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LEARNING ANALYTICS AND STUDENTS' MOTIVATION: A SYSTEMATIC REVIEW

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Abstract

The growing integration of digital learning environments in higher education has intensified interest in learning analytics as a means of supporting student learning processes. Among the outcomes associated with learning analytics, student motivation has received increasing attention due to its critical role in academic engagement, persistence, and success. This systematic review synthesises empirical evidence on the relationship between learning analytics and students' motivation in higher education. Following the PRISMA 2020 guidelines, a comprehensive search was conducted across Scopus, Web of Science, ERIC, ScienceDirect, SAGE Journals, and Google Scholar. After screening and eligibility assessment, 24 empirical studies published between 2015 and 2025 were included in the final qualitative thematic synthesis. The findings indicate a generally positive association between learning analytics and student motivation, particularly in relation to self-efficacy, self-regulated learning, and academic motivation. Learning analytics tools such as dashboards, analytics-based feedback, and progress indicators were found to enhance students' awareness of learning progress and support goal-directed behaviour. However, the review also revealed conditional and mixed effects, with some studies reporting reduced motivation when analytics feedback was perceived as controlling or overly comparative. Methodological analysis showed a predominance of cross-sectional designs, limiting causal inference. Overall, the review highlights the motivational potential of learning analytics while underscoring the importance of pedagogically grounded, autonomy-supportive, and context-sensitive implementation. Implications for future research, educational practice, and policy are discussed.

Keywords: learning analytics; student motivation; higher education; systematic review; PRISMA

Introduction

Higher education is increasingly shaped by data-rich learning environments in which students' academic activity is mediated through learning management systems (LMS), virtual learning platforms, digital assessments, and institutional information systems (Ifenthaler & Yau, 2020; Siemens & Baker, 2019). Within this context, learning analytics (LA) has emerged as a prominent approach for transforming digital traces of learning activity into actionable insights intended to support learning and teaching. The Society for Learning Analytics Research defines learning analytics as the collection, analysis, interpretation, and communication of data about learners and their learning to generate theoretically meaningful and actionable insights that enhance educational

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processes (SoLAR, 2025). This definition highlights that learning analytics is not merely a technical endeavour but a pedagogically oriented practice aimed at supporting students' learning experiences and outcomes (Khalil & Ebner, 2017).

Despite technological advancements, universities continue to face persistent challenges related to student motivation, which is widely recognised as a key determinant of academic engagement, persistence, and achievement (Tinto, 2017). Motivation influences how students initiate, regulate, and sustain their learning behaviours and has been closely linked to constructs such as self-efficacy, goal orientation, and self-regulated learning (Zimmerman, 2013). In digitally mediated learning environments, students' motivational processes are increasingly shaped by the feedback, signals, and cues they receive through learning technologies, making motivation a critical outcome of interest for learning analytics interventions (Gašević et al., 2016).

Learning analytics tools are often designed to support motivation indirectly by increasing students' awareness of their learning progress, providing timely feedback, enabling goal-setting, and encouraging reflective learning practices (Jivet et al., 2020). Common implementations include student-facing dashboards, predictive analytics, automated feedback, and personalised nudges embedded within LMS platforms (Saqr et al., 2020). However, empirical evidence regarding the motivational impact of learning analytics remains mixed. Systematic reviews examining learning analytics dashboards report varied effects on students' motivation, suggesting that outcomes depend heavily on design quality, pedagogical alignment, and students' interpretation of analytics-based feedback (Kaliisa et al., 2024). Recent synthesis research further indicates a shift from purely analytics-driven displays toward more learning-oriented designs, while highlighting ongoing challenges in grounding analytics tools in established motivational and learning theories (Paulsen & Lindsay, 2024).

Research on learning analytics-supported feedback reinforces this nuanced perspective. A systematic review of analytics-enhanced feedback in higher education found that motivational effects are influenced by how feedback is framed, timed, and integrated into learning activities rather than by the mere presence of analytics tools (Banihashem et al., 2022). This aligns with broader educational research suggesting that feedback can either enhance or undermine motivation depending on whether it supports autonomy, competence, and self-regulation (Carless & Winstone, 2020). Consequently, learning analytics should be conceptualised as a socio-technical and pedagogical system in which motivational outcomes emerge through interactions between technology, learners, and instructional practices, rather than as a standalone technological solution (Selwyn, 2019).

