame. Specifically, the study aims to: 1. Build an ELMS framework that combines AI-generated assessments and descriptive analytics to support data-driven academic management;

2. Check how accurate and reliable the descriptive analytics models are in giving real-time performance insights; and

3. Evaluate system usability and information quality by using standard methods to review user experience, interface design, and system usefulness.

CONCEPTUAL FRAMEWORK

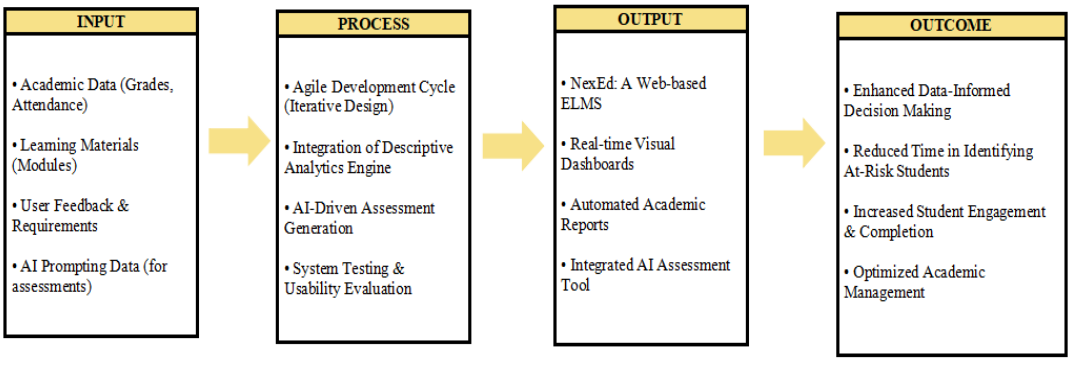

Figure 1. IPOO Model

The project begins with the collection of raw data, such as student records, which are processed by AI assessment tools. During the Process stage, an Agile approach is employed to develop the system, with iterative improvements to the analytics engine based on regular testing and user feedback. The Output is the NexEd platform, featuring interactive dashboards and automated tools for administrators. In the Outcome phase, the system enhances student participation and enables teachers to identify struggling students more efficiently. This framework demonstrates how raw data is transformed into visual insights that support timely and informed decision-making by educators.

METHODS

Research Design

A developmental research design combined with a descriptive–evaluative approach was used to design, develop, and assess NexEd: An Electronic Learning Management System with Descriptive Analytics.

Developmental research is well-suited for this context because it systematically develops, tests, and refines educational technologies and systems. This methodology is widely applied in instructional design and technology-based studies aimed at producing functional and effective products. According to Richey and Klein, developmental research involves iterative cycles of design, development, and evaluation to ensure that the resulting system aligns with user needs and performs effectively. Recent studies, including those by Ellis and Levy (2019), Lee and Reeves (2022), and Broadbent et al. (2023), emphasize that developmental research fosters innovation in digital learning environments by integrating design with empirical validation, thereby advancing evidence-based educational technologies.

A descriptive–evaluative approach was also used to assess the system's usability, functionality, and effectiveness after development. Descriptive study collects data to characterize user experiences, while evaluative research measures overall quality and performance. Creswell and Creswell (2018) explain that descriptive designs identify patterns and user perceptions, whereas evaluative methods determine if a system achieves its intended outcomes. Recent studies in educational technology highlight the value of integrating development and evaluation to ensure usability and instructional effectiveness (e.g., Alharbi and Drew, 2021). Combining developmental and descriptive–evaluative designs ensures a fully functional learning management system and provides empirical evidence of its effectiveness, usability, and user acceptability

The study implemented an Educational Data Analytics Framework comprising data collection, preprocessing, analysis, and visualization.

Tools and Technologies:

The system utilized **PHP** for data processing, **SQL** for database management, and **JavaScript-based charting libraries (e.g., Chart.js)** for visualization.

Data Processing Pipeline:

- Data Collection: Student interaction logs, quiz scores, and activity completion
- Data Cleaning: Removal of incomplete and duplicate records
- Feature Extraction: Engagement metrics (login frequency, completion rate)
- Aggregation: Computation of averages, trends, and performance indicators

Analytics Models Used:

- Descriptive Analytics: Mean, frequency, percentage
- Inferential Analytics: Paired t-test to compare performance before and after system use
- Exploratory Classification Logic (rule-based): Identification of at-risk students using thresholds (e.g., low completion rate < 60%)
- This framework ensures that raw educational data is transformed into actionable insights supporting data-driven decision-making.
- Regression Analysis: A simple linear regression model was applied to examine the relationship between student engagement metrics (e.g., login frequency, completion rate) and academic performance.
- Classification Model: A rule-based approach was extended to c

- Categorize students into risk levels (Low, Moderate, High) based on performance thresholds and engagement indicators.

