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AI-powered learning analytics for metacognitive and socioemotional development: a systematic review

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Introduction: This systematic review explores how AI-powered Learning Analytics (LA) contribute to the development of metacognitive and socioemotional competencies in educational settings.
Method: Following the PRISMA guidelines, a total of 161 peer-reviewed articles published between 2013 and 2023 were retrieved from the Scopus database and analyzed.
Results: The findings reveal a predominant focus on predictive (46%) and prescriptive (28%) analytics, while descriptive (16%) and social-affective (10%) approaches remain significantly underrepresented. This imbalance raises critical concerns regarding the extent to which current LA implementations support higher-order competencies such as self-regulation, reflection, emotional awareness, and collaborative learning. The study identifies four major categories of LA—descriptive, predictive, prescriptive, and social-affective—and examines their pedagogical implications considering learner-centered principles.
Discussion: Special attention is given to the potential of LA to scaffold metacognitive strategies and foster socioemotional growth, particularly when designed with transparency, learner agency, and emotional sensitivity. Ultimately, the review advocates for a more balanced and human-centered research agenda, calling for the redefinition of educational quality through the integration of holistic learner development in AI-enhanced learning environments.

KEYWORDS

learning analytics, Artificial Intelligence, educational technology, data driven learning, personalized education

1 Introduction

In the dynamic landscape of the 21st century, where advancements in technology continue to shape various aspects of human life, education stands at the forefront of transformation (Tang and Lim, 2018). Amidst this context, the integration of digital technologies arrives with the promise of revolutionizing traditional paradigms of teaching and learning, paving the way for innovative methodologies. Notably, as highlighted by Greiff (2020), central to this evolution is the emergence of Learning Analytics (LA) and Artificial Intelligence (AI), two pillars that hold immense promise in optimizing educational processes and outcomes. Consequently, as we delve deeper into the realms of the Fourth Industrial Revolution, understanding the synergistic relationship between learning analytics, artificial intelligence, and education becomes imperative for educators, policymakers, and researchers alike.

At the core of this digital transformation lies learning analytics, a field that leverages the vast amounts of data generated within educational contexts to enhance decision-making, personalize learning experiences, and improve student outcomes (Knight and Anderson, 2016). As mentioned by Padakanti and Moraes (2023), LA involves the collection, analysis, and interpretation of data from various learning environments, including online courses, learning management systems, and educational software. Additionally, as indicated by Tang and Lim (2018), by harnessing the power of data analytics, educators gain valuable insights into student behavior, engagement patterns, and learning progress, enabling them to make informed instructional decisions.

Beyond their capacity to inform academic interventions, LA and AI are increasingly recognized for their potential to support broader educational goals, particularly the development of metacognitive and socioemotional competencies. These skills—such as self-regulation, reflection, emotional awareness, and collaboration—are essential for navigating complex, technology-mediated learning environments. As noted by Li et al. (2024), LA can facilitate the early identification of students at risk and support timely interventions, while Russell et al. (2020). Moreover, Er et al. (2021) and Karaoglan Yilmaz and Yilmaz (2022) highlight the increasing role of AI in detecting affective states and self-regulatory behaviors, paving the way for more inclusive and responsive educational environments.

In this regard, Learning Analytics serve not only to optimize content delivery but also to illuminate the processes through which learners engage with, monitor, and regulate their own learning.

As Naujokaitiene et al. (2020) and Oliva-Cordova et al. (2021) point out, these technologies can provide educators with evidence to evaluate and refine instructional strategies, promoting continuous improvement. When integrated with AI techniques such as machine learning, natural language processing, and affective computing, LA systems are further enhanced in their ability to recognize patterns of interaction, detect emotional fluctuations, and recommend personalized strategies that support both cognitive and socioemotional development.

Despite the rapid growth of AI-powered Learning Analytics (LA) in educational research, most studies have prioritized cognitive and performance-oriented indicators, such as student achievement, dropout prediction, and content optimization. While these developments have improved instructional decision-making, significantly less attention has been given to understanding how LA systems can foster the development of metacognitive and socioemotional competencies. Regarding the above, there is a lack of integrative analyses that explore the pedagogical design, implementation strategies, and educational impact of LA tools that explicitly support skills such as self-regulation, emotional awareness, reflective thinking, or collaborative learning. This underrepresentation is especially critical given the growing emphasis on holistic education and 21st-century skills. Furthermore, no previous systematic review has comprehensively examined how different types of LA—descriptive, predictive, prescriptive, and social-affective—align with these broader goals within diverse educational settings. This gap highlights the need to rethink current data-driven practices through a human-centered, developmental lens.

To address this gap, the present study systematically reviews empirical research on AI-powered Learning Analytics, focusing on their potential to enhance metacognitive and socioemotional development. The article is structured as follows: the next section presents the conceptual and theoretical background underpinning LA applications in this domain. This is followed by the methodology section, which describes the data sources, inclusion criteria, and review protocol which included some structural elements of the PRISMA framework. The results section presents a typology of LA categories and analyzes their distribution across educational levels and learning objectives. Finally, the discussion then interprets these findings considering pedagogical implications and concludes by proposing a research agenda that places learner agency and emotional development at the center of AI-enhanced education.