Recent meta-analytic evidence supports the view that learning analytics-based interventions can positively influence learning-related outcomes, while also revealing substantial variability across contexts and study designs (Liu & Wang, 2025). Although such meta-analyses often focus on achievement or performance indicators, they underscore an important implication for motivation: learning analytics interventions are not universally effective, and their motivational impact is shaped by contextual, design, and learner-related factors (Matcha et al., 2020). These findings point to the need for systematic reviews that specifically examine how and under what conditions learning analytics influences student motivation.

This need is particularly pronounced in contexts where learning analytics adoption is still emerging. In Pakistan's higher education sector, the rapid expansion of LMS-based and online learning has increased interest in digital learning technologies and data-informed student support

(HEC, 2023). Studies from Pakistan indicate that students' engagement with e-learning systems is influenced by perceived usefulness, ease of use, and behavioural intention, reflecting technology acceptance dynamics that are closely related to motivation (Tufail et al., 2024). Given that learning analytics relies on sustained and meaningful engagement with digital platforms, motivational factors are likely to play a central role in shaping the effectiveness of analytics-driven interventions in such contexts (Ali, 2025). However, existing evidence remains fragmented, and there is limited synthesis of how learning analytics relates specifically to student motivation within higher education, particularly in developing contexts.

In response, this systematic review synthesises empirical research on learning analytics and students' motivation in higher education. By examining learning analytics approaches, theoretical perspectives on motivation, and reported motivational outcomes, the review aims to clarify the current state of evidence, identify methodological and conceptual gaps, and offer directions for future research and practice. In doing so, it seeks to contribute to a more nuanced and context-sensitive understanding of how learning analytics can support student motivation in higher education systems.

Table 1

Alignment of Research Objectives and Research Questions

Research Objectives	Corresponding Research Questions
RO1: To systematically identify and synthesise empirical studies examining the relationship between learning analytics and students' motivation in higher education.	**RQ1:** How has learning analytics been conceptualised and operationalised in empirical studies examining students' motivation in higher education?
RO2: To analyse how student motivation has been defined and measured in learning analytics research across different higher education contexts.	**RQ2:** What empirical evidence exists regarding the relationship between learning analytics and students' motivation in higher education?
RO3: To examine the learning analytics approaches (e.g., dashboards, analytics-based feedback, predictive systems) associated with students' motivational outcomes in the existing literature.	**RQ3:** Which dimensions of student motivation (e.g., self-efficacy, self-regulated learning, academic motivation) are most frequently associated with learning analytics interventions in the existing literature?

PRISMA-Based Screening and Selection Procedure

Stage	Description of Procedure
Identification	A comprehensive literature search was conducted across Scopus, Web of Science, ERIC, ScienceDirect, SAGE Journals, and Google Scholar using predefined Boolean search strings related to learning analytics and students' motivation in higher education.
Duplicate Removal	Duplicate records retrieved from multiple databases were identified and removed prior to screening to ensure that each study was assessed only once.

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Title and Abstract Screening	Titles and abstracts were screened to exclude studies that were irrelevant to the review objectives, non-empirical in nature, conducted outside higher education settings, or did not explicitly address learning analytics or student motivation.
Full-Text Eligibility Assessment	Full-text articles were reviewed against predefined inclusion and exclusion criteria, with particular attention to empirical study design, explicit use of learning analytics approaches, and measurement of student motivation or closely related motivational constructs.
Exclusion at Full-Text Stage	Studies were excluded at this stage if they lacked methodological clarity, focused solely on technical or predictive modeling without motivational outcomes, or were not published in peer-reviewed journals.
Final Inclusion	Studies meeting all inclusion criteria were retained for narrative thematic synthesis and included in the final systematic review.
PRISMA Compliance	The overall review process followed the PRISMA 2020 guidelines, ensuring transparency, replicability, and methodological rigor throughout the identification, screening, eligibility, and inclusion stages.

