

Research Proposal

“ The Influence AI-Driven Learning Management Systems (LMS) and Learning Analytics (LA): Impacts on Teachers’ Decision-Making in K–12 Education Based on Recent Research”

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Table of Content

Abstract.....	3
Introduction.....	4
Background.....	4
Problem Statement	5
Research Objectives.....	5
Research scope	6
Literature review.....	7
Research Methodology	11
Procedure for Data Extraction and Analysis.....	12
Expected Outcomes.....	13
Gantt chart.....	14
References.....	15

Abstract

The impact of AI-driven learning analytics dashboards on K–12 educators' instructional decision-making is investigated in this review of the literature. According to recent research, these dashboards—which are driven by adaptive technologies, machine learning algorithms, and predictive analytics—offer teachers practical insights to help them plan lessons, evaluate students' progress, identify at-risk students, and provide focused interventions. The effectiveness of these AI tools depends not only on the dashboards' technical design but also on teachers' perceptions, competence, and system trust, according to a synthesis of ten recent studies. Although there are still few longitudinal and large-scale studies, quantitative evidence shows improvements in the early identification of at-risk students, improvements in the quality of feedback, and increases in instructional efficiency. The review highlights research gaps, especially in the areas of real-world classroom validation, standardized effect metrics, and the integration of teacher-centered design principles. All things considered, learning analytics dashboards powered by AI show great promise for improving data-driven decision-making in K–12 classrooms.

Chapter1:

Introduction:

The way teachers access and analyze classroom data has changed as a result of the incorporation of Artificial Intelligence (AI) into educational technologies. A crucial part of AI-powered learning management systems (LMSs), learning analytics (LA) dashboards provide real-time visualization and predictive insights that can help educators make wise teaching decisions. These tools are being used more often in K–12 education to track learning progress, identify at-risk students, monitor student engagement, and improve lesson planning. According to recent research (Barthakur et al., 2024; Pan, 2024; Weidlich et al., 2025), although AI-driven dashboards have a great deal of potential to improve teaching methods, their effectiveness depends on teachers' capacity to understand and act upon the analytics they provide. Furthermore, issues with data quality, ethical issues, system usability, and teacher readiness have been identified as crucial elements influencing adoption and efficacy. In order to provide a thorough understanding of how AI-based dashboards affect teacher decision-making in K–12 contexts and to identify research gaps that can guide future studies, this literature review synthesizes findings from ten recent studies.

Background:

In order to better understand and optimize learning and the environments in which it takes place, learning analytics (LA) refers to the gathering, measurement, analysis, and reporting of data about learners and their contexts. Large datasets, including student performance metrics, engagement logs, and interaction patterns, can be processed by LA dashboards when they are integrated with AI-driven LMS platforms to produce predictive insights that help teachers make decisions about how to teach. According to studies (Hershkovitz et al., 2024; Azzopardi et al., 2023), AI-supported dashboards help identify students who are at risk of performing poorly early on, offer real-time feedback for tailored instruction, and optimize lesson pacing and content. Additionally, factors related to teachers, such as their digital competency, confidence in AI recommendations, and capacity to convert analytics into instructional actions, impact how effective these tools are (Alotaibi, 2024; Khor & K., 2024). While AI dashboards show promise, a number of systematic reviews stress that in order to fully assess their influence on instructional decision-making, longitudinal studies, standardized metrics, and actual classroom implementations are required (Banihashem et al., 2022; Toofaninejad et al., 2025). This review

identifies opportunities for improving research and practice in the field and offers insights into how AI-driven LA dashboards support teachers in K–12 education by synthesizing recent evidence.

Problem Statement

Teachers now have much greater access to real-time data, predictive insights, and automated feedback processes because of the integration of AI-driven Learning Analytics (LA) and Learning Management Systems (LMS). Recent studies have demonstrated that AI-enhanced learning management system platforms enhance data visibility, customize learning paths, and facilitate the early detection of students who may be at risk (Dashboard/K-12 Decision Systems Review, 2024/2025; Banihashem et al., 2022; Gligorea et al., 2023). Notwithstanding these developments, teachers frequently find it difficult to decipher LA reports and turn them into insightful teaching decisions. Limited data literacy, inadequate training, unclear data interpretation frameworks, and differing degrees of confidence in AI-generated recommendations are some of the obstacles that have been documented in studies (Hershkovitz & Forkosh-Baruch, 2024; Pan, 2024).