2 Background and theoretical framework

The integration of Learning Analytics and Artificial Intelligence in education is part of a broader transformation aligned with the principles of Education 4.0, which calls for personalized, adaptive, and learner-centered approaches to teaching and learning (Chituc, 2021). This transformation is driven by the increasing availability of educational data and the capabilities of intelligent systems to interpret it in meaningful ways. Within this context, LA and AI are not only tools for improving academic outcomes but recently, in a combined way, are also being explored by a few and emerging literature as mechanisms to foster deeper learning processes, including metacognitive development and socioemotional awareness (Homaira, 2024).

Learning Analytics, as defined by Knight and Anderson (2016), encompass the collection, measurement, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning. This definition has evolved to include not only performance indicators but also patterns of engagement, behavior, and affect. As Padakanti and Moraes (2023) point out, LA draw from diverse data sources such as learning management systems, digital assessments, and educational software, offering educators actionable insights into students' learning trajectories. When augmented by AI techniques, LA become capable of modeling complex learner profiles and dynamically adapting to their evolving needs.

The pedagogical value of LA lies in its capacity to support informed decision-making and intervention strategies. For instance, Tang and Lim (2018) emphasize the use of data to identify students in need of support, while Li et al. (2024) stress the importance of early detection of disengagement and risk factors. These affordances are particularly relevant for fostering metacognitive competencies—such as goal-setting, planning, monitoring, and self-evaluation—which are foundational for autonomous and lifelong learning. Karaoglan Yilmaz and Yilmaz (2022) highlight how LA can be employed to assess learners' use of metacognitive strategies, offering real-time feedback that promotes self-regulation.

Moreover, the emergence of affective and social analytics within the LA landscape reflects a growing recognition of the role of emotions, motivation, and interpersonal dynamics in the learning process. Er et al. (2021) point to the use of emotion-aware systems to identify frustration, confusion, or lack of engagement, allowing for timely and targeted pedagogical interventions. Similarly, Russell et al. (2020) describe how LA tools can inform the design of learning environments that are responsive not only to cognitive progress but also to emotional and social dimensions. These developments align with the broader objective of creating inclusive educational ecosystems that support the whole learner.

From a theoretical standpoint, and as can be seen further in the results section of this review, the convergence of LA and AI with metacognitive and socioemotional frameworks enables a richer understanding of learning as a multidimensional process. Learning is no longer viewed solely in terms of content mastery but as an experience shaped by internal regulation mechanisms and interpersonal interaction. In this regard, the integration of predictive and prescriptive analytics with affective and social components represents a paradigm shift: one that moves educational technology from a reactive to a proactive, learner-sensitive model. As noted by Naujokaitiene et al. (2020), this shift demands not only technological innovation but also pedagogical intentionality in designing systems that genuinely enhance students' capacity to reflect, regulate, and relate.

In this review, the interpretation of Learning Analytics applications is theoretically grounded in two complementary frameworks. First, Self-Regulated Learning theory (SRL) (Zimmerman, 2013; Gambo and Shakir, 2021) informs our understanding of how LA systems can support metacognitive processes such as goal-setting, monitoring, and reflection. Second, the Social and Emotional Learning (SEL) framework (Shriver and Weissberg, 2020) provides a basis for evaluating the potential of LA tools to foster emotional regulation, empathy, and collaborative skills. These frameworks underpin the classification and analysis of the selected studies in terms of their contribution to holistic learner development.

In addressing these challenges, educational stakeholders have the opportunity to leverage the transformative potential of AI and Learning Analytics to promote equity, diversity, and inclusion in education (Gedrimiene et al., 2023). In this sense, by adopting a holistic approach that integrates ethical considerations, data privacy safeguards, and inclusive pedagogical practices, educators can harness the power of technology to create more accessible, inclusive, and equitable learning environments for all learners.

Considering the social sciences-oriented research on Learning Analytics published in journals indexed in Scopus, is evident that it is a still emerging topic but with a notable growing trend. On the other hand, when compared with published studies on the integration of AI into Learning Analytics, it is evident that there is an important research gap, as shown in Figure 1. This Figure illustrates the evolution and intersection of scholarly publications on Learning Analytics and the integration of Artificial Intelligence (AI) in education, based on data retrieved from the Scopus database. The visual trend analysis shows that while research on LA has experienced steady growth since 2015, publications explicitly addressing the synergy between LA and AI remain comparatively scarce. This disparity highlights a significant research gap in the field, reinforcing the need for more integrative studies that explore how AI-powered analytics can enhance not only cognitive performance but also metacognitive and socioemotional competencies.

Given this gap and the rapid evolution and interdisciplinary nature of Learning Analytics and Artificial Intelligence in education, a comprehensive literature review becomes essential in synthesizing existing knowledge and identifying future directions in applying these technologies to contribute to metacognition and socioemotional development.

3 Method

The methodological design of this systematic review was based on established approaches previously applied in high-quality educational reviews (Page et al., 2021). To enhance transparency and methodological rigor, we incorporated key components from the PRISMA 2020 framework—specifically the processes of identification, screening, and eligibility—to structure the literature selection protocol. These stages are visually summarized in Figure 2, which highlights the filtering process that led to the final inclusion of studies. While the review is grounded in an educational research tradition, the integration of PRISMA elements strengthens its replicability and supports a more robust documentation of the corpus construction.

3.1 Review protocol design

3.1.1 Determining review's purpose

To conduct this review in an organized and coherent manner, three guiding questions were established: What categories of Learning Analytics are related to metacognitive and socioemotional development? What capabilities are highlighted in Learning Analytics? and, which of these capabilities can be strengthened using Artificial Intelligence?

