

Literature review Title :“AI-Driven Learning Management Systems (LMS) and Learning Analytics (LA): Impacts on Teachers’ Decision-Making Based on Recent Research”

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Summary research papers:

Paper1: A systematic review of studies on decision-making systems for teaching and learning in K-12.

Dashboards utilized as decision-support tools for teachers in K–12 settings are examined in this analysis, which reveals underutilization of richer student profiles and little real-world classroom evaluation. It offers suggestions for dashboard design (such as context, explainability, and actionability) that enhance teacher adoption and decision efficacy. **(Barthakur et al., 2024)[1]**

Methods: Systematic literature review focused on dashboards and evaluation in real classrooms

Why it is relevant: the main user interface (UI) is Dashboard where LA/AI outputs meet teachers' decision processes This report explains which designs aid or facilitate teachers' decision-making.

Authors:

- Abhinava Barthakur
- Rebecca Marrone
- Shadi Esnaashari
- Vitomir Kovanovic
- Shane Dawson

Year: June 2024

Paper2 : A systematic review of the role of learning analytics in enhancing feedback practices in higher education.

The application of learning analytics (LA) to enhance feedback and decision-making in technology-mediated learning contexts is mapped out in this systematic review. It combines common LA features (dashboards, prediction models, warnings), reported outcomes, and study kinds. The analysis identifies a persistent gap: many LA tools are technically sound but when it comes to reel It is not appreciated in the classroom and teachers cannot take decision-making situations. **(Banihashem et al., 2022)** [2].

Methods : Systematic search and synthesis of literature from databases related to education and computer science.

Why it is relevant: in this paper Provides an overview of learning analytics (LA) features and evidence about whether LA tools influence teacher practice.

Authors:

- Seyyed Kazem Banihashem
- Omid Noroozi
- Stan van Ginkel
- Leah P. Macfadyen
- Harm J.A. Biemans

Year: 16 November 2022

Paper3 : Adaptive Learning Using Artificial Intelligence in e-Learning

investigating and assessing AI/ML methods for adaptive learning in LMSs and other e-learning platforms. describes student modeling, item selection algorithms, and evidence of improved engagement or outcomes. It also highlights how teachers' responsibilities are changing from imparting knowledge to facilitating and analyzing data. **(Gligorea et al., 2023)[3]**.

Methods: methodical mapping of AI methods in e-learning and assessment outcomes.

Why it is relevant: provides evidence of classroom effects and changes in teacher roles, along with specific AI/ML techniques that drive LMS features that educators will engage with.

Authors:

- Ilie Gligorea
- ORCID
- Marius Cioca
- Romana Oancea
- Andra-Teodora Gorski
- Hortensia Gorski
- Paul Tudorache

Year : 6 December 2023

Paper4: Instructors' Perceptions of the Use of Learning Analytics for

Data-Driven Decision Making.

An empirical study that uses surveys and interviews to find out how higher education instructors feel about, trust, and use learning analytics dashboards. shows that instructor acceptability, perceived utility, and data literacy have a significant impact on whether analytics are used to influence instructional decisions. The paper discusses real-world challenges that teachers face, such as interpretability, timeliness, and false positives. **(Hershkovitz & Forkosh-Baruch, 2024) [4].**

Mixed methods: analysis of self-reported use cases, instructor survey, and qualitative interviews.

Why it matters: Examines teacher decision-making behavior directly, as well as the human aspects that influence whether AI/LA in LMSs will alter that behavior.

Authors :

- Arnon HersHKovitz
- Alex Ambrose
- Tal Soffer

year: 29 October 2024

Paper5: A Systematic Review of Learning Analytics Incorporated Instructional Interventions on Learning Management Systems.

According to pan et al (2024) in this systematic review focused on the design and assessment of LA interventions in LMS contexts as well as LA integration into LMS platforms. It tracks different types of interventions (like visual dashboards, predictive at-risk alerts, and automatic feedback) and evaluates their impact on student outcomes and teacher behavior. It also addresses methodological issues that call into question claims about the causal influences on teacher choices. **(Pan et al., 2024) [5]**

Methods: Evaluation designs, feature coding, and review of LA interventions.

Why it matters: It is helpful to compare the empirical data regarding whether teachers truly utilize technical LA affordances in LMSs to modify instruction.