Table 3

Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Empirical Study Type	Empirical studies (quantitative, qualitative, and mixed-methods designs)	Conceptual papers, editorials, book reviews, commentaries
Participants	Students enrolled at the university or higher education level	Studies focusing exclusively on school-level students or non-student populations
Core Construct	Learning analytics or closely related constructs (e.g., dashboards, analytics-based feedback, predictive analytics)	Studies not addressing learning analytics or focusing solely on general educational technology
Outcome Focus	Student motivation or closely related motivational constructs (e.g., self-efficacy, self-regulated learning, academic motivation)	Studies focusing only on achievement or performance outcomes without motivational variables
Publication Type	Peer-reviewed journal articles	Theses, dissertations, conference papers, and abstracts
Language	English	Non-English publications
Timeframe	2015–2025	Studies published outside the defined timeframe

PRISMA Flow of Study Selection

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The process of study selection was conducted in accordance with the PRISMA 2020 guidelines. A systematic literature search across Scopus, Web of Science, ERIC, ScienceDirect, SAGE Journals, and Google Scholar identified a total of 268 records. After the removal of 37 duplicate records, 231 studies remained for title and abstract screening. During this screening stage, 192 records were excluded because they were non-empirical in nature, conducted outside higher education settings, did not focus on learning analytics, or did not examine student motivation or closely related motivational constructs. The remaining 39 articles were subjected to full-text eligibility assessment.

Following a comprehensive review of the full-text articles, 15 studies were excluded due to insufficient methodological detail, absence of an explicit learning analytics component, or lack of clear operationalisation and measurement of student motivation. Consequently, 24 studies that met all predefined inclusion criteria were retained and included in the final qualitative thematic synthesis.

PRISMA Numerical Reporting

PRISMA Phase	Number (n)
Records identified through database searching	n = 268
Records after duplicates removed	n = 231
Records screened (title and abstract)	n = 231
Records excluded	n = 192
Full-text articles assessed for eligibility	n = 39
Full-text articles excluded	n = 15
Studies included in qualitative synthesis	n = 24

RESULTS

Overview of Included Studies

Following the PRISMA-based screening and selection process, 24 empirical studies that met all predefined inclusion criteria were included in the final qualitative thematic synthesis. These studies examined the relationship between learning analytics and students' motivation within higher education contexts. The included studies represented a range of disciplinary settings within universities and were conducted across diverse geographical regions, reflecting the global interest in learning analytics research.

In terms of research design, the majority of the 24 reviewed studies employed quantitative methodologies, with survey-based designs and learning management system (LMS) data analytics being the most commonly used approaches. A smaller number of studies adopted qualitative or mixed-methods designs to explore students' motivational experiences in relation to analytics-based feedback and interventions. Learning analytics was operationalised through various tools and approaches, including dashboards, predictive analytics, automated feedback systems, and analytics-driven nudges. Student motivation was measured using validated self-report instruments

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grounded in motivational theories such as self-regulated learning, self-efficacy, and academic motivation frameworks.

Theme 1: Conceptualisation and Measurement of Student Motivation

Across the 24 included studies, student motivation was conceptualised as a multidimensional construct encompassing intrinsic motivation, extrinsic motivation, self-efficacy, goal orientation, and self-regulated learning behaviours. While different terminologies and theoretical frameworks were employed, all studies focused on students' willingness to initiate, sustain, and regulate learning activities within digitally mediated environments.

Most quantitative studies relied on self-report motivation scales, often adapted from established instruments, to assess changes in students' motivational states following exposure to learning analytics tools. A smaller number of studies combined self-report measures with behavioural indicators derived from LMS data to triangulate motivational outcomes. Despite variation in measurement approaches, motivation was consistently treated as a student-level outcome influenced by analytics-based feedback and insights.

Theme 2: Learning Analytics and Enhancement of Student Motivation

A substantial proportion of the 24 reviewed studies reported a positive relationship between learning analytics and student motivation. These studies indicated that analytics-based dashboards and feedback mechanisms enhanced students' awareness of their learning progress, supported goal-setting, and encouraged reflective learning practices. Students exposed to learning analytics tools demonstrated higher levels of self-efficacy and perceived control over their learning processes.