3.1.2 Eligibility criteria

To determine which studies would be selected and which excluded from this review, two main criteria for document inclusion and exclusion were established. Firstly, we prioritized studies that provide concrete and verifiable evidence by only including articles presenting research findings. This excludes a range of documents that, although valuable in other academic contexts such as literary reviews, letters to the editor, editorials, reflective essays, books, and book chapters, do not meet the focus required for this review. Secondly, to ensure the relevance of the selected material to the central theme of the review, articles were required to mention the topic of study either explicitly or implicitly in the title or abstract.

This measure ensures that all included studies are directly related to the field of interest, thereby facilitating a more coherent and focused analysis aligned with the review's objectives. This rigorous approach in document selection helps maintain a high level of relevance and quality in the final analysis.

3.1.3 Information sources

For the purposes of this systematic review, the Scopus database was selected as the primary source of bibliographic

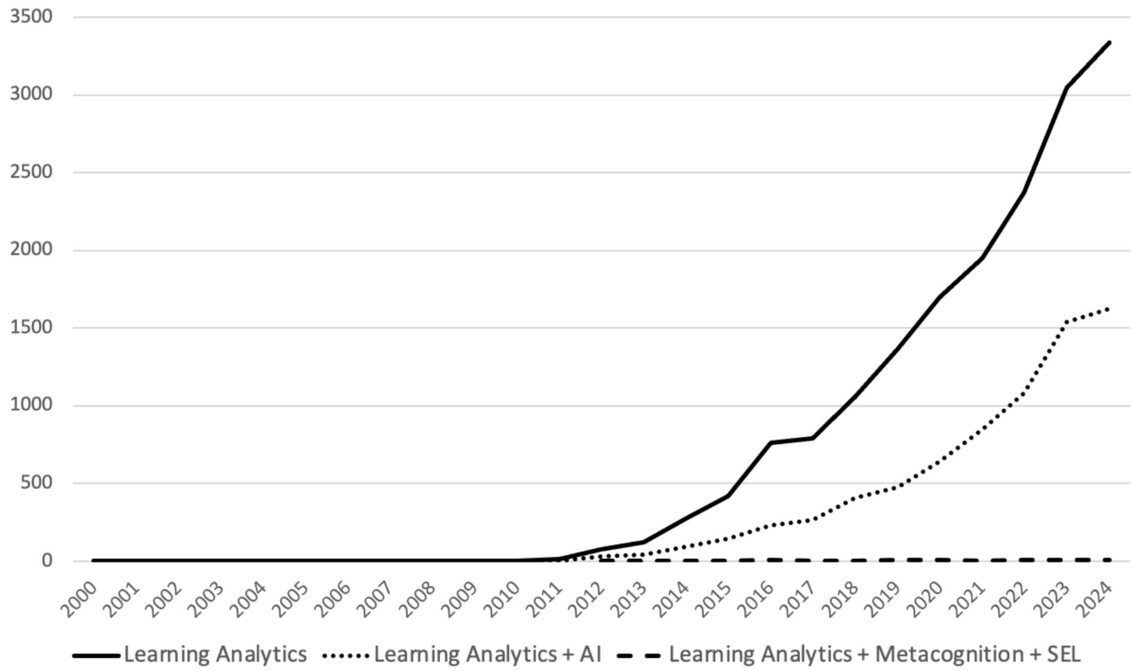

FIGURE 1
Research on Learning Analytics and Artificial Intelligence.

records. This decision was based on several strategic and methodological considerations (Chaparro-Martínez et al., 2016). First, Scopus provides comprehensive coverage of peer-reviewed literature in the fields of education, social sciences, psychology, and interdisciplinary studies, including journals that specialize in learning technologies, artificial intelligence in education, and educational psychology. Compared to other academic databases such as Web of Science or ERIC, Scopus includes a broader range of high-impact journals, particularly in international and interdisciplinary research contexts.

Second, Scopus offers advanced search and filtering capabilities that allowed for a precise delimitation of the corpus. These include Boolean combinations, keyword mapping, document type filtering (e.g., articles, reviews), and subject area categorization, all of which were essential for aligning the retrieved studies with the inclusion and exclusion criteria defined for this review. Finally, the decision to work with a single but robust database was grounded in quality control and procedural clarity. While multi-source reviews may increase coverage, they also introduce higher risks of duplication, inconsistency in metadata, and increased complexity in cleaning and normalizing records. Given the objective of this review—to assess how LA contributes to metacognitive and socioemotional development—ensuring analytical depth and consistency was prioritized over exhaustive coverage.

3.1.4 Search strategy

In developing the search strategy for the systematic review, an initial phase of standardizing terms was implemented. This critical step involved harmonizing and selecting keywords with equivalent or very similar meanings to ensure comprehensive coverage and obtain a broader and more comparable set of results across different information sources. This practice helped to prevent the omission of relevant studies due to variations in terminology. Consequently, the following specific search string was formulated and established: (TITLE-ABS-KEY("Learning Analytics") AND (LIMIT-TO (SUBJAREA,"SOCI"))), which was designed to filter and retrieve relevant literature within the social sciences area related to learning analytics.

The search strategy was designed to ensure both comprehensiveness and relevance in identifying studies focused on Learning Analytics (LA) in educational contexts. To this end, the descriptor "Learning Analytics" was applied to titles, abstracts, and keywords in the Scopus database, while additional filters restricted the corpus to publications in the field of Education between 2013 and 2023.