Authors:

- Zilong Pan
- Lauren Biegley
- Allen Taylor
- Hua Zheng

Year: 2024

Paper6:AI-Driven Learning Management Systems: Modern Developments, Challenges and Future Trends during the Age of ChatGPT

A thorough analysis of the AI features being used in LMSs, including chatbots, automated grading, content recommendation, personalization, and predictive analytics. The study categorizes AI characteristics and discusses technical and ethical concerns (bias, transparency), as well as possible educational benefits. It also highlights how important teacher-centered design is to make realistic classroom decisions that are backed by data. **(Qazi et al., 2024) [6]**.

Methods: Taxonomy of AI features in commercial and academic management systems and a review of the literature.

Why it matters: Strong technical understanding of what "AI-driven LMS" means and what analytics instructors could observe.

Authors:

- Sameer Qazi
- Muhammad Bilal Kadri
- Muhammad Naveed
- Bilal A. Khawaja
- Sohaib Zia Khan,
- Muhammad Mansoor Alam
- Mazliham Mohd Su'ud

Year :15 August 2024

Critical Analysis

Technical environment: how AI and analytics are used in current LMSs.

Technical environment: the application of analytics and AI in modern LMS. Modern learning management systems use AI capabilities such as chatbots and tutoring agents, resource recommender systems, automated assessment and feedback, predictive "at risk" models, student modeling and adaptive sequencing, and dashboards that show performance and behavior data. Examining mapping AI techniques reveals common inputs (clickstream, submission and grading data, time on task, forum interactions) and recurring machine learning techniques (classification/regression for risk prediction, collaborative/content based recommenders, Bayesian/IRT student models for adaptation). These components work together to create the technological benefits that educators encounter, like a personalized learning path suggested by the system or a warning sign that indicates a student's probability of failing. Since output interpretability, latency, and signal quality limit whether, it is essential to understand these algorithms and data sources. These components work together to create the technological benefits that educators encounter, like a personalized learning path suggested by the system or a warning sign that indicates a student's probability of failing. Understanding these techniques and data sources is essential because a teacher's ability to act upon outputs is limited by their signal quality, latency, and interpretability.

Teachers' access to analytics: dashboards and user interfaces.

The primary place where AI/LA outputs satisfy teachers' assessments is the dashboard, also known as the teacher user interface. Dashboards can range in complexity from learner profiles that incorporate performance, engagement, and affect proxies to as simple as lists of students who are at risk. Dashboards and user interfaces were re-presented to educators. Several design elements that predict actionability are highlighted in reviews of dashboards in K–12 and higher education. These elements include contextualized metrics (not raw counts), avoiding information overload, integrating with workflow (e.g., one-click actions to message or assign remediation), and clearly explaining what predictions mean and their uncertainty.

However, many dashboards offer multiple signals at once, do not include links to specific instructional replies, or do not include context (the reason a student was alerted), all of which reduce instructor adoption. Thus, these UI design choices mediate whether AI outputs lead to concrete decisions.

Perceptions, trust, and data literacy among teachers.

Teachers' readiness to embrace analytics is significantly influenced by perceived utility, system trust, and data literacy. According to mixed-methods studies of instructors, acceptance is driven by perceived actionability (does the dashboard suggest what I can do?), in clear statement or clear situation (can I understand why the system flagged a student?), and prior beliefs about teaching (teachers with more traditional, instructor-centered approaches may still take actions when the analytics are clearly helpful). Data literacy the ability to read signs, understand statistical uncertainty, and assess false positives is often cited as a gating factor because even well-designed dashboards fail when teachers mistrust or misinterpret the signals. These issues are mitigated through training, explanation features (explainable AI), and co-design with educators. In a nutshell, human factors are equally as significant as mathematical accuracy.

Empirical data demonstrates the influence on teachers' decision making .

While certain LA/LMS treatments result of changes in teacher behavior (e.g., increased focused messaging, differentiated assignments, or earlier outreach to students), there is little solid classroom-level causation evidence, according to systematic reviews and meta-analyses. Instead of measuring observed, long term instructional improvements and downstream student learning, many studies are pilots, lab-based simulations, or assessments that gauge intermediate outcomes (dashboard views, self-reported intentions). Predictive alerts, dashboards, and automated feedback are common interventions in LMS contexts, according to reviews that specifically address LA. However, few use cluster randomized controlled trials or longitudinal mixed-methods studies that can link changes in teacher behavior to analytics rather than innovation or research support. The practical implication is that while there are encouraging outcomes, there are still few general assertions that AI/LMS consistently alter teachers' decision making in many circumstances.

