

Leveraging Learning Analytics in Formative Assessment: Insights from a Scoping Review of Blended Learning Courses in Higher Education

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Abstract

In recent years, the expansion of advanced digital technologies in the learning field has caused a deep change in educational platforms and revolutionized the tools and systems that support online learning. Within this context, the rapid development of Learning Analytics (LA) in blended and online higher education has transformed assessment practices, enabling personalized feedback and more targeted instructional strategies. This scoping review investigates how LA is integrated into formative assessment practices within blended learning courses in higher education. By analysing 13 selected studies, the review identifies the main techniques, purposes, and roles attributed to LA, such as student profiling, predictive modeling, teacher support, and feedback automation. The restricted number of papers examined could limit the broader applicability of the conclusions. However, findings highlight how LA is increasingly employed to support formative assessment in blended higher education, with methods such as process mining, predictive modeling, and visualization enabling more precise monitoring of student learning and the provision of timely, personalized feedback. Yet, the pedagogical challenge lies in ensuring that these tools are not reduced to mere instruments of control, but are instead leveraged to foster engagement, support teachers' decision-making, and promote more inclusive and meaningful learning experiences.

Keywords: Learning Analytics, Formative Assessment, Scoping Review, Blended Learning, Higher Education.

Article submitted: 28/07/2025; accepted: 04/12/2025

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Acknowledgements

This article is based on research conducted within the framework of the Italian PRIN project *Active Online Assessment in Higher Education (2023-2025)* (PRIN – Grant 2022 – Prot. 2022F74XBL). The authors jointly contributed to the conceptualization and development of the manuscript. For transparency and clarity, individual contributions are specified as follows: Elena Gabbi was responsible for Sections 3, 4.2, and 5; Claudia Baiata contributed to Sections 2 and 4.1; while Sections 1 and 6 were developed by Maria Ranieri.

1. Introduction

In recent years, digital technologies have become increasingly pervasive in higher education (HE), reshaping not only the tools available for instruction but also the modalities through which learning is organized and delivered. One of the most prominent developments in this context is the growing adoption of blended learning - a pedagogical model that combines face-to-face instruction with online components. Blended learning has proven particularly well-suited to the demands and flexibility of university education, offering opportunities for personalized learning pathways and asynchronous engagement (Hughes, 2025). However, while teaching practices have progressively evolved to incorporate digital infrastructures, assessment practices in these innovative contexts remain underdeveloped and often disconnected from the technological affordances of modern learning environments.

This gap became especially evident during and after the COVID-19 pandemic, a period which saw the rapid proliferation of online assessment systems – most notably, remote proctoring tools designed to monitor academic integrity. Yet, such systems primarily function as surveillance mechanisms, aimed at preventing misconduct rather than supporting meaningful learning processes with negative consequences on students' engagement (Marano et al., 2024). They offer limited potential for formative assessment – that is, assessment conceived as an integral part of teaching and learning, aimed at guiding students' development and promoting reflection, self-regulation, and improvement.

In response to these challenges, the Italian PRIN project, *Active Online Assessment in Higher Education (2023-25)*, set out to investigate how digital technologies might enhance assessment in online and blended HE settings. Within this context, the current study focuses on the field of Learning Analytics (LA), an emergent and promising area that leverages educational data to better understand and support learning (Romero & Ventura, 2020). Despite its potential, the application of LA to formative assessment in university-level blended learning contexts remains relatively unexplored.

This study seeks to address this gap by examining how LA can be used to support and enrich formative assessment practices in HE, particularly within blended learning contexts. It investigates the ways in which LA tools and methodologies can transform assessment from a static, summative process into a dynamic, ongoing dialogue between students and educators - one that fosters deeper engagement, timely feedback, and continuous improvement. Specifically, the study aims to identify the key techniques employed in current research and practice, their intended pedagogical purposes, and the extent to which they contribute to reshaping assessment practices. In doing so, it explores how LA can help create more responsive learning environments that adapt to students' needs in real time and more data-informed educational models that empower instructors to make better decisions.

2. Background

Over the past few years, the expansion of advanced digital technologies in the learning field has caused a deep change in educational platforms and revolutionized the tools and systems that support online learning. High-tech developments in Learning Management Systems (LMS) have significantly boosted interactions between teachers and students, as well as among students themselves. Furthermore, they have supported and driven the creation of automated strategies for data collection, enabling more effective monitoring of learners' progress and comprehension levels. Since this paper explores the relationship between LA and formative assessment within blended learning environments, it is relevant to examine how these concepts naturally complement each other. By understanding how LA can support formative assessment, educators can better personalize their teaching approaches, ultimately creating more meaningful and effective learning experiences for students in HE.