Although the review explores the role of Artificial Intelligence in enhancing the capabilities of Learning Analytics, the descriptor "Artificial Intelligence" was intentionally not included in the search string. This decision is grounded in two key considerations. First, the field of LA has increasingly integrated AI techniques as part of its core analytical tools (e.g., predictive modeling, natural language processing, sentiment analysis), meaning that many relevant studies apply AI-based methods without explicitly labeling them as such in titles or keywords. Second, including "Artificial Intelligence" as a mandatory term in the search could have narrowed the scope and excluded valuable research that addresses metacognitive or socioemotional dimensions through LA, even if AI was used implicitly or as a backend technology. By prioritizing the construct of Learning Analytics as the central focus and later coding for the presence of AI-related techniques during the data extraction phase, the strategy allowed for a more inclusive

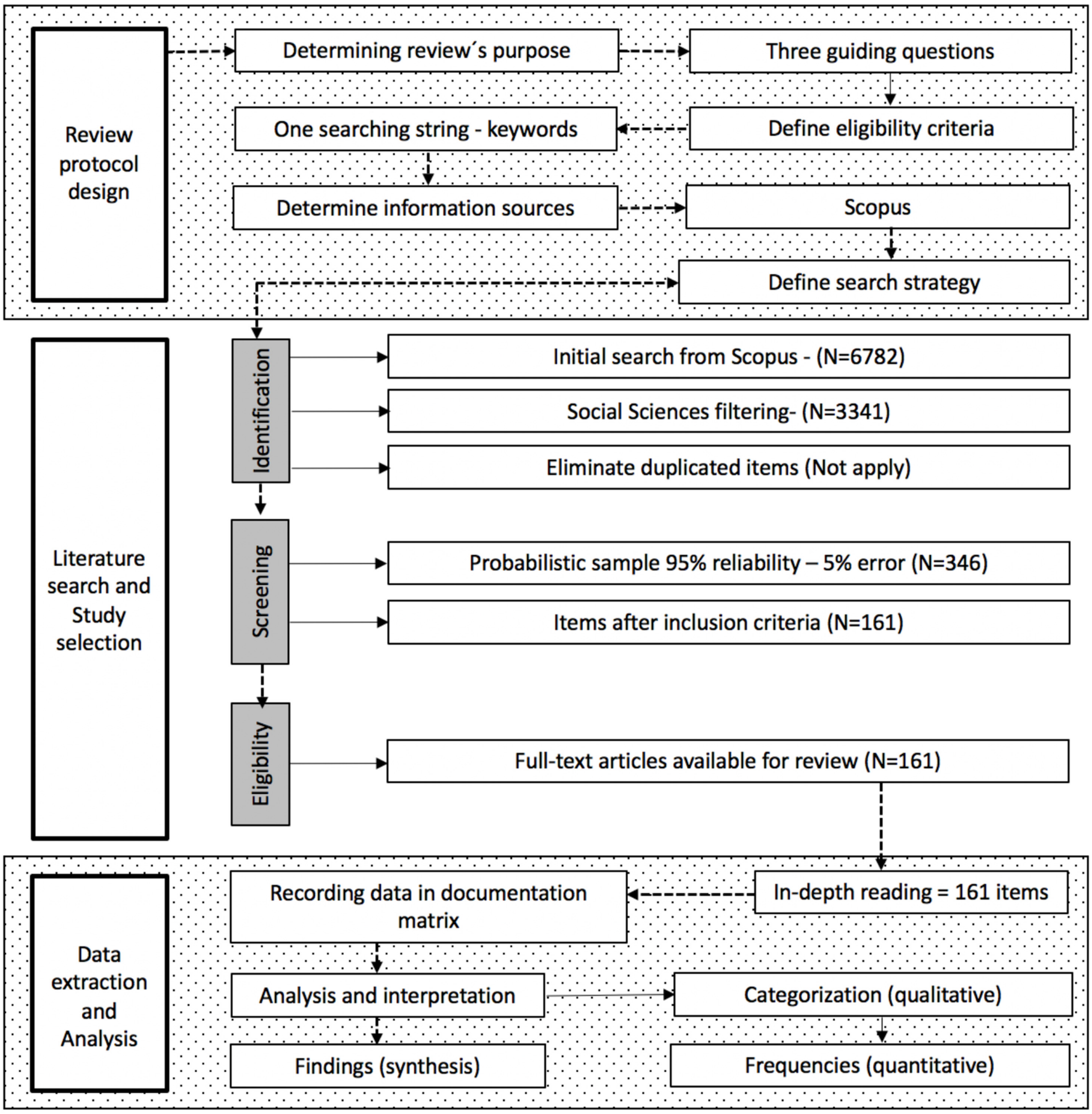

FIGURE 2
Review process.

and representative corpus aligned with the review's objective: to understand how LA—particularly when enhanced by AI—supports metacognitive and socioemotional development in education.

3.2 Literature search and study selection

3.2.1 Identification, screening and eligibility

Following the application of the search string in the Scopus database, an initial collection of 6,782 documents was retrieved. To further refine and focus the search on the intended field, these documents were subjected to a Social Sciences topic filtering, decreasing the number of relevant documents to 3,341 items. Subsequently, a probabilistic sample size with 95% reliability and 5% error was produced, configuring a set of 346 documents. Then, these documents went through an abstracting process in which the previously defined inclusion and exclusion criteria were applied, with which 161 articles were finally selected that would go on to the next phase of in-depth reading.