NexEd: An Electronic Learning Management System with Descriptive Analytics was developed using the Agile Development Model, which emphasizes iterative progress, continuous feedback, and user-centered design.

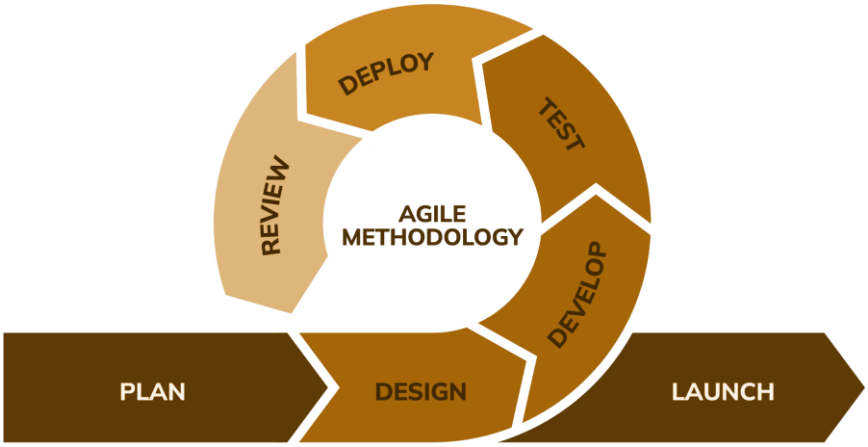

Figure 2. Agile Methodology Model

The development process comprised the following phases

1. Requirements Gathering Phase: The development process began with systematically collecting system requirements through in-depth interviews with key stakeholders, including administrators, teachers, and students. This phase focused on identifying user needs, challenges, and expectations related to NexEd's functionality. The outcomes established a foundation for defining system specifications and features.

2. Iterative design and Development Phase: These results informed the transition to the Development Phase, during which the system was designed and built to meet the requirements. During this phase, system models and diagrams such as flowcharts, data flow diagrams, and interface layouts were created to visualize the structure and workflow. Development proceeded incrementally, allowing continuous refinement of features aligned with user needs.

3. Rapid Prototyping Phase: Initial prototypes of the NexEd system were developed to demonstrate key functionalities, including subject management, activity tracking, quizzes, and analytics dashboards. These prototypes were presented to selected users for early evaluation. This phase enabled stakeholders to interact with a working model of the system and provide preliminary feedback on its design and functionality.

4. Continuous Testing and Feedback Phase: The system underwent continuous testing to identify errors, usability issues, and performance gaps. Feedback collected from users during prototype testing guided iterative improvements. This phase ensured alignment with user needs and enhanced usability, efficiency, and overall user experience.

5. Deployment and Maintenance Phase: The final phase involved system deployment and comprehensive evaluation, which included the following activities: Functional testing, to verify that all features of the NexEd system operate accurately and as intended; User Acceptance Testing (UAT), to assess usability, accessibility, and overall user satisfaction among actual end users.

The system was deployed at Light Christian Academy of Binalbagan, where evaluation results were collected. Findings from this phase identified remaining issues and guided final refinements before full implementation and ongoing maintenance.