Mechanisms: how analytics can affect choices (and when they don't work)

When analytics do have an impact on teachers' decisions, the process typically goes like this:

(1) the system presents a brief, contextualized signal (such as a student's abrupt decrease in assignment time combined with missed deadlines).

(2) the dashboard provides an explanation or next steps

(3) the teacher incorporates that signal into an already existing workflow (grading, parent communication, small-group instruction). The transition from insight to action is facilitated by interventions that incorporate action routes, such as message templates, automatic grouping tools, or brief formative exercises. Failures happen when signals are noisy, delayed, inadequately explained, or unrelated to teachers' daily routines; when teachers worry about data being used for surveillance or liability; or when institutional incentives fail to promote formative applications of analytics. These mechanisms highlight the need of sociotechnical fit and action-oriented design.

Connections.

- Actionability and teacher value: When student data is relevant and simple to utilize, teachers are typically willing to take action.
- Technical and non-technical obstacles: every study identifies obstacles, including limited and evaluation of the real world, quality of data, interpretability, privacy, and integration into workflows.
- LMS integration and dashboards as key delivery channels: The best usage of LA and AI capabilities is when they are integrated into LMSs or dashboards that assist teachers in making decisions; several studies concentrate on K–12 dashboards or LMS interventions.

Conflict:

- Differentiate the levels of evidence: consider controlled or short-term experimental gains as encouraging, but demand classroom-scale, long-term assessments for assertions regarding long-term effects.
- Instead of just displaying more data, co-design dashboards with teachers by involving them in the selection of metrics, visualization, and workflow integration.

- Increase teacher capacity and trust by combining technical features with explainability, professional development, and straightforward suggested actions (not just flags).
- Ethics-by-design: before expanding personalization features, put privacy, fairness checks, and human-in-the-loop decision points into place.

Limits to morality, and unexpected repercussions

Biased predictions that repeat disparities, false positives that result in misdirected remediation, teacher debilitation if decisions become automated without monitoring, and privacy concerns over student data collected at scale are just a few of the urgent ethical and practical problems associated with AI-LMS. Without governance—transparent model documentation, teacher oversight, data minimization, and explicit restrictions on the use of analytics—technical solutions (bias audits, uncertainty estimation) are helpful but insufficient. Interventions must maintain professional judgment and encourage thoughtful use because there is a risk of over depend on teachers may act on an algorithmic suggestion without question. Surveys and studies consistently propose training teachers in data interpretation and integrating explainable AI algorithms.

Literature gaps and potential to improve the further research.

The same gaps are found in all systematic reviews:

- (1) a lack of long-term, classroom-level causal studies (cluster RCTs or quasi-experimental designs) that measure both student outcomes and teacher behavioral change.
- (2) a lack of research on fidelity of use, or how teachers actually use dashboards over time.
- (3) a lack of attention to diverse contexts (most work is concentrated in higher education or well-resourced schools).

(4) a need to test teacher centered design interventions that combine analytics with actionable prompts, training, and workflow integration. Future research should give priority to mixed methods designs that record both qualitative explanations of reasoning and quantitative changes in teacher behavior. It should also assess practical metrics (such as time to action, the applicability of suggested interventions, and teachers trust trajectories) in addition to accuracy metrics.

Useful suggestions for the developers.

- The combined evidence leads to specific, progressive recommendations:
- make dashboards actionable by linking signals to specific pedagogical steps
- emphasize explainability by showing which inputs led to a prediction and its uncertainty
- integrate workflow through automated scaffolds, templates, or one-click actions
- invest in teacher capacity building through co-design workshops, data literacy, and interpretation practice. Policy should require equity audits, data governance, and model documentation. Funding should also be allocated to longitudinal pilots that evaluate whether analytics enhance instruction and learning in an equitable way.

These approaches respect teachers' professionalism and aim to supplement their judgment rather than take its place.