A most cited definition of Siemens and Gašević (2012, p. 1) describes LA as “the measurement, collection, analysis, and reporting of data about learners, learning environments, and contexts to understand and optimize learning and their environments”. Its primary objective consists in fostering student learning and providing new spaces to investigate educational environments. Both researchers and practitioners can utilize LMS dashboards and other external tools to extract, visualize, and analyse data, not only to monitor student progress, but also to enhance teaching practices and foster professional development (Ranieri & Gabbi, 2021; Gabbi, 2023). This information enables them to craft targeted interventions and develop personalized learning experiences for students (Bulut et al., 2023). Most LA techniques – such as visualization, classification, clustering, and association analysis – have already been effectively implemented within the educational field (Romero & Ventura, 2020). A disconnect remains

between the analytical outputs generated by data-processing algorithms and their effective interpretation to positively impact students' learning experiences. As highlighted by Wise (2014), greater attention should be given to the process of translating data into meaningful enhancements within learning environments. Multimodal solutions that integrate text and images can further increase the support provided to educators given their ability to identify complex, evolving learning behaviors and to offer meaningful "insights about learners' cognitive, metacognitive and emotional states" (Yan et al., 2024, p. 1903).

Empirical studies suggest that LA-based feedback can enhance students' perception of feedback and support improvements in their academic performance, particularly through scalable, data-driven approaches (Pardo et al., 2019). Moreover, Guzmán-Valenzuela et al. (2021) refer to the image of a virtuous and iterative cycle wherein learners generate data in the LMS platform based on their interactions with the online applications, as well as their engagement with the provided resources and assessments. This data is then used to inform and modify teachers' instructional practices, which, in turn, influence and modify students' behaviors and cognitive patterns, creating a continuous feedback loop. Regarding potential concerns arising from extensive use of LA, the authors cited above highlight some controversial aspects, such as the reduced autonomy of teachers and students, while the control mainly remains in the hands of central organizations, keen to prioritize grades and statistics over students' interest, motivation, and learning satisfaction. A second aspect to consider calls into question the Rosenthal effect: since LA aims to identify at-risk students, it may unintentionally contribute to labeling them and reinforcing teacher bias, potentially leading to lowered expectations for vulnerable or disadvantaged learners. In addition, the methods by which LA collects, analyses, and interprets data should be examined, as they may lead to misinterpretation and, in terms of privacy, could potentially restrict user freedom and raise concerns about data collection, storage, and usage.

These reflections underscore the necessity for careful consideration of both pedagogical and ethical dimensions when integrating LA and assessment into educational contexts. When such considerations are carefully balanced with practical application, this approach can significantly enhance the quality of blended and online university courses, making education more inclusive, equitable, and continuously responsive to students' evolving needs. It is largely acknowledged that LA offers substantial advantages for both students and teachers, contributing to provide personalized feedback and targeted support, with improved outcomes for everyone involved.

LA has therefore emerged as a promising educational approach designed to understand and optimize learning outcomes, effectively supporting formative assessment practices, enhancing student engagement, and fostering improved

academic achievement. In the practice of formative assessment, consequently, digital learning environments combined with Automatic Assessment Systems play a strategic significance, as Barana et al. (2019) highlight. These authors emphasize several key functions through which a digital learning environment can effectively assist educational activities. Such functions play a crucial role in: supporting students and teachers in designing and creating tools and operational strategies; providing and personalizing these resources to the intended users; gathering both quantitative and qualitative data on student interactions, like material usage, participation in activities, and performance metrics; analysing the data generated by students during training sessions; delivering individual feedback to students based on their performance; and offering comprehensive data analyses to both teachers and students to inform future learning and instructional strategies.

In Yan's (et al., 2021) systematic review, 52 studies were analysed, revealing the key factors that shape how teachers perceive and implement formative assessment. The findings suggest that teachers' decisions and practices are influenced by personal aspects, such as their attitude toward assessment and prior training, as well as contextual elements, including the level of support within their institution and the overall school environment. In this context, LA can complement and enhance formative assessment by providing data-driven insights that guide instructional decisions in terms of didactic and pedagogical choices. It can also support student learning, by offering feedback that is both timely and tailored to their individual needs, while also giving teachers insights and opportunities for appropriate intervention. Assessment and LA can have beneficial interactions in both directions. For instance, if predictive modeling indicates that students who struggle with a particular section of the course are at high risk of failing later on, instructors can step in sooner with tailored tutorials, extra resources, or peer mentoring to help them get back on track. To increase its validity and reliability, LA can make use of assessment-related tools, hypotheses, and techniques. At the same time, the discipline of evaluation may also benefit from the insight provided by LA. In assessment research, LA may also be employed to test open-ended theories and examine existing testing methods (Gašević, Greiff, & Shaffer, 2022).

The use of analytical tools enables teachers to provide LA based personalized feedback, particularly helpful in large student cohorts. By leveraging extensive data previously collected on student behavior, educators can generate timely and tailored feedback messages that respond to individual learning needs (Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019). Personalized feedback based on LA is an outstanding demonstration of how cutting-edge technology may enhance educators' skills. In situations where providing tailored feedback to students would typically be difficult, such as in large classes with hundreds or thousands of attendees, technology can facilitate the delivery of personalized

feedback. The teacher creates feedback templates, or “IF-THIS-THEN-THAT” scripts, instead of writing traditional feedback messages to each student. Automated messages would in this scenario follow multiple and differentiated responses, based on the student’s outcomes. The system then uses information about the students and their learning processes to transform the templates into individualized feedback (Merikko, Saqr, & Ihantola, 2022).