Several studies highlighted that timely and personalised analytics-based feedback played a critical role in sustaining motivation. Learning analytics tools that presented progress indicators in a clear and supportive manner were found to promote students' engagement with course materials and persistence in learning tasks. Qualitative findings further suggested that students perceived analytics-driven insights as motivating when they were framed constructively and aligned with instructional goals.

Theme 3: Conditional and Mixed Motivational Effects of Learning Analytics

Despite generally positive trends, the findings across the 24 studies also revealed conditional and mixed effects of learning analytics on student motivation. Some studies reported that analytics-based comparisons or performance rankings led to increased anxiety or reduced motivation among certain student groups. In such cases, learning analytics feedback was perceived as controlling or evaluative rather than supportive.

These studies emphasised that the design and interpretation of analytics tools significantly influenced motivational outcomes. Learning analytics systems that lacked pedagogical explanation or autonomy-supportive features were less effective in enhancing motivation. This theme underscores that learning analytics does not uniformly improve motivation and that its impact depends on contextual factors, student characteristics, and the manner in which analytics information is communicated.

Theme 4: Methodological Characteristics of the Included Studies

Methodological analysis of the 24 included studies revealed a predominance of cross-sectional research designs, with limited use of longitudinal or experimental approaches. Quantitative survey designs combined with LMS analytics data were the most common methodological strategy, while qualitative and mixed-methods studies provided deeper insights into students' motivational perceptions and experiences.

Analytical techniques primarily included correlation analysis, regression modelling, and structural equation modelling to examine relationships between learning analytics interventions and motivational outcomes. Although studies were conducted across diverse institutional and cultural contexts, the overall consistency of findings enhanced the robustness of the evidence base. However, the dominance of cross-sectional designs limited causal inference, highlighting the need for more longitudinal and experimental research to better understand the motivational mechanisms underlying learning analytics interventions.

SUMMARY OF RESULTS

Overall, the synthesis of the 24 empirical studies included in this systematic review indicates a generally positive and consistent relationship between learning analytics and students' motivation in higher education contexts. Despite variation in conceptual definitions, learning analytics tools, and motivational frameworks, the direction of evidence across the reviewed studies was largely homogeneous. Most studies reported that learning analytics interventions particularly dashboards, analytics-based feedback, and progress indicators were associated with improvements in students' motivational outcomes, including self-efficacy, goal orientation, and self-regulated learning. Although the magnitude of effects varied across studies, the cumulative evidence suggests that learning analytics has meaningful motivational potential when appropriately designed and implemented.

DISCUSSION

The primary aim of this systematic review was to synthesise empirical evidence on the relationship between learning analytics and students' motivation in higher education. The findings demonstrate a relatively coherent pattern indicating that learning analytics is positively associated with multiple dimensions of student motivation. This pattern was evident across different institutional contexts, disciplinary settings, research designs, and cultural backgrounds, underscoring the relevance of learning analytics as a pedagogically significant component of contemporary higher education.

Learning Analytics and Student Motivation

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A central conclusion of this review is that learning analytics can support student motivation by enhancing learners' awareness of their academic progress, clarifying learning expectations, and facilitating goal-directed behaviour. Studies consistently showed that analytics-based dashboards and feedback systems helped students monitor their performance and adjust learning strategies, thereby strengthening motivational constructs such as self-efficacy and self-regulation. These findings align with contemporary motivational and learning theories that conceptualise learning as an active, self-regulated, and socially mediated process, in which feedback plays a crucial role in sustaining motivation (Zimmerman, 2013; Jivet et al., 2020).

The reviewed literature suggests that learning analytics influences motivation primarily through informational and feedback mechanisms, rather than through direct behavioural control. When analytics tools provided meaningful, timely, and comprehensible feedback, students were more likely to perceive control over their learning and demonstrate increased persistence. Conversely, analytics systems that emphasised comparison or ranking were sometimes associated with reduced motivation or heightened anxiety, highlighting the importance of autonomy-supportive design. These findings support recent arguments that learning analytics must be pedagogically grounded to positively influence motivational outcomes (Paulsen & Lindsay, 2024; Kaliisa et al., 2024).