3.3 Data extraction and analysis

Subsequently, a detailed reading of the articles that made up the final group of selected documents was carried out and, in an organized and systematic manner, key data that answered the three guiding questions of the review were extracted and recorded in a specifically designed documentation matrix to facilitate comparative analysis and synthesis of information in subsequent stages of the study. The data collected and

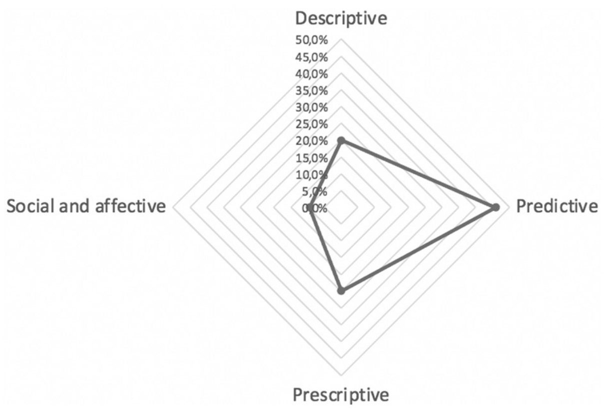

FIGURE 3
Review process.

recorded in the documentation matrix were analyzed using two complementary approaches. The data analysis combined quantitative and qualitative procedures to ensure a comprehensive understanding of the selected studies. Quantitatively, a frequency analysis was conducted to classify articles by year of publication, type of learning analytics (descriptive, predictive, prescriptive, social-affective), educational level, and primary focus (e.g., metacognition, socioemotional development). This enabled the identification of research trends and distributional imbalances.

In parallel, a qualitative content analysis was carried out to examine the pedagogical implications, conceptual underpinnings, and ethical dimensions discussed in each study. The coding framework was developed iteratively, guided by the theoretical constructs of Self-Regulated Learning (SRL) and Social and Emotional Learning (SEL). Codes were clustered into thematic categories using an inductive-deductive approach and triangulated to assess how different types of LA addressed metacognitive and socioemotional dimensions in practice. This dual-layered analysis allowed us to trace not only the prevalence but also the pedagogical depth of AI-driven LA interventions across the literature.

4 Results

4.1 About learning analytics

Recent research on Learning Analytics shows that its main categories or dimensions have not developed evenly; on the contrary, at least two of them have progressed significantly more than the others, as shown in Figure 3. This uneven development invites us to reflect on the potential impact it may have on students' metacognition and socioemotional development.

To provide a clearer overview of the analytical orientations present in the selected studies, the Table 1 summarizes the distribution, defining characteristics, and illustrative applications of the four identified Learning Analytics categories. These categories—descriptive, predictive, prescriptive, and social-affective—reflect distinct levels of data processing complexity and pedagogical intent. The table also highlights the relative prevalence of each category in the reviewed corpus and their typical implementations in educational settings. This classification serves as a foundation for the critical interpretation offered in the discussion section.

According to Valle et al. (2021), Descriptive Learning Analytics focuses on compiling and analyzing data to describe and understand existing behaviors and patterns. This category is crucial for providing an overview of student activities and interactions within the learning environment. On the other hand, Zakharova and Jarke (2024), indicate that Predictive Learning Analytics uses statistical models and algorithms to forecast potential future outcomes based on historical data, which is essential for anticipating student needs or issues before they arise. Furthermore, although in a different direction, Hooshyar et al. (2023) point out that Prescriptive Learning Analytics goes beyond prediction, offering recommendations on specific actions that could improve learning outcomes. This category focuses on the practical application of insights to formulate effective interventions. Additionally, Ott and Liesaputra (2022) address Affective Learning Analytics as a way to understand and respond to students' emotional and motivational states, which is critical for addressing aspects of learning related to emotional well-being. Finally, Castellanos-Reyes et al. (2023) refer to Social Learning Analytics as a way to examine interactions among students and the use of social networks and collaborative platforms to foster a more integrated and effective learning community.

4.1.1 About descriptive learning analytics

In the review, 32 of the 161 articles examined (19.9%) specifically focused on Descriptive Learning Analytics. This analysis highlighted that 39.4% of the publications within the descriptive category focused on student engagement monitoring, followed by interaction in virtual learning environments with 33.3%. Additionally, 12.1% of the studies were dedicated to the impact of educational interventions, while 9.1% focused on the early detection of learning difficulties. Examples of these studies include Phillips et al. (2011), Beer et al. (2012), Hui and Farvolden (2017), and Ibañez et al. (2020).

Despite their foundational role, the findings of this review indicate that DLA remains underrepresented in the literature, particularly when compared to predictive and prescriptive approaches. This relative lack of focus is significant considering that descriptive data visualization and feedback can play a critical role in fostering metacognitive awareness. By making learning behaviors explicit—such as time spent on tasks, frequency of interaction, or resource usage—DLA offers learners the opportunity to monitor and reflect on their own processes, which are core aspects of self-regulated learning. When properly designed, descriptive dashboards can promote learner autonomy, support planning and goal setting, and encourage iterative self-evaluation. Therefore, the limited research attention given to DLA represents a missed opportunity for advancing scalable metacognitive scaffolds in digital learning contexts.

4.1.2 About predictive learning analytics

Furthermore, a total of 74 articles (46.0%) within the predictive category of Learning Analytics focused on anticipating educational behaviors or outcomes. In this analysis, 42.9% of the publications

TABLE 1 Categorization of studies by learning analytics approach and applications.