As this article examines university courses implementing blended learning, a brief definition is provided to frame the theoretical discussion and clarify the term’s usage. Blended learning, increasingly adopted in HE for its flexibility and inclusivity, supports formative assessment by allowing students to engage with content at their own pace and follow personalized learning paths (Hughes, 2025). While the concept has evolved to include diverse pedagogical models and digital tools, this study adopts Graham’s (2006) definition: the integration of traditional face-to-face and distributed learning systems. This understanding informs the analysis within the LA framework.

3. Method

This study investigates the application of LA in conjunction with formative assessment tools to support student learning through continuous feedback and adaptive instructional strategies. The focus is on HE blended learning environments, where digital technologies facilitate the collection and analysis of learning data. This research is a component of a broader state-of-the-art review that aimed to determine the variety of tools and approaches used worldwide to support ongoing evaluation, feedback, and learners’ active participation in blended learning contexts.

Few systematic reviews and critical syntheses have investigated the relationship between LA, assessment, and dashboard use in HE (Banihashem et al., 2022; Guzmán-Valenzuela et al., 2021; Matcha et al., 2019; Zhang et al., 2023). The use of LA for feedback support extends beyond simply making feedback more manageable for educators who are often overwhelmed; it also enables more diversified and tailored feedback, assisting learners in acquiring and developing effective learning strategies and skills (Banihashem et al., 2022). Moreover, the literature review by Zhang et al. (2023), encompassing school education and lifelong learning, shows that LA in formative assessment enhances digital learning by delivering timely and actionable feedback to both students and instructors. The study reviewed identify various purposes of LA in formative assessment, such as generating feedback for students, offering feedback for instructors, creating learner profiles, facilitating peer assessment, monitoring student performance, identifying learning strategies, and providing

automatic instant corrections. However, persistent challenges concern the translation of theoretical constructs into measurable learning variables (Guzmán-Valenzuela et al., 2021) and the limited grounding of LA dashboards in self-regulated learning theory, which constrains their potential to support metacognition and inform effective learning strategies (Matcha et al., 2019).

While existing reviews have highlighted the potential of learning analytics (LA) to enhance feedback practices, their specific operationalization within formative assessment processes in blended university contexts remains insufficiently explored. To address this gap, this study examines the presence and role of LA in formative assessment strategies within blended learning settings. Specifically, the study aims at answering two research questions: 1) Which techniques are employed, and for what purposes, in the application of LA within university blended learning courses that incorporate formative assessment strategies? 2) What roles could LA play in the formative assessment process within HE blended learning contexts?

This study adopts a scoping review approach, aiming to provide a preliminary overview of the scope and nature of existing literature on a given topic (Paré, Trudel, Jaana, & Kitsiou, 2015). These reviews are mostly conducted to assess the breadth, range, and focus of research activities, and to determine the feasibility of a full systematic review, or else to identify gaps in the existing body of knowledge (Cooper, Hedges, & Valentine, 2019). The literature review was undertaken through the following process (Moher et al., 2015): defining the research problem and questions, searching for relevant literature, reviewing and evaluating the search results, analysing, coding, and synthesizing the findings, and finally, reporting the review.

The paper collection process aimed to identify relevant studies by integrating multiple approaches for literature analysis to combine the advantages and capabilities of artificial intelligence with research methods. This included the use of generative artificial intelligence technologies - such as Scopus AI, an innovative add-on to the Scopus database, and Elicit, a research assistant AI tool – alongside conventional methods, such as string searches in the Scopus database. This approach aligns with recent scholarly discussions on integrating AI into research practices (Gatrell, Muzio, Post, & Wickert, 2024). The integration of Scopus AI and Elicit into the literature review process enhances discovery by uncovering relevant works beyond disciplinary or terminological boundaries, revealing emerging trends through visual mappings, and reducing the effort needed to process large datasets, yet it remains difficult to reproduce and subject to constant evolution in its algorithms and data sources. The AI-based search was conducted to expand the scope of inquiry by formulating two initial questions: one focused on toolkits for formative assessment in blended learning environments and the other on frameworks and guidelines for formative

assessment and evaluation in HE blended learning. Researchers then selected specific in-depth questions generated by the system for further exploration. Additionally, a targeted search was performed on Scopus using the following search string: “blended AND learning AND formative AND assessment.”

The inclusion criteria comprised studies that investigated HE settings, published within the last decade (2014-2024) and written in English. Specifically, studies were selected based on the following parameters: i) *Publication type*: Peer-reviewed articles and conference papers, both empirical and conceptual; ii) *Educational context*: Higher education institutions; and iii) *Intervention*: LA applied in blended learning courses that incorporate formative assessment strategies. Studies were excluded if they focused solely on fully online or fully in-person learning, addressed summative assessment or general evaluation, or were conducted in primary and secondary education, vocational training, lifelong learning, or informal learning contexts.

To fully address the study objectives, a data extraction tool was developed to collect a variety of data to analyse the studies. Firstly, the basic study features were coded to accurately describe the selected searches. Subsequently, to answer RQ1 and RQ2, during the analysis phase, each paper was inductively or deductively coded according to three key dimensions (Table 1).