Conclusion

By presenting timely, individualized insights, AI-driven learning management systems and learning analytics have the potential to significantly improve teachers' formative decision making. However, technical prowess by itself does not translate into impact in the classroom. According to the evidence, key mediators include UI design, interpretability, trust, integration with teacher workflows, and teacher data literacy. Research and implementation must concentrate on teacher centered design, thorough classroom evaluation, and governance that upholds equity and professional autonomy if we are to go from promising prototypes to strong classroom benefits. To put it briefly, create analytics, measure how teachers use the tools in the field, and work with them to make the next instructional step clear and simple.

Table of Reviewed Papers

Authors & Year	Title / Focus	Research Aim	Methods / Data	Key Findings	Strengths	Limitations	Relevance to Topic
Banihashem et al., 2022	Systematic review of learning analytics	To investigate how learning analytics enhance instruction in various educational settings	comprehensive analysis of LA research from several databases	LA's advantages in prediction, personalization, and early warnings were noted; adoption, ethics, and data quality concerns were brought to light.	Broad reach, excellent synthesis, and emphasis on practical constraints	Absence of emphasis on K–12; scant examination of AI-powered systems	explains the background and fundamentals of LA's decision-making role.
Pan et al., 2024	Systematic Review of Learning Analytics	To examine LA's methods, trends, and results between 2012 and 2023	systematic review with a structure	Strong evidence of LA's potential for retention and personalization was found; however, gaps in teacher-facing resources and long-term research were noted.	current scope; thorough	Variability in included methodologies; little attention paid to LMS-specific systems	provides a current overview of LA's advancements and issues pertaining to AI-LMS.

Hershkovitz & Forkosh-Baruch, 2024	Views of educators regarding learning analytics	To investigate how educators view and utilize LA dashboards	Empirical study (survey/interviews)	Teachers appreciate LA but lack training; workflow integration, clarity, and trust are necessary for adoption.	emphasizes teacher conduct and offers useful insights.	Due to the small sample size, perceptions might not accurately reflect actual classroom use.	focuses on how human factors impact the adoption of dashboards and LMSs.
Qazi et al., 2024	AI-Driven Learning Management Systems	To map the capabilities of contemporary AI in LMS systems	Review and survey of narrative AI-LMS systems	finds AI features for chatbots, analytics, automation, and personalization, forecasts quick AI integration	extensive and forward-looking; includes a wide range of AI tools	More conceptual than experimental; less empirical evidence	demonstrates the connection between learning analytics and decision support and AI-driven LMS tools.
Gligorea et al., 2023	AI-Powered Adaptive Learning	To investigate how e-learning is enhanced by AI-driven adaptive learning	An analysis of intelligent systems that are adaptive	reports enhanced performance and learner engagement in AI-adaptive systems.	Strong theoretical foundation and a clear explanation of adaptive models	Focus mostly on higher education, little evidence of actual deployment	relates customized pathways pertinent to LA dashboards to AI algorithms.
Dashboard Decision Systems	systematic evaluation of K–12 dashboards	To assess the K–12 dashboards' usability and	K–12 dashboards are systematically reviewed.	Dashboards often lack actionability; teachers face	Strong focus on K–12; practical and	There is little evidence of implementation, and many	Directly related to comprehending how teacher decisions are

Review (2024/2025)		design for teacher decision- making		data overload; real-world classroom adoption is low	pedagogical insights	dashboards are prototypes.	supported by AI/LA dashboards
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References:

1. Dashboard / K-12 decision systems review (2024/2025). Systematic review of dashboards as decision-making systems in K-12 (ResearchGate / ACM / SAGE entries). ([ResearchGate](#))
2. Banihashem, S. K. et al. (2022). A systematic review of the role of learning analytics in enhancing feedback practices in higher education. ([sciencedirect.com](#))
3. Gligorea, I. et al. (2023). Adaptive Learning Using Artificial Intelligence in e-Learning. (MDPI; open access). ([MDPI](#))
4. HersHKovitz, A. & Forkosh-Baruch, A. (2024). Instructors' Perceptions of the Use of Learning Analytics. (MDPI; open access). ([MDPI](#))
5. Pan, Z. (2024). A Systematic Review of Learning Analytics (Journal of Learning Analytics). ([learning-analytics.info](#))
6. Qazi, S. et al. (2024). AI-Driven Learning Management Systems: Modern Developments, Challenges and Future Trends. ([sciencedirect.com](#))