Category	Description	% of studies	Key characteristics/tools	Sample applications
Descriptive LA	Reports learning data (e.g., time on task, resource use)	16%	Dashboards, activity logs	Tracking platform usage or progress visualization
Predictive LA	Anticipates future performance or risk	46%	Machine learning models, early warning systems	Dropout prediction, exam forecasting
Prescriptive LA	Recommends actions or resources based on learner data	28%	Adaptive feedback systems, intelligent tutoring	Resource suggestion, personalized learning paths
Social-affective LA	Analyses emotions, social interactions, or engagement signals	10%	Emotion recognition, discourse analysis, sentiment mining	Monitoring collaboration, affect-aware tutoring

in the predictive category focused on the early detection of learning difficulties and at-risk students, followed by student engagement monitoring with 24.7%. Additionally, 22.1% dedicated to the analysis of interaction in virtual learning environments and student performance, while 15.6% focused on measuring the impact of educational interventions and educational decision-making and planning.

Regarding the first group, several studies highlighted the effectiveness of predictive modeling and data analysis in identifying at-risk students early in the academic process, enabling timely interventions to improve student outcomes and retention rates. Particularly, the studies showed how predictive models and data visualizations could significantly enhance student success by identifying patterns and factors influencing academic performance and emphasized the effectiveness of virtual environments for monitoring student progress and capturing detailed interaction data essential for predictive analysis (Essa and Ayad, 2012; Romero-Zaldivar et al., 2012; Smith et al., 2012). On the other hand, other studies, such as Marbouti et al. (2016), Lu et al. (2018), Howard et al. (2018), Gray and Perkins (2019), and Russell et al. (2020), addressed learning analytics for the early prediction of at-risk students and strengthening engagement and learning outcomes in collaborative learning environments.

In addition to the above, several studies focused on the application of learning analytics to enhance student engagement and improve retention rates in educational programs. These studies demonstrated how dynamic learning analytics could significantly increase student retention by facilitating more informed and timely interventions and by enabling the adaptation of resources and pedagogical strategies (De Freitas et al., 2015; Herodotou et al., 2019; Soffer and Cohen, 2019; Chen et al., 2020; Ulfa and Fatawi, 2021).

Regarding the third group of studies, there was a strong focus on developing and evaluating predictive models and machine learning algorithms to accurately forecast student academic performance. The studies included in this group showed the potential of learning analytics to identify successful students, predict student outcomes and performance. Some of these studies are Kotsiantis et al. (2013), Zacharis (2015), Jo et al. (2015), Buenaño-Fernández et al. (2019), Iatrellis et al. (2021), Mubarak et al. (2021), Yagci (2022), and Pérez Sánchez et al. (2022).

Also, some studies focused on the broader application of learning analytics in educational decision-making and planning processes, emphasizing the critical importance of teacher engagement in using analytic data to effectively support students (Herodotou et al., 2020; Niyogisubizo et al., 2022).

While PLA offer clear benefits in terms of identifying students in need of intervention, their contribution to metacognitive or socioemotional development is often indirect. Typically, predictions are delivered to instructors or administrators, with limited involvement or awareness on the part of the learner. As such, PLA tends to serve institutional or instructional decision-making more than it does learner reflection or agency. To enhance their developmental impact, predictive systems would need to be accompanied by transparent feedback loops that allow learners to understand and engage with the factors influencing their own trajectories. In this way, PLA could evolve from a diagnostic tool into a catalyst for self-regulated learning and proactive behavioral change.

4.1.3 About prescriptive learning analytics

In this regard, 40 articles focused on prescriptive Learning Analytics (24.8%), seeking to offer recommendations based on data analysis to improve educational processes. This analysis revealed that 46.3% of publications in the prescriptive category were dedicated to analyzing interaction in virtual learning environments, followed by student engagement monitoring with 39.0%, while 9.8% focused on improving lesson planning and sequencing. Examples of these studies can be found in Beer et al. (2012) and Kotsiantis et al. (2013).

In theory, PrLA are well positioned to support metacognitive development, especially in helping students learn how to select appropriate strategies, monitor progress, and adjust approaches. However, as with PLA, the review shows that the majority of prescriptive systems are externally driven, meaning that decisions are made for the learner, not with the learner. This raises concerns about over-automation and the potential reduction of learner agency. For PrLA to truly foster metacognition, they must incorporate explanatory and reflective components, enabling students to understand the rationale behind recommendations and to evaluate their relevance. Similarly, socioemotional development is rarely addressed explicitly in PrLA systems, despite their potential to guide learners in managing frustration, building resilience, or engaging in collaborative behaviors. Expanding the scope of prescriptive models to include affective and motivational variables would significantly increase their value in supporting holistic learning processes.

4.1.4 About social and affective learning analytics

Regarding this topic, 15 articles were analyzed (9.3%), which addressed the interaction dynamics among participants in the educational process, and 2 additional articles focused on Affective Learning Analytics, which evaluates students' emotional states to more effectively adapt educational interventions. Examples of the above can be found in Dahish and Maih (2023), Chen et al. (2022), Antoniou et al. (2020), and Ott and Liesaputra (2022).

Social and Affective Learning Analytics aim to capture interactions, emotional states, and relational dynamics among learners and between learners and content. These may include indicators of collaboration, communication patterns, or affective responses inferred from text, behavior, or biometric data. Despite their promise, SaLA remains the least represented category in the current review, a finding that reveals a critical gap in the literature.