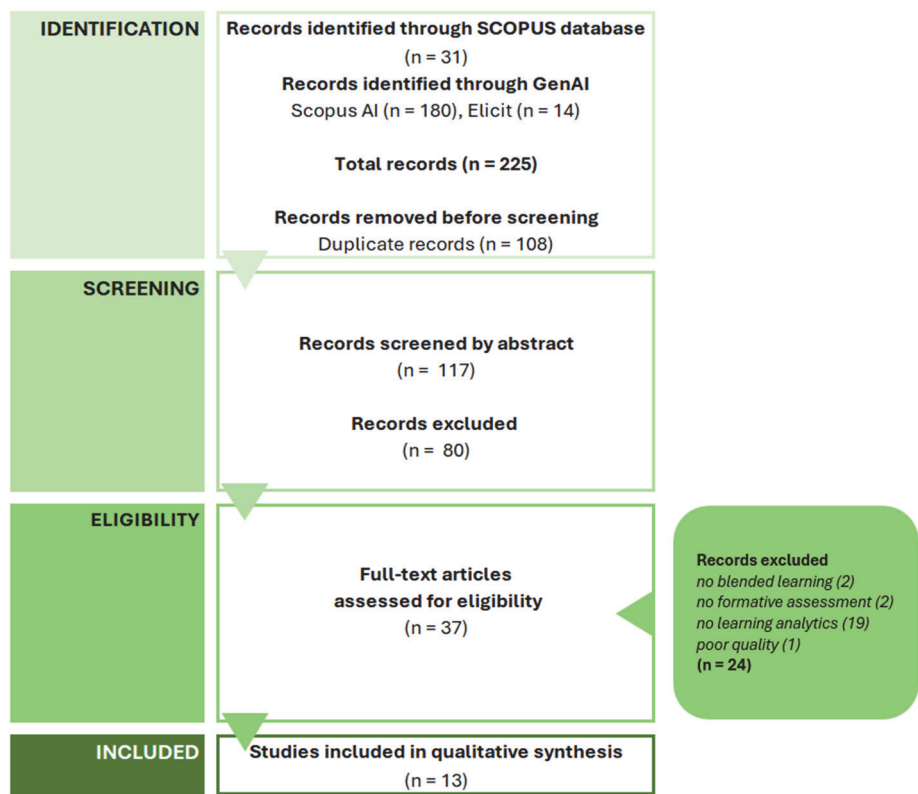
Table 1 - Coding categories

Dimension	Categories
LA techniques (Romero & Ventura, 2020)	Cluster analysis
	Process mining
	Machine learning and data-based systems
	Multimodal LA
	Regression analysis
	Visual LA
Purposes of LA application	Profiling and predictive modeling of students
	Teacher assistance for assessment
	Monitoring student activities
	Data visualization
	Automation of feedback
	Adaptation and personalization
LA’s function in relation to formative assessment	Collecting evidence on formative assessment
	Enriching the formative assessment process
	Designing data-based tools for formative assessment

The entire screening and analysis process was carried out in parallel by three researchers, following a pilot phase during which the collaborative extraction and coding table was tested and aligned through the joint analysis of three articles.

This initial calibration ensured consistency in the application of the coding criteria throughout the review. The data, structured within a data extraction tool, were independently coded and cross-checked by multiple researchers. Any discrepancies in interpretation were subsequently discussed and resolved through consensus to ensure methodological rigor. An aggregative synthesis approach (Sandelowski & Barroso, 2003) was employed to present the results extracted through the coding process, categorized by type of findings.

Figure 1 - Flowchart of the study selection process using GenAI tools and database searches



As illustrated in Figure 1, the search conducted on the previously mentioned criteria produced a total of $N = 225$ records. Duplicate records ($N = 108$) were first removed to eliminate overlaps across different search tools. Articles that did not align with the study’s focus were then excluded based on predefined criteria. This screening process refined the literature corpus, ensuring that only the most relevant and significant studies were retained for the final analysis ($N = 13$). The next section outlines the characteristics of the selected studies and

provides a summary of the literature review findings in relation to the research questions.

4. Results

4.1 Background information on the included publications

The selected studies, listed in the Appendix, argued about the use of LA in HE settings, examining its different applications for improving learning environments in the realm of formative evaluation and blended learning. As seen in Table 2, the analysis of the scholarly contributions demonstrates a relatively uniform distribution of research output over a decade, with a slight concentration in 2017, 2019, and 2020. Notably, no publications were recorded in 2016, while in the most recent years, the research output appears to have stabilized without significant variation.

Table 2 - Overview of the Studies Included

Authors	Year	Geographical area	Research area of the studies	Document type	Type of study/ methodology
Biswas & Bhattacharya	2024	Asia	Computer Science and Engineering	Journal	Empirical
Borter	2023	n.a.	Psychology	Journal	Empirical
Clutterbuck & Lewis	2019	Australia	Business and Informatics	Journal	Empirical
Comerford, Mannis, DeAngelis, Kougioumtzoglou & Beer	2018	n.a.	Engineering	Journal	Conceptual
Koh, Tee, Suresh & Caleon	2020	n.a.	n.a.	Conference paper	Empirical

Kohnke, Fong & Chen	2022	Asia	English for Academic Purposes	Journal	Empirical
Moraes Marenzi & Kantz	2015	Europe	Medical	Conference paper	Empirical
Nguyen	2017b	n.a.	n.a.	Journal	Empirical
Pardo, Jovanovic, Dawson, Gašević & Mirriahi	2017	Oceania	Computer engineering	Journal	Empirical
Paredes & Hsiao	2021	n.a.	Computer Science	Journal	Empirical
Tempelaar, Rienties & Giesbers	2014	Europe	Mathematics and statistics	Conference paper	Empirical
Titov, Kurilov, Titova & Brikoshin	2019	Russia	n.a.	Journal	Empirical and conceptual
Xiaogun & Yiwei	2020	Asia	Engineering	Conference paper	Empirical

A geographic analysis of the included studies reveals that 3 research papers investigated LA in blended learning environments within Asian universities, and an additional one in Russia. Two studies were conducted in European institutions. However, five studies did not specify their geographical scope or university affiliations, limiting the possibility of a comprehensive data retrieval.