The need for data-informed teaching is partially met by current solutions, such as dashboards, automated alerts, and AI recommendation systems; however, these systems frequently put data presentation ahead of pedagogical usability. Many AI-powered learning management systems (LMS) fall short in matching analytics results to the real-world demands of classroom decision-making, especially for educators who are not accustomed to working with large amounts of data (Qazi et al., 2024). Because of this, learning analytics' potential to improve instructional decisions is still not fully realized.

Research is obviously needed to understand how AI-driven LMS and LA tools affect teachers' decision-making, what obstacles they encounter when utilizing these systems, and which particular features or features can enhance instructional responsiveness and decision accuracy. To improve the design of AI-enabled learning platforms and increase teachers' ability to make data-driven decisions that enhance student learning, it is imperative to look into these gaps.

Research Objectives

Primary Goal:

to investigate how teachers' instructional decisions are influenced by AI-driven learning management systems and learning analytics tools, and to pinpoint the main system elements and issues that hinder their efficient use.

Specific Objectives:

1. To examine how instructors currently make decisions about their lessons using AI-driven learning management systems and learning analytics.
2. To determine the main obstacles educators face when analyzing and utilizing data produced by AI-enabled learning management systems.
3. To assess how well the current analytics dashboards and AI-powered LMS features support precise and prompt teacher decisions.
4. To ascertain how well teachers can use AI-generated insights in relation to their data literacy levels.

Research Scope:

The studies that have been published in the last five years (2019–2025) that look into the application of AI-driven learning analytics dashboards in K–12 educational settings are the main focus of this review. The scope consists of:

- Technological focus: AI methods incorporated into LMS dashboards, including machine learning algorithms, adaptive learning, and predictive analytics.
- Decision-making focus: Teachers make decisions about instruction, such as lesson design, student evaluation, early intervention, and tailored feedback.
- Research types that offer quantitative or qualitative proof of dashboard impact include empirical studies, systematic reviews, and experimental research.
- Exclusions: Research that concentrated only on higher education, AI development that was purely technical and had no educational application, or research that did not emphasize teacher decision-making.

The study guarantees relevance to K–12 teachers' instructional practices while reflecting recent advancements in AI-supported learning analytics as noted in the ten chosen studies by restricting the review to these areas.

Chapter 2 (Literature review):

1. With the specific goal of evaluating how these tools influence teacher and school decisions, Barthakur, Marrone, Esnaashari, Kovanovic, and Dawson (2024) examined the literature on dashboards and learner-profile systems as decision-making supports in K–12 contexts. The authors synthesized previous research using a systematic review method that focused on dashboards, learner profiles, and models for decision-making. They observed a worrying lack of real-world classroom implementations and longitudinal evaluations, contending that dashboards frequently underutilize available data and present limited, time-bound snapshots rather than developmental learner profiles. In order to better support teacher decision-making and early intervention, their findings suggest creating more detailed learner profiles and conducting more field evaluations.

2. In order to map improvements, difficulties, and future trends, particularly in the wake of generative AI, Qazi et al. (2024) examined current developments in AI-driven Learning Management Systems (LMSs). AI features in LMSs, such as adaptive content sequencing, automated feedback, and predictive analytics, are becoming more prevalent, according to the paper, which employs a broad literature-survey approach (reviewing recent technical and applied studies). Nevertheless, the authors highlight implementation challenges (privacy, integration, teacher trust) and stress the need for human-centered design so that predictive outputs are actionable for teachers. The survey quantitatively compiles evidence from dozens of recent systems and their evaluation metrics, noting that different studies have different effect sizes based on teacher uptake and context.

3. HersHKovitz, Ambrose, and Soffer (2024) examined how instructors view learning analytics and how their opinions influence action (data-driven choices). The study reports instructors' attitudes toward data importance and their self-reported propensity to act on analytics using a mixed methods design (survey + interviews). Positive views of data use were significant predictors of taking action. The authors also discovered that, despite the fact that many instructors have traditional, instructor-centered perspectives on teaching, they are still willing to make pedagogical adjustments when analytics

offer clear, practical guidance. This suggests that perceived usefulness and interpretability are important mediators of teacher decision-making. For precise Ns, refer to the survey/sample details in the article.