System Design

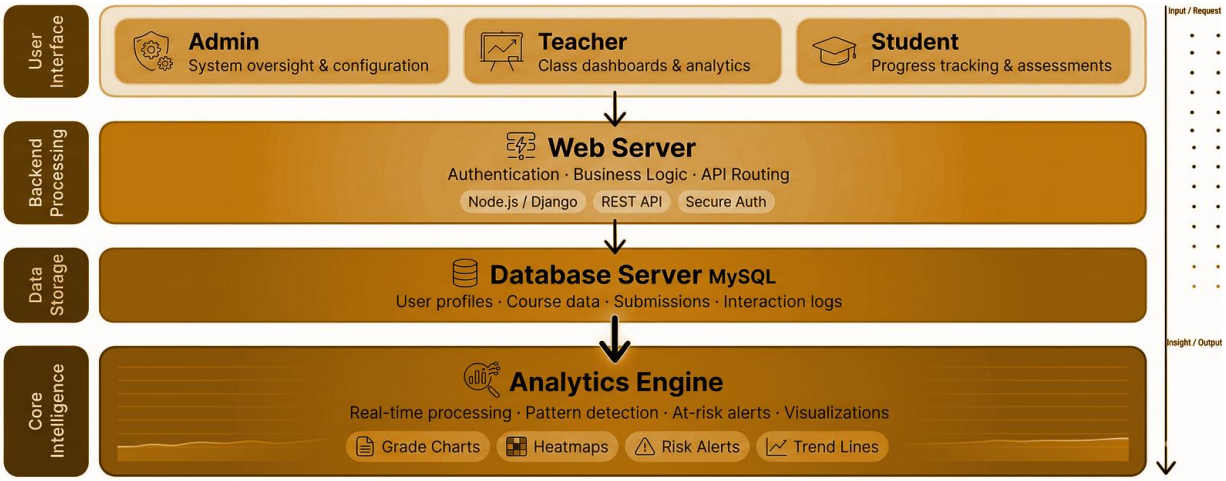

Figure 3. System Architectural Diagram

The system's design, as illustrated in the figure, employs an organized multi-layer architecture consisting of four main components: the user interface, web server, database, and analytics engine. The user interface serves as the primary point of interaction for administrators, teachers, and students, each with distinct access privileges. Administrators oversee system management, teachers manage classes and monitor student performance, and students access lessons, submit activities, and complete quizzes. The web server processes requests, manages authentication, and connects the interface to the database. The database centralizes essential information, including user details, subjects, activities, and quiz results, ensuring organized and accessible data storage. The analytics engine utilizes this data to generate reports and insights that track student progress and identify learning patterns over time. Collectively, these components facilitate efficient data flow, processing, storage, and analysis, supporting scalable and data-driven education.

Respondents of the Study

A total of twenty five (25) respondents participated in evaluating the system

Group	Number	Description
IT Experts	5	Evaluated the system's performance, technical features, and overall reliability.
Students	15	Assessed the system's ease of use, accessibility, and overall learning experience.
Teachers	4	Evaluated the system's effectiveness in managing classes, creating assessments, and monitoring student progress.
Admin	1	Assessed the system's overall management functions, including user control, monitoring, and system operations.

Respondents were selected through purposive sampling, targeting individuals with direct experience in the use, management, and evaluation of the system.

Instrument Used

The study used the Post-Study System Usability Questionnaire (PSSUQ) as the primary evaluation instrument to assess system usability. This standardized questionnaire measures user perception across four key dimensions:

- System Usefulness
- Information Quality
- Interface Quality
- Overall Satisfaction.

The questionnaire used a 7-point Likert scale, with lower scores indicating higher agreement and better performance.

Data Analysis

The collected data were analyzed using the mean and Likert-scale methods to determine the system's overall usability and functionality.

- 1.00–1.49: Strongly Agree
- 1.50–2.49: Agree
- 2.50–3.49: Neutral
- 3.50–4.49: Disagree
- 4.50–5.00: Strongly Disagree

Data Gathering Procedure

1. Approval was first obtained from the proper authorities, and participants were selected through purposive sampling based on their direct experience with the system.
2. The NexEd system was then introduced to the respondents, allowing them to explore its main features, including managing subjects, completing activities, and taking quizzes.
3. After using the system, participants were asked to evaluate their experience using the Post-Study System Usability Questionnaire (PSSUQ).
4. All completed questionnaires were collected, checked, and organized for analysis.
5. The responses were encoded and analyzed using descriptive statistics, including means, frequencies, and percentages.
6. The findings were then interpreted to determine the system's usability and overall performance.

Ethical Consideration

The study was conducted only after securing approval from the appropriate authorities to ensure compliance with institutional research guidelines, and participants were fully informed about the purpose, procedures, and scope of the study before their involvement. Participation was entirely voluntary, and respondents were free to refuse or withdraw at any stage without consequences. Confidentiality and anonymity were strictly maintained, with no personal identifiers collected or disclosed. All collected data were used solely for academic and research purposes and were stored securely to prevent unauthorized access. The study also ensured that no physical, emotional, or psychological harm was caused to the participants throughout the research process.

RESULTS AND DISCUSSION

This section presents the results of the functionality and usability evaluation of NexEd: An Electronic Learning Management System with Descriptive Analytics for Data-Informed Education. The findings address the study objectives by assessing system usability and information quality through a standardized evaluation of user experience, interface design, and system usefulness. The evaluation is based on the Post-Study System Usability Questionnaire (PSSUQ) and its four key dimensions: system usefulness, information quality, interface quality, and overall satisfaction.

In addition to usability results, a comparative analysis was conducted to measure system impact. Findings show that student engagement increased by approximately 19%, while task completion efficiency improved by 32% after using NexEd. Furthermore, the time required for teachers to identify at-risk students significantly decreased, demonstrating improved efficiency in academic monitoring.