Regarding the disciplinary focus, most of the selected studies (5) investigated LA in university departments of Computer Engineering, Computer Science, and Engineering. An additional one focuses on Business and Informatics. However, three out of the thirteen studies failed to provide specific details about their disciplinary scope, thereby hindering a comprehensive comparison across all studies. In terms of publication type, the majority of the selected papers (9) were published in journals, while the remaining 4 appeared in conference proceedings, suggesting a preference for journal-based dissemination of research findings in this domain. From a methodological perspective, a quantitative approach was the most commonly employed (7

cases), followed by three studies adopting a mixed-methods approach, while the remaining contributions were qualitative, including theoretical proposals and applied concept analyses.

42 Techniques, purposes and functions of Learning Analytics in university blended learning courses with formative assessment

LA aims to improve the educational process by systematically measuring learning-related data and providing informative feedback to students and teachers to support the regulation of learning. In the selection process, thirteen papers mention the use of LA in HE contexts, exploring various applications of this technology to enhance the educational experience in the field of formative assessment and blended learning contexts. To analyse the presence of LA in formative assessment, the studies were classified based on the specific techniques employed (Romero & Ventura, 2020). This categorization highlights the different analytical approaches used to collect, process and interpret student data (Table 3).

Table 3 - Categories of Learning Analytics techniques used

LA techniques	Definition	References (N = 13)
Cluster analysis	Grouping students or learning materials based on patterns of learning and interaction.	Borter, 2023
Process mining	Analysing student behavior through digital traces, including sequences of course participation, grades, and timestamps.	Clutterbuck & Lewis, 2019; Pardo et al., 2017; Titov et al., 2019; Xiaogun & Yiwei, 2020
Machine learning and data-based systems	Identifying hidden insights in data using models that autonomously adapt to new information.	Biswas & Bhattacharya, 2024; Comerford et al., 2018
Multimodal LA	Connecting the physical and the digital learning spaces during practice-based learning activities.	Paredes & Hsiao, 2021
Regression analysis	Predicting student performance and detecting behavioral patterns.	Kohnke et al., 2022; Nguyen, 2017; Tempelaar et al., 2014
Visual LA	Utilizing computational tools and interactive visualization techniques to analyse and interpret educational phenomena.	Koh et al., 2020; Morais et al., 2015

Among the techniques identified, process mining is the most frequently used, appearing in four of the thirteen studies. It enables researchers to analyse student behavior through digital footprints, revealing learning sequences,

assessment patterns, and engagement over time. Regression analysis, used in three studies, helps predict student performance and detect behavioral trends, supporting data-driven decisions. Visual LA also appear in two studies, employing computational and interactive visual tools to interpret complex learning data more effectively. Other techniques, such as cluster analysis, machine learning, and multimodal LA, are each mentioned in only one study.

Besides the technical features, the 13 studies examine different goals of LA’s use, including profiling and predictive modeling of students, teacher assistance for assessment, visualization of assessments for students, detection of student engagement and automation of feedback, as seen in Table 4.

Table 4 - Categories of Learning Analytics application purposes

LA purposes	Definition	References (N = 13)
<i>Profiling and predictive modeling of students</i>	Analysis of learner data to identify profiles and predict academic performance or risk.	Biswas & Bhattacharya, 2024; Borter, 2023 Kohnke et al., 2022; Nguyen, 2017; Tempelaar et al., 2014
<i>Teacher assistance for assessment</i>	Support for instructors in evaluating student work and decision-making through data-driven insights	Clutterbuck & Lewis, 2019; Paredes & Hsiao, 2021
<i>Monitoring student activities</i>	Tracking learners’ engagement, participation, and behaviors within digital learning environments.	Titov et al., 2019; Xiaogun & Yiwei, 2020
<i>Data visualization</i>	Representation of learning data through visual formats and dashboards to enhance interpretation and pedagogical decisions.	Koh et al., 2020; Morais et al., 2015
<i>Automation of feedback</i>	Generation of timely, data-based feedback for students without direct human intervention.	Pardo et al., 2017
<i>Adaptation and personalization</i>	Dynamic adjustment of learning pathways, content, or feedback to meet individual learner needs.	Comerford et al., 2018

Five articles focus on the use of LA for profiling and predictive modeling of students. Biswas and Bhattacharya (2024) present an “intelligent real-time feedback” system that uses a machine learning–based prediction and classification model to support in-class teaching. The system generates automated feedback by classifying student performance during lessons. Teachers appreciated the reduced burden of real-time feedback, while students responded positively to its effectiveness and usability. Another study applies cluster analysis to identify meaningful self-regulated learning behaviors