4. To evaluate the empirical effects on teaching and learning, Pan (2024) carried out a systematic review of interventions that incorporated learning analytics into LMS environments. Following PRISMA-style procedures, the review synthesized evidence from several empirical studies and came to the conclusion that LA-incorporated interventions can increase targeted teacher interventions and frequently improve instructors' situational awareness (e.g., early identification of at-risk students). Pan suggests more consistent metrics (e.g., percentage improvement in retention, number of timely interventions) to measure the impact of LA on teacher decision outcomes, despite the fact that there are few large-scale controlled trials and heterogeneity in study designs.

5. A systematic review by Banihashem, Noroozi, van Ginkel, Macfadyen, and Biemans (2022) mapped the ways in which learning analytics have improved feedback practices in higher education. They discovered that LA tools enhance feedback loops by categorizing students' needs, assisting with formative feedback, and guiding instructor choices regarding pacing and remediation through the use of stringent inclusion criteria and thematic synthesis. Quantitatively, their synthesis reveals recurring trends among the included studies (many studies reported quantifiable increases in the timeliness of feedback and identification of at-risk learners), but it also draws attention to the fact that the majority of empirical research is focused on higher education rather than K–12 settings.

6. Adaptive Learning Using Artificial Intelligence in e-Learning (MDPI, 2023) by Azzopardi et al. examined adaptive learning systems that employ AI to customize content delivery. By automating lower-level personalization tasks so teachers can concentrate on higher-order pedagogical decisions, adaptive AI techniques (rule-based adaptivity, Bayesian knowledge tracing, and reinforcement learning variants) frequently produce measurable gains in learning outcomes (reported in many primary studies as percentage increases in post-test scores or improvements in mastery rates). To guarantee that the results are pedagogically valid, the review requires thorough validation and teacher participation in the adaptivity loop.

7. Alotaibi (2024) examined the opportunities and ethical/operational difficulties associated with integrating AI and LMS in higher

education. The study reports that AI-LMS integrations often result in improvements in automated formative assessment, personalized content delivery, and administrative automation. However, it also highlights significant concerns about data privacy, equity, and the reliance of outcomes on teacher competency and institutional support. The study used a systematic review method (PRISMA) to synthesize approximately fifty items. The review emphasizes that AI's benefits for teacher decision-making are conditional: AI outputs are more likely to alter instructional choices in settings where teachers are trained and systems are interpretable.

8. By combining conceptual and empirical research, Khor & K. (2024) provided a systematic review on the function of learning analytics in assisting personalized learning. In terms of methodology, the authors used systematic inclusion/exclusion criteria and coded studies for data types, analytics methods, and outcome measures. They discovered that while LA systems frequently report improvements in personalized outcomes and increases in engagement (many studies reported measurable gains in engagement metrics and improvements in particular learning outcomes), they also frequently point out the dearth of long-term evidence regarding sustained teacher behavior change and the scarcity of controlled experimental designs in K–12 environments. In order to make aggregated quantitative synthesis possible, the paper suggests that future LA studies use standardized effect metrics (e.g., % change in mastery, effect size).

9. Weidlich, Jivet, Woitt, Orhan Göksün, Kraus, & Drachsler (2025) investigated how student feedback literacy and highly informative LA-generated feedback interact to influence attitudes and results. They compared basic automated feedback with high-information analytic feedback using a controlled experimental design in collaborative learning contexts. They found that, with moderation effects from participants' feedback literacy, the high-information feedback group demonstrated statistically significant improvements in perceived feedback helpfulness and self-regulated learning indicators. The design and richness of LA outputs determine the likelihood of teacher and student uptake and consequential decision changes, according to the study's quantitative results (reported effect sizes and p-values in the article).

10. In their systematic review of learning analytics in medical education, Toofaninejad et al. (2025) emphasized the uses, advantages, and difficulties of LA in professional training settings. The review synthesized several empirical studies using PRISMA-style searching and found that LA

interventions frequently support instructors' diagnostic decision-making (e.g., identifying knowledge gaps, recommending remediation), with numerous studies demonstrating improvements in formative assessment accuracy and student performance indicators. Additionally, the paper highlights domain-specific problems (assessment validity, multimodal data integration) that impact the reliability of LA's support for instructor decisions; this warning is also pertinent to K–12 teacher decision contexts.

Chapter 3 (Research methodology)

Research methodology:

1. Design of Research

A Systematic Literature Review (SLR) design is used in this investigation. The methodological techniques employed in the ten chosen papers—many of which made use of systematic reviews, learning analytics frameworks, and empirical evaluations within AI-enhanced educational systems—align with the selection of SLR.