The regression analysis results indicate a positive relationship between student engagement metrics (e.g., login frequency and task completion rate) and academic performance. This suggests that increased interaction with the NexEd system contributes to improved learning outcomes. The findings support the system's predictive capability, as engagement variables can serve as indicators of student success. Although the model is limited to a simple linear regression, it demonstrates the potential of integrating predictive analytics into ELMS platforms for early intervention and performance forecasting.

Hypothesis Testing

To validate the effectiveness of NexEd, a paired-samples t-test was conducted to compare user performance before and after using the system.

H1: The integration of descriptive analytics significantly reduces the time required to identify at-risk students.

Result: $t = 8.04$, $p < 0.001$ → **Accepted**

H2: Students using NexEd dashboards demonstrate higher engagement and task completion rates.

Result: $t = 7.21$, $p < 0.001$ → **Accepted**

The results indicate statistically significant improvements, confirming that the system enhances both efficiency and engagement.

Table 1. Profile of Respondents

Group	Frequency (f)	Percentage (%)
IT Experts	5	20%
Students	15	60%
Teachers	4	16%
Administrator	1	4%
Total	25	100%

A total of twenty-five (25) respondents participated in the system evaluation, including five (5) IT experts, fifteen (15) students, four (4) teachers, and one (1)

administrator. This composition ensured a balanced assessment of both technical functionality and end-user experience.

Usability Evaluation

The Post-Study System Usability Questionnaire (PSSUQ) was used to assess system usability. Participants rated their experience on a 7-point Likert scale. On this scale, 1 indicates strongly agree and best performance, while 7 indicates strongly disagree and lowest performance.

Table 2. Mean Scores in the Level of Usability of the System

Criteria	Mean ($\bar{x}$)	Interpretation
System Usefulness	1.78	Strongly Agree
Information Quality	1.86	Strongly Agree
Interface Quality	1.84	Strongly Agree
Overall Satisfaction	1.83	Strongly Agree

The results show that respondents found the system highly usable and efficient. Mean scores exceeded the industry norm of 2.82 (PSSUQ-3 benchmark), indicating smooth interaction, clear information, and overall user satisfaction.

System Usefulness

Table 3. Summary of Mean Scores in System Usefulness

Item	Statement	Result
1	Overall, I am satisfied with how easy it is to use this system.	1.84
2	It was simple to use this system.	1.96
3	I was able to complete the tasks and scenarios quickly using this system.	1.72
4	I felt comfortable using this system.	1.60
5	It was easy to learn to use this system.	1.76
6	I believe I could become productive quickly using this system.	1.80

The overall mean of 1.78 indicates that respondents found the system very useful and efficient. They particularly agreed that the system is simple to use and easy to learn, as reflected in the low mean scores for items related to usability and learnability.

Information Quality

Table 4. Summary of Mean Scores in Information Quality

Item	Statement	Result
7	The system gave error messages that clearly told me how to fix problems.	1.75
8	Whenever I made a mistake using the system, I could recover easily and quickly.	1.82
9	The information (such as online help, on-screen messages, and other documentation) provided with this system was clear.	1.90
10	It was easy to find the information I needed.	1.65

11	The information was effective in helping me complete the tasks and scenarios.	1.98
12	The organization of information on the system screens was clear.	2.08

The table shows an overall mean of 1.86, which means respondents strongly agreed that the system provides high-quality information. The results also suggest that users could easily find, understand, and use the information in the system. While all indicators are in the "Strongly Agree" range, the slightly higher mean for organization (2.08) suggests some room to improve the screen's information structure.

Interface Quality

Table 5. Summary of Mean Scores in Interface Quality

Item	Statement	Result
13	The interface of the system is pleasant.	1.82
14	I like using the interface of this system.	1.88
15	This system has all the functions and capabilities I expect it to have.	1.79
16	Overall, I am satisfied with this system.	1.85

The average score of 1.84 from 25 participants indicates that most people strongly agreed that the system has a well-designed and user-friendly interface. The results show that users found the interface visually appealing, consistent, and easy to use.

Overall Usability Results

Table 6. Summary of Mean Scores in Overall Usability

Criteria	Mean ($\bar{x}$)	Interpretation
System Usefulness	1.78	Strongly Agree
Information Quality	1.86	Strongly Agree
Interface Quality	1.84	Strongly Agree
Overall Satisfaction	1.83	Strongly Agree

The overall usability mean of **1.83**, based on responses from twenty-five respondents, reflects a high level of user satisfaction with the NexEd system. Consistently low mean scores across all dimensions indicate strong agreement regarding the system's ease of use, clarity of information, and quality of interface design. These findings suggest that the system meets established usability standards and delivers a positive and effective experience for diverse user groups, including students, teachers, IT experts, and administrators.