This lack of emphasis is especially striking given the centrality of socioemotional skills—such as empathy, emotional regulation, collaboration, and resilience—in contemporary conceptions of quality education. Affective and social analytics offer unique possibilities for supporting emotionally informed pedagogical decisions, fostering social presence in online environments, and designing interventions that respond to learners' emotional needs. Moreover, SaLA can provide learners with feedback on their own emotional and interpersonal patterns, thereby supporting the development of emotional self-awareness and social competence. The underrepresentation of this category signals the need for increased research attention and technological innovation to realize the potential of LA as a tool for advancing the affective dimensions of learning.

The reviewed studies in this category focused on capturing learners' emotional states, motivation levels, or patterns of social interaction. Common tools included facial expression analysis, sentiment analysis of forum messages, and sociometric tracking of peer collaboration. For example, one study used natural language processing to detect emotional tone in students' reflective writing, providing real-time feedback to support emotional regulation. Another study analyzed turn-taking patterns in group chats to assess socio-cognitive engagement during online collaboration. However, while technically sophisticated, most SaLA studies lacked robust pedagogical integration, and few made their analytics outputs accessible to learners themselves. This indicates a promising but underdeveloped line of research within the broader LA field.

4.2 About the capabilities highlighted in learning analytics

After reviewing the selected articles, several shared characteristics among the studies on Learning Analytics have been identified. These characteristics underscore the remarkable ability of Learning Analytics not only to elevate educational outcomes but also to promote a more inclusive and adaptable learning environment. Based on this analysis, we detail the common characteristics identified below.

4.2.1 Prediction of student performance and retention

As mentioned earlier in the data analysis related to the first guiding question of the review, one of the primary uses of Learning Analytics focuses on predicting and improving student performance and retention. In this regard, researchers such as Kotsiantis et al. (2013) and Marbouti et al. (2016) have applied this technology to identify early factors influencing online learning, such as time allocation, self-discipline, motivation, peer support, technical delivery and organizational culture. Similarly, Gray and Perkins (2019) have demonstrated that early attendance and engagement are key indicators for predicting student retention, identifying at-risk students from the initial stages of the semester.

4.2.2 Application of machine learning techniques

The integration of Machine Learning techniques in the educational field through Learning Analytics has also shown promising results. For example, Buenaño-Fernández et al. (2019) have used these methods to develop predictive models that evaluate student attendance and academic performance. On the other hand, Zacharis (2015) applied a multivariate approach to analyze how various variables affect student performance in blended courses, such as student attendance and engagement metrics, active participation in creating content, reading and posting messages, files viewing, prior academic history or socioeconomic factors.

4.2.3 Student engagement as a key indicator

Student engagement emerges as a fundamental indicator of academic success. Studies conducted by Soffer and Cohen (2019) and Gray and Perkins (2019) underscore how engagement metrics can predict successful course completion. Regarding this, Herodotou et al. (2019) highlight the importance of consistent interpretation of these data by teachers to improve educational intervention.

4.2.4 Data-driven interventions

Data-driven interventions are essential for fostering engagement and improving learning outcomes. Works such as those by Lu et al. (2018) and De Freitas et al. (2015) show how Learning Analytics can be used to increase university retention through dynamic data analysis. Examples of the above areeEarly identification of at-risk students by analyzing patterns in academic performance, tailoring support and resources to meet the individual needs of students, providing continuous and actionable feedback, monitoring student interactions with course materials and participation and fostering a sense of community among students. Additionally, Gray and Perkins (2019) and Soffer and Cohen (2019) have demonstrated how predictive models and engagement analysis can be integrated into student support mechanisms for more effective interventions.

4.2.5 Personalization of learning

The personalization of learning through Learning Analytics also plays a crucial role. Buenaño-Fernández et al. (2019), as well as Zacharis (2015), highlight how predictions of learning behavior can lead to personalization and improvement of teaching strategies, adapting educational resources to individual student needs. This approach not only improves student engagement but also academic success.

4.2.6 Ethical and privacy considerations

It is essential to consider ethical and privacy implications when implementing Learning Analytics. Gray and Perkins (2019) and Herodotou et al. (2019) emphasize the need for responsible data management and a clear ethical framework, ensuring that technological innovation in education respects the integrity and privacy of students.

4.3 About the capabilities of learning analytics and its relationship with Artificial Intelligence

In the various studies analyzed, several common Artificial Intelligence techniques were identified that could be applied by the authors to improve learning and teaching in diverse educational environments. Among these techniques are advanced predictive models, automatic content personalization and learning behavior analysis, which allow for understanding how students interact with course content and adapting teaching strategies and enable the adaptation of educational materials according to individual student needs and preferences. The above was mentioned by several authors such as Mubarak et al. (2021), Chan et al. (2021), Ulfa and Fatawi (2021), Iatrellis et al. (2021), and Chen et al. (2020).

Furthermore, the same authors highlighted the proactive interventions and continuous evaluation and feedback, which utilize intelligent systems to identify and support at-risk students before they face significant difficulties and allow for providing immediate feedback to students on their progress and areas for improvement. Also, optimization of learning resources is discussed and involves evaluating and improving the effectiveness of educational materials to align them with course needs and objectives. Regarding this, it is noteworthy that these AI techniques can be powerful tools for improving the effectiveness and personalization of learning in diverse educational environments.