(Borter, 2023). The results shows that the benefit of additional formative assessments depended on students' time investment: high-effort students (with above-average time and additional engagement) improved significantly, while low-effort and efficient clusters showed no measurable gains. Notably, engaging with assessments prompted a shift in learning behavior, increasing the proportion of students in the efficient cluster, which correlated with higher academic performance. Moreover, Kohnke et al. (2022) use LA to explore how student engagement with formative assessments predicts performance in English for Academic Purposes courses. Students invested considerable effort in multimodal tasks and strived to perform well, demonstrating the formative potential of these assessment formats. The fourth paper analyzes how different types of interactivity affect learning outcomes using regression models (Nguyen, 2017). Results show that student–student interaction has the strongest predictive value, followed by student – teacher and student – content interaction, indicating the importance of peer engagement in blended learning. Finally, Tempelaar et al. (2014) investigate predictive modeling using three data sources: LMS tracking data, students' learning dispositions, and results from computer-assisted formative assessments. Their longitudinal study reveals that formative assessment outcomes are the most powerful predictors of academic performance and early risk detection, while LMS data alone have limited predictive value.

Regarding teacher assistance in assessment, two key studies stand out. Clutterbuck and Lewis (2019) present a logging worksheet – described as a “formative assessment artifact” – that grants instructors immediate access to students' problem-solving processes. This tool enables rapid evaluation of the logic applied, supporting timely and high-quality feedback, including insights into response times. Similarly, Paredes and Hsiao (2021) describe the development of WebPGA, a web-based application that digitizes, grades, and distributes paper-based assessments in blended programming courses. The system integrates multimodal LA from physical and digital environments and provides students with dashboards detailing results, grading, and feedback. Findings show that students, particularly high-performing and improving ones, engaged actively in reviewing their assessments, especially when guided. They were also able to identify misconceptions in their work.

In relation to activity monitoring, Titov et al. (2019) propose a model that uses computer-aided techniques in blended learning to measure students' actual study time. Similarly, Xiaogun and Yiwei (2020) analyse learning processes through project and online discussion data, streamlining evaluation. Their findings reveal a strong correlation between online participation, peer evaluation, and final grades, showing that students who are more active in discussions tend to achieve better academic results.

Another purpose for which LA has been applied is the implementation of visualization systems for the assessment. One article focuses on a visual analytics approach based on self and peer ratings of a domain-general, four-dimensional teamwork competency measure (Koh et al., 2020). A digital formative assessment approach was designed for blended learning environments, focusing on visual analytics, awareness, reflection, and goal-setting. To evaluate its effectiveness, a quasi-experimental study with an embedded mixed-methods design was conducted. The results indicate that the applied design principles played a key role in enhancing students' learning and self-reflection on their teamwork competencies. The other paper illustrates a formative assessment strategy based on visualization techniques designed to support teachers' awareness and reflection in university learning contexts that integrate technology-enhanced learning activities into the curriculum (Moraes et al., 2015). The authors build on the LearnWeb Design Framework to design and implement a Formative Assessment extension that supports the monitoring of the learning process to increase awareness and support reflection in a specific learning scenario.

Two additional studies from the literature review examine the application of LA in university settings, specifically focusing on personalized feedback and adaptive systems. Pardo et al. (2017) explore how analytics can address the challenge of delivering personalized feedback at scale. Their algorithm generates tailored comments for each student and activity, which are compiled into a single feedback message delivered via a virtual environment or email. Results indicate a positive correlation between these messages and both student satisfaction with feedback and academic performance. Finally, Comerford et al. (2018) present an adaptive system that tracks student progress and delivers personalized feedback, directing learners toward simpler or more advanced versions of the same content. Based on two case studies in engineering education, the study shows that embedding formative assessment within interactive applications – replacing traditional video lectures – enhances the integration of assessment into students' self-directed learning in flipped classrooms.

To answer the second research question on how LA contributes to formative assessment processes, the studies were analysed based on an additional inductive coding theme. Table 5 shows the three key roles of LA in formative assessment emerged from the classification of the articles: (1) collecting evidence to support formative assessment, (2) enhancing the formative assessment process, and (3) designing data-based tools specifically for formative assessment.

Table 5 - Roles of LA in the formative assessment process

LA function	Definition	References (N = 13)
<i>Collecting evidence on formative assessment</i>	Gathering data on student learning to provide concrete information that informs ongoing assessment and guides instructional decisions.	Borter, 2023; Kohnke et al., 2022; Nguyen, 2017; Tempelaar et al., 2014; Xiaogun & Yiwei, 2020
<i>Enriching the formative assessment process</i>	Using LA to improve the effectiveness of formative assessment by making student progress visible, supporting reflection, and facilitating feedback.	Clutterbuck & Lewis, 2019; Paredes & Hsiao, 2021; Titov et al., 2019
<i>Designing data-based tools for formative assessment</i>	Creating technological tools that leverage LA to deliver personalized feedback, adapt instruction, and actively support the formative assessment cycle.	Biswas & Bhattacharya, 2024; Comerford et al., 2018; Koh et al., 2020; Morais et al., 2015; Pardo et al., 2017

The first category, LA for assessing the impact of the chosen formative assessment method, involves systematically collecting and analysing evidence of students’ learning processes. This approach enables data-driven insights to evaluate the effectiveness of assessment strategies and optimize instructional practices. The predominant focus across the five studies is on academic performance, with some exploring its relationship with self-regulated learning (Borter, 2023) and interaction (Nguyen, 2017).