Using the SLR approach, the researcher can find trends, compare results, and examine how AI-driven learning analytics and learning management systems help teachers make decisions in particular educational settings.

2. Information Sources and Search Methodology

Similar to the databases used by the authors of the chosen studies, the reviewed papers were gathered from reputable academic databases: Scopus, Web of Science, ERIC, IEEE Xplore, ScienceDirect, and SpringerLink

Combinations like "AI-driven learning analytics" and "Learning management systems and teacher decision-making" were used in an organized keyword search strategy. • "Educational data mining in K-12 settings" • "AI in personalized learning" • "Dashboard analytics for teachers" • "Models for predicting student performance"

To guarantee coverage and accuracy, boolean operators (AND/OR) were employed.

3. Criteria for Inclusion and Exclusion

Criteria for Inclusion

Studies that were published between 2019 and were included. 2. Investigated

the use of AI, LMS, or learning analytics in educational settings. 3. Reported results pertaining to teacher decision-making, including instructional planning and assessment choices • Decisions about intervention or support • Keeping an eye on student performance 4. Were conference papers or peer-reviewed journal articles. 5. Offered models, frameworks, or empirical data pertinent to AI-assisted instruction.

Exclusion Standards

Research that: 1. Only considered student viewpoints without taking into account teacher decision-making was disqualified. 2. Discussed AI conceptually without providing any supporting data. 3. Were not released in English. 4. Were non-peer-reviewed sources, book chapters, or dissertations.

4. Procedure for Data Extraction and Analysis

The following procedures were used to screen, filter, and analyze the chosen articles in accordance with PRISMA-style guidelines:

First Step: Recognition

Duplicates were eliminated and search results were exported.

Step 2: Examining

To determine their applicability to AI-driven LMS, learning analytics, and teacher decision-making, titles and abstracts were examined.

Step 3: Qualifications

The inclusion/exclusion criteria were applied to full texts.

Step 4: Extraction of Data

The following important details were taken from each article: • research goal; • context and sample; • AI/LA tools or models utilized; • teacher-focused outcomes; • decision-making domains • key conclusions; • restrictions and suggestions

Step 5: Synthesis of Themes

Predictive analytics supporting early intervention; dashboard analytics enhancing instructional planning; AI models supporting differentiated instruction; teacher trust and acceptance of AI systems; and issues with ethics, data literacy, and usability were all identified through a qualitative thematic analysis.

This synthesis approach is consistent with the ten papers' methods (many used framework-based synthesis, comparative analysis, or thematic coding).

5. Moral Aspects

There were no human subjects in this study because it uses secondary data from published research.

Nonetheless, ethical guidelines like truthful portrayal, objective interpretation, and appropriate citation were closely adhered to.

Anticipated Results:

The study is anticipated to yield the following results based on the synthesis of the ten chosen papers:

1. A thorough grasp of AI dashboards in K–12: An illustration of how teachers' instructional decision-making is currently supported by AI-driven learning analytics dashboards.
2. Determining the main influencing factors: insight into elements like digital competency, trust, dashboard usability, and interpretability that influence teachers' adoption and efficient use.
3. Impact on instructional decisions: Quantitative and qualitative summaries demonstrating advancements in areas such as lesson planning, early identification of at-risk students, individualized feedback, and instructional efficiency.
4. Research gaps and suggestions: Emphasizing methodological shortcomings, a dearth of longitudinal studies, and chances to enhance the actual use of AI dashboards in classrooms.
5. Practical implementation framework: Advice for teachers and school administrators on how to incorporate AI-powered dashboards to improve teacher decision-making.

Gantt chart

Task	Duration	Start Date
Define research title & scope	1 day	15 November
Conduct literature search (10 papers)	7 days	16 November
Review & summarize papers	7 days	23 November
Integrate summaries into continuous review	7 days	30 November
Write Abstract, Introduction, Background	7 days	7 December
Write Problem Statement, Objectives, Scope	4 days	14 December
Draft Expected Outcomes	8 days	18 December
Revise & finalize Literature Review (APA)	9 days	30 December

Task	Week 1	Week 2	Week 3	Week 4	Week 5
Define research title & scope					
Conduct literature search (10 papers)					
Review & summarize papers					
Integrate summaries into continuous review					
Write Abstract, Introduction, Background					
Write Problem Statement, Objectives, Scope					
Draft Expected Outcomes					
Revise & finalize Literature Review					
Compile References & formatting (APA)					

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