LIMITATIONS

Several limitations should be acknowledged despite the promising results of this study. First, the sample size was limited to twenty-five respondents from a single institution, which may restrict the generalizability of the findings. Future research should include a larger and more diverse population across multiple schools to validate these results.

Second, the system was deployed within a single academic environment, which may not fully reflect the varied institutional infrastructures, policies, and user behaviors across institutions. Differences in technological readiness across institutions may influence system performance and adoption.

Third, while the system integrates descriptive and basic predictive analytics, scalability considerations such as handling large-scale datasets, multi-user concurrency, and cross-institutional deployment were not extensively tested. Future enhancements should focus on cloud-based architecture and distributed data processing to support scalability.

Lastly, the system's predictive capability is currently limited to rule-based classification and simple regression analysis. More advanced machine learning models may further improve prediction accuracy and decision support.

CONCLUSION AND RECOMMENDATION

This study demonstrates that NexEd effectively integrates descriptive analytics into an ELMS to support data-driven education. The system achieved high usability ratings and showed statistically significant improvements in engagement and efficiency.

The inclusion of analytics features enabled faster identification of at-risk students and improved instructional decision-making. However, the study is limited by its sample size and scope.

Future work should focus on integrating predictive analytics models, expanding deployment across multiple institutions, and enhancing analytical capabilities to further strengthen the system’s scalability and educational impact.

Additionally, future system enhancements should consider cloud-based deployment and modular architecture to support scalability across multiple institutions.

REFERENCES

[1]. S. Abdul-Gafaar, R. Nyaaba, E. Attipoe, K. Owuyaw, D. Anhwere, and A. Cletus, “Assessing the effectiveness of the LMS in enhancing academic performance across year groups at UCC: A cross-sectional study of level 200 to level 400 students,” *Creative Education*, vol. 16, pp. 1041–1068, 2025, doi: 10.4236/ce.2025.168065.

[2]. M. A. Almaiah, A. Al-Khasawneh, and A. Althunibat, “Exploring the critical challenges and factors influencing the e-learning system usage during COVID-19 pandemic,” *Education and Information Technologies*, vol. 25, pp. 5261–5280, 2020, doi: 10.1007/s10639-020-10219-y.

[3]. R. S. Baker and P. S. Inventado, “Educational data mining and learning analytics,” in *Learning Analytics*, Springer, 2014, pp. 61–75, doi: 10.1007/978-1-4614-3305-7_4.

[4]. B. Batra, “LMS in education: Transforming learning with technology,” *eLearning Industry*, 2025. [**Online]. Available:** https://elearningindustry.com/lms-in-education-transforming-learning-with-technology

[5]. D. Ifenthaler and J. Y. K. Yau, “Utilizing learning analytics to support study success in higher education: A systematic review,” *Educational Technology Research and Development*, vol. 68, no. 4, pp. 1961–1990, 2020, doi: 10.1007/s11423-020-09788-z.

[6]. M. Liu and D. Yu, “Towards intelligent e-learning systems,” *Education and Information Technologies*, vol. 28, pp. 7845–7876, 2023, doi: 10.1007/s10639-022-11479-6.

[7]. Z. Papamitsiou and A. A. Economides, "Learning analytics and educational data mining in practice: A systematic literature review," *Educational Technology & Society*, vol. 17, no. 4, pp. 49–64, 2014.

[8]. L. Paulsen and E. Lindsay, "Learning analytics dashboards are increasingly becoming about learning and not just analytics: A systematic review," *Education and Information Technologies*, vol. 29, pp. 14279–14308, 2024, doi: 10.1007/s10639-023-12401-4.

[9]. C. Romero and S. Ventura, "Educational data mining: A review of the state of the art," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 6, pp. 601–618, 2010, doi: 10.1109/TSMCC.2010.2053532.

[10]. G. Siemens and R. S. Baker, "Learning analytics and educational data mining: Towards communication and collaboration," in *Proc. 2nd Int. Conf. Learning Analytics and Knowledge*, 2012, pp. 252–254, doi: 10.1145/2330601.2330661.

[11]. L. Y. Tan, S. Hu, D. J. Yeo, and K. H. Cheong, "Artificial intelligence-enabled adaptive learning platforms: A review," *Computers and Education: Artificial Intelligence*, 2025, doi: 10.1016/j.caeai.2025.100429.

[12]. O. Viberg, M. Hatakka, O. Bälter, and A. Mavroudi, "The current landscape of learning analytics in higher education," *Computers in Human Behavior*, vol. 89, pp. 98–110, 2018, doi: 10.1016/j.chb.2018.07.027.