LA for supporting formative assessment entails the analysis of student data to identify learning patterns and extract meaningful insights from the feedback process. In the three studies, educators utilized automated tools that facilitated and enhanced the assessment process. LA tools in this context are used to make the learning process visible while students practice autonomously (i.e., making available the attempts made by the students, in Clutterbuck & Lewis, 2019), boost students’ ability to review their work to support blended-instruction classes and allow teachers to interpret the time spent on the platform, providing deeper insights into learners’ engagement and progress.

The third category includes five studies that design formative assessment tools incorporating LA techniques. In these cases, the prototypes provide feedback to students or facilitate the adaptation of instruction. Examples include a machine-led real-time feedback system released through an app that uses students’ academic performance prediction models and real-time engagement statistics (Biswas & Bhattacharya, 2024), an adaptive system that steers students towards different presentations of the same source material in a

flipped classroom setting (Comerford et al., 2018) and visual analytics tool for self-reflection about teamwork competency (Koh et al., 2020).

In conclusion, the three perspectives on the role of LA for formative assessment reveal distinct yet complementary approaches to enhancing the learning process. While the first focuses on evaluating assessment methods with data-driven insights, the second emphasizes enhancing the feedback process by adding relevant elements for teachers and the third explores the development of tools that directly interact with the learning journey and adapt to students' needs. Together, these perspectives demonstrate the diverse ways in which LA can be employed to improve formative assessment practices and contribute to the overall goal of improving academic performance and supporting student development but with a different degree of involvement of automated tools within the teaching practice.

5. Discussion

The selected studies illustrate the potential of LA to transform various facets of HE, from improving assessment practices to fostering deeper student engagement, particularly in technology enhanced contexts. Concerning the specific LA techniques employed, the varied application of the tools illustrates the diverse ways in which LA can be used to enhance formative assessment, with process mining, regression analysis, and visual LA standing out as particularly influential methodologies. The process mining widespread use in the selected studies suggests an emphasis on understanding the progression of learning activities and identifying potential areas for intervention. The results are consistent with Banihashem et al. (2022), highlighting the predominant use of data mining techniques for providing feedback in formative assessment contexts.

Moreover, the data on the application of LA for formative assessment and blended learning in university contexts reveals a clear focus on profiling and predictive modeling, with five papers dedicated to this purpose. This indicates a relevant interest in understanding and forecasting student behavior and performance. Teacher assistance for assessment is represented in a small number of studies, with two papers noting the potential of tools to support educators in evaluating and providing feedback. Visualization techniques and monitoring student activities are similarly limited, appearing in two papers each, suggesting initial attention to visualizing data and tracking student engagement rather than widespread application. As stated by Stanja et al. (2023), in the specific context of STEM education, visual dashboards can offer summarized representations of student data to assist teachers in selecting

effective interventions, even though reference to learning theories remains essential for effective practices (Matcha et al., 2019). Additionally, automation of feedback and adaptive systems are less frequently explored, with only one paper each, suggesting potential areas for further development.

Finally, the function of LA tools varies in their application for the formative assessment. In some cases, they primarily serve a monitoring role, tracking student learning processes without direct intervention. In other instances, they are integrated into teachers' formative assessment practices, supporting decision-making by providing data-driven insights while still allowing educators to interpret and act upon the results. Additionally, certain tools operate autonomously, offering adaptive solutions to support learning in blended educational contexts. A significant development in this direction would involve using data extracted from online formative assessments as a foundation for building predictive LA models (Bulut et al., 2023).

The limited number of studies indicates that, while initial efforts have demonstrated potential benefits for student learning and faculty support, there is a clear need for further investigation. Longitudinal research is crucial to understand the sustained effects of LA interventions on learning outcomes over time, while cross-disciplinary comparisons could reveal how context-specific factors influence both implementation and efficacy. Moreover, the diversity of approaches and tools discussed highlights the potential impact of LA to enhance both teaching and learning outcomes. On one hand, it is possible to observe the support provided to teachers and students by automated systems, even in real-time. On the other hand, LA allows for a deeper understanding of the effects of assessment tools and the design of educational activities.

Automated systems embedded within LA frameworks provide some advantages by delivering immediate, real-time support to both educators and students (Merikko et al., 2022; Pardo et al., 2019). For instance, real-time feedback mechanisms enable instructors to offer prompt, tailored responses, thereby enhancing comprehension and addressing issues swiftly. While LA can facilitate feedback delivery, making it more detailed and personalized - particularly for large classes - it also enables the provision of a broader variety of feedback with distinct purposes, leading to positive outcomes (Banihashem et al., 2022). Such systems also streamline the management of substantial volumes of student data, allowing for ongoing monitoring of academic progress and engagement levels, focusing on the actual relevant data (Guzmán-Valenzuela et al., 2021). This capability can support educators in adapting their teaching strategies dynamically and providing timely assistance, while explicit attention to ethical implications is essential to ensure that technological innovation aligns with pedagogical and social values (Wise, 2014).