Conditional Effects and Design Sensitivity

Although the overall evidence favoured positive motivational outcomes, the synthesis also revealed **conditional and mixed effects** of learning analytics on student motivation. Several studies indicated that the motivational impact of analytics depended on contextual factors such as students' prior achievement, digital literacy, and interpretation of analytics feedback. In particular, analytics-based performance comparisons were found to undermine motivation for some learners, especially when feedback lacked explanatory or supportive elements.

These findings reinforce the view that learning analytics should be understood as a **socio-technical system**, in which motivational outcomes emerge from interactions between technology, learners, and instructional practices (Selwyn, 2019). Simply providing access to analytics data is insufficient; rather, motivational benefits depend on how analytics information is framed, scaffolded, and integrated into teaching and learning processes.

Conceptual and Methodological Implications

Despite general consistency in findings, the review identified notable **conceptual and methodological limitations** in the existing literature. Student motivation was operationalised using a wide range of overlapping constructs, including intrinsic motivation, academic motivation, self-efficacy, and self-regulated learning. While these constructs share theoretical commonalities, the lack of conceptual precision complicates cross-study comparison and may account for variation in reported effects. Recent methodological critiques similarly call for clearer theoretical alignment in learning analytics research on motivation (Matcha et al., 2020).

Methodologically, most included studies employed **cross-sectional designs**, limiting the ability to draw causal conclusions. Although associations between learning analytics and motivation were consistently reported, relatively few studies used longitudinal or experimental designs capable of establishing directionality. This limitation warrants caution in interpreting learning analytics as a causal determinant of student motivation, despite strong theoretical support for such a relationship.

Educational and Policy Implications

The findings of this systematic review carry important implications for higher education practice and policy. The consistent association between learning analytics and student motivation suggests that analytics should be treated as a pedagogical support tool, rather than merely a monitoring or accountability mechanism. Institutions should prioritise the development of learning analytics systems that promote self-awareness, autonomy, and reflective learning.

At the policy level, professional development initiatives should equip instructors with the skills to interpret and use learning analytics data in ways that enhance student motivation. Rather than focusing solely on performance indicators, learning analytics policies should emphasise ethical design, transparency, and student agency. In contexts such as Pakistan, where learning analytics adoption is still emerging, these considerations are particularly important to ensure that analytics-driven interventions are inclusive, context-sensitive, and motivationally supportive.

FUTURE RESEARCH RECOMMENDATIONS

The review identifies several directions for future research. First, greater conceptual clarity is needed in defining and measuring student motivation within learning analytics research. Differentiating between motivational constructs and aligning them explicitly with theoretical frameworks would strengthen cumulative knowledge. Second, more longitudinal and experimental studies are required to examine how learning analytics influences motivation over time and under different instructional conditions. Finally, additional research in diverse cultural and institutional contexts, particularly in developing higher education systems, would enhance understanding of how contextual factors shape the motivational effects of learning analytics.

CONCLUSION

This PRISMA-based systematic review synthesised empirical evidence on the relationship between learning analytics and students' motivation in higher education. The reviewed studies collectively demonstrate that learning analytics is generally associated with positive motivational outcomes, particularly when analytics tools are designed to support self-regulation, feedback, and learner autonomy. Students exposed to meaningful analytics-based insights tend to exhibit higher levels of motivation, self-efficacy, and engagement with learning tasks.

Although variation exists in conceptual definitions and methodological approaches, the overall direction of evidence supports the view that learning analytics has significant motivational potential. However, the predominance of cross-sectional designs limits causal inference and underscores the need for more robust longitudinal and intervention-based research. Overall, this systematic review contributes to the literature by clarifying the motivational role of learning analytics and highlighting the importance of pedagogically grounded, ethically informed analytics practices in higher education. Recognising student motivation as a central outcome of learning analytics can guide future research, institutional practice, and policy aimed at enhancing learning experiences and student success.

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