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Overview of Research on Higher Education Teachers' Involvement in Learning Analytics

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Background and purpose: This systematic literature review focuses on the use of learning analytics among higher education teachers, who play a key role in collecting, analysing, and interpreting data. Empirical studies from the period between 2011 and 2024 were analysed to understand the role of teachers in learning analytics and the antecedents and outcomes of its use.
Methods: A systematic literature review was conducted to reduce research bias and ensure repeatability. The relevant articles identified were analysed in two phases, first with a descriptive analysis and then with an in-depth qualitative synthesis.
Results: The literature review reveals two predominant trends in how higher education teachers use learning analytics. The first focuses on the use of learning analytics technologies to solve specific problems, while the second considers learning analytics in the context of broader pedagogical practices of teaching and learning. The paper also discusses antecedents and outcomes of the use of learning analytics among higher education teachers, highlights gaps in existing research, and suggests further research directions in this field.
Conclusion: This paper provides an overview of recent literature on the use of learning analytics among higher education teachers. The findings clarify the role of teachers in the use of learning analytics and provide insights into the antecedents and outcomes of its use that are also relevant to other stakeholders and decision-makers in higher education.

Keywords: Learning analytics, Higher education, Teachers' perspective, Systematic literature review

1 Introduction

Learning analytics (LA), which involves collecting and analysing data about learners to improve educational outcomes, was initially a niche interest of a few researchers. Due to the rise of online learning, the availability of rich learning data and rapid technological changes, LA is now widely used in all educational settings, including schools, higher education, workplace training, and informal learning environments (Ferguson et al., 2019; Hernández-de-Menéndez et al., 2022). One of the recent trends is multimodal LA, which offers a breakthrough approach to understanding the learning process by integrating diverse information from different data sources, such as eye-tracking and digital tracing data, and enhancing the capabilities of data processing and modelling techniques, such as data mining, machine learning, and deep learning, to uncover hidden patterns in this extensive data (Pei et al., 2021; Sghir et al., 2023) and support the optimisation of learning environments.

The history of LA can be traced back to the pre-digital era, when teachers assessed and evaluated courses mainly by collecting data from learners, initially by examining student performance (quantitative data) and later also by

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examining the frequency of student behaviour based on observations they made during their lectures. In the 1950s, the introduction of programmed instruction using teaching machines was a significant advance, which led to the development of computer-assisted instruction systems such as Programmed Logic for Automatic Teaching Operations in the 1960s. At the same time, adaptive computer-assisted instruction began to develop, which was customised to the individual learner, as the work of Richard Chatham Atkinson shows. The 1980s saw the emergence of intelligent tutoring systems that used artificial intelligence to provide personalised learning experiences. The rise of online learning in the 1990s, facilitated by learning management systems such as Blackboard and Moodle, further revolutionised data collection and pedagogical practices. The term "Educational Data Mining" (EDM) gained prominence in 2011, focusing on analysing educational data to improve learning outcomes. The founding of the Society for Learning Analytics Research (SoLAR) in 2011 and the first international conference on Learning Analytics and Knowledge (LAK) in 2015 marked the formal recognition of LA (Ye, 2022). Since then, the number of publications in this area has increased exponentially.

From a research perspective, the majority of published studies focus either on the use of LA in higher education, the challenges involved or the outcomes of using LA. These studies consider different stakeholders in LA, usually focusing on students, teachers or managers or a combination of these (Mahmoud et al., 2020). According to Hernández-de-Menéndez et al. (2022), few primarily focus on improving the teaching process or