In addition to immediate support, LA serves as a methodological tool for gaining a deeper understanding of the impact of formative assessment tools and instructional design on learning outcomes. By analysing data from diverse sources, such as student performance metrics and digital traces, educators can evaluate the efficacy of various assessment methods and instructional approaches. This analytical process facilitates the refinement of educational activities, ensuring alignment with learning objectives and student needs. In conclusion, LA could contribute to evidence-based enhancements in educational design, thereby augmenting the quality and effectiveness of teaching experiences and instructional design (Gašević et al., 2022).

These findings underscore a persistent tension in the use of formative assessment in blended learning, despite its widespread adoption in HE (Hughes, 2025). While automated systems are often used for control rather than engagement (Marano et al., 2024), this review highlights emerging practices that better align with the pedagogical potential of technology, calling for a more intentional and formative use of digital tools to support feedback, participation, and personalization.

This study contributes to understanding how LA intersects with formative assessment in blended learning contexts; however, certain limitations should be acknowledged. The first limitation of this study is that it did not specifically search for LA using targeted keywords and search questions, but rather represents a further exploration of a broader investigation on formative assessment in blended learning courses. Moreover, the number of papers analysed was limited, which may affect the generalizability of the findings. Additionally, an important consideration is that the innovative AI-supported approach used for the literature search influenced the selection process, meaning it cannot be regarded as entirely systematic. Furthermore, the unavailability of certain papers at the time of retrieval may have led to the omission of critical empirical evidence relevant to this review.

6. Conclusion

The current study offers a synthesis of how LA are currently utilized to support formative assessment practices within blended learning within HE. The findings suggest that LA holds promising potential to enhance instructional practices by making student learning processes more visible, measurable, and adaptable. However, the evidence remains limited and emergent, reflecting a small and selective body of literature. While LA can provide nuanced insights into student engagement with course content, learning activities, and assessments, the studies reviewed are often context-specific, short-term, and

lack generalizability. Similarly, the mapping of techniques such as process mining, predictive modeling, and visual analytics illustrates current capabilities but cannot yet support broad conclusions about their effectiveness across diverse HE contexts. Furthermore, the diverse purposes these techniques serve - from monitoring student engagement to automating formative feedback - highlight the strategic value of LA in enhancing both the immediacy and the pedagogical relevance of feedback processes. This can be particularly critical in complex, large-scale, and digitally mediated learning environments, where traditional forms of assessment and feedback often prove insufficient. In HE contexts, where assessment sometimes relies on control-oriented solutions such as online proctoring systems which mainly aim to safeguard academic integrity but contribute little to pedagogy, LA tools shows potential to bridge instructional intentions and learner experiences. However, evidence of its effectiveness remains limited. Unlike proctoring tools, which emphasize surveillance, LA can theoretically support more responsive and personalized formative feedback by offering insights into student behavior, engagement, and progress, yet current applications are mostly small-scale, context-specific, and insufficiently evaluated to confirm broader pedagogical impact.

From a HE perspective, the implications of this study are twofold. First, it signals the need for institutions to integrate formative assessment frameworks more deliberately into the pedagogical and instructional design of blended learning courses, thereby moving beyond the predominant reliance on summative evaluations that often offer limited, retrospective insights. Embedding formative assessment as a core component of course design can foster a more continuous and process-oriented view of learning, where feedback is not merely evaluative but serves as a formative driver for student improvement and self-regulation. Second, it illustrates how LA can serve as a catalyst for pedagogical innovation, enabling educators to personalize instruction, identify at-risk students at earlier stages, and dynamically adapt learning pathways based on real-time evidence of student progress and engagement. In this role, LA application can evaluate the effectiveness of ongoing assessment practices and improve their efficiency, although their adoption remains limited. These capabilities are especially relevant in university settings where student cohorts are large, heterogeneous, and increasingly diverse in terms of background, learning styles, and academic preparedness.

Furthermore, blended learning environments present unique opportunities for the effective implementation of LA. The hybrid structure - combining face-to-face and digital components - not only facilitates the continuous collection of rich interaction data but also offers flexible touchpoints for integrating adaptive feedback and self-regulated learning strategies (Hughes, 2025). LA

thus becomes instrumental in closing the feedback loop, fostering a more dialogic and learner-centered approach to assessment (Guzmán-Valenzuela et al., 2021).

However, the study also points to critical areas for further development. Greater attention must be paid to building the assessment literacy of faculty, ensuring that educators are equipped to interpret and act upon analytics outputs in pedagogically sound ways. Additionally, ethical concerns around data privacy, algorithmic bias, and student autonomy must be addressed to foster responsible and transparent use of LA tools.

In conclusion, this research highlights the emerging potential of LA to support formative assessment in HE blended learning courses, suggesting that they could contribute to more responsive and evidence-informed teaching practices. However, current evidence remains limited, and further research is needed to better understand how these tools can be effectively integrated and to assess their impact on learning outcomes in diverse university contexts in the pursuit of high-quality, student-centered learning in the digital age.

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APPENDIX

Articles included in the study

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