The analysis of the opportunities for implementing Artificial Intelligence in the characteristics of Learning Analytics reveals a wide range of possibilities for improving education and student performance. The above highlights how AI can enhance various facets of educational analysis and offer innovative solutions to address the changing needs of students in digital and in-person learning environments.

Regarding all the above, the results revealed an uneven distribution of Learning Analytics approaches, with a strong emphasis on predictive and prescriptive methods and a noticeable underrepresentation of descriptive and social-affective applications. While many studies employed technically advanced tools, relatively few demonstrated clear alignment with metacognitive or socioemotional educational goals. Moreover, learner-facing feedback mechanisms and transparency in data use remained limited across categories. These findings highlight the need to reorient LA design and research toward more human-centered, ethically responsible, and pedagogically grounded practices—issues further addressed in the following discussion.

5 Discussion

The comprehensive review and analysis of the literature on Learning Analytics and its intersection with Artificial Intelligence have yielded significant insights and implications for the educational landscape. The results indicate that most of the studies are framed within predictive and prescriptive approaches, while descriptive and social-affective dimensions appear as marginal.

These findings are consistent with previous systematic reviews, which have reported a predominance of predictive and prescriptive approaches in the field of Learning Analytics (Ramaswami et al., 2023; Susnjak, 2024). While such methods provide actionable insights for institutional decision-making, they often prioritize technical sophistication over learner-centered outcomes, leaving limited space for applications that explicitly foster metacognition and socioemotional growth. This imbalance raises critical concerns about the scope of current LA research, suggesting that the field risks reinforcing a performance-driven paradigm rather than advancing a holistic conception of educational quality.

Although technical developments are evident, a pedagogical gap persists in how these analytics are applied in real educational contexts. This distance between technical potential and pedagogical application represents one of the central challenges in the consolidation of LA as a field. In the case of Social and Affective Learning Analytics (SaLA), the proportion of studies is still incipient, but it signals a new line of work focused on socioemotional and collaborative processes.

In contrast, the emerging body of Social-Affective Learning Analytics (SaLA) illustrates the potential of AI-enhanced tools to capture learners' emotional states, interpersonal dynamics, and collaborative engagement (Jin et al., 2022). These contributions are significant because they align with the broader goals of Social and Emotional Learning frameworks, offering pathways to integrate empathy, self-regulation, and teamwork into data-informed practices. However, our analysis also shows that SaLA research remains fragmented, often limited to experimental or small-scale studies, and rarely translated into large-scale educational interventions. Bridging this gap requires not only technical refinement but also pedagogical frameworks that ensure learners have access to, and can act upon, the socio-affective insights generated.

Another relevant aspect is the limited evidence on the involvement of learners in the use of analytics. Most systems and studies are oriented toward providing information to teachers or institutions, while students remain passive recipients of feedback. This situation contrasts with the principles of learner-centered pedagogy, which emphasize agency, autonomy, and reflection.

Beyond the technical and pedagogical dimensions, our findings also resonate with ongoing debates on the ethical challenges of AI in education. Scholars have emphasized that issues such as transparency, fairness, and learner agency must be integral to the design of LA systems (Ungerer and Slade, 2022). The limited attention to these concerns across the reviewed studies highlights the need for frameworks that balance predictive accuracy with ethical responsibility. Concluding this discussion, we argue that AI-powered Learning Analytics should move toward a human-centered paradigm—one that not only informs instructional decision-making but also empowers learners as reflective, emotionally aware, and socially engaged participants in their own education.

5.1 Implications

The findings of this review suggest important implications for both research and practice. For educational practitioners, the dominance of predictive and prescriptive LA highlights the necessity of critically questioning the pedagogical purposes behind analytics tools and ensuring that they genuinely contribute to the development of learners' metacognitive and socioemotional capacities. For policy makers, the review underscores the urgency of designing policies and ethical frameworks that guarantee transparency and student participation in the use of AI-powered analytics. For researchers, the observed gaps invite the adoption of integrative frameworks—such as Self-Regulated Learning and Social and Emotional Learning—that can guide the design of LA systems aligned with holistic educational goals.

5.2 Future research directions

Future studies should expand the exploration of Social-Affective Learning Analytics by moving beyond small-scale or experimental implementations toward systemic applications in real educational settings. There is also a need to investigate how LA can be meaningfully integrated into teaching practices to enhance student agency, metacognitive reflection, and socioemotional growth. Moreover, future research should prioritize interdisciplinary approaches, connecting computer science, psychology, pedagogy, and ethics, to design AI systems that balance technical innovation with human development. Finally, longitudinal studies are required to assess the sustained impact of LA interventions on learner outcomes over time.

6 Limitations

This review is not exempt from limitations. First, the search was restricted to the Scopus database, which, while comprehensive, may exclude relevant studies indexed elsewhere. Second, the focus on English-language publications could have limited the inclusion of valuable contributions published in other languages. Third, although the combination of quantitative and qualitative analyses enriched the interpretation of results, the synthesis necessarily involved a degree of subjectivity in the coding and categorization processes. Recognizing these limitations, the review nonetheless provides a rigorous and transparent account of current research trends and gaps in AI-powered Learning Analytics.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

AP: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. OB: Conceptualization, Validation, Writing – original draft, Writing – review & editing. AC: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. LF: Conceptualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Correction note

A correction has been made to this article. Details can be found at: 10.3389/feduc.2025.1717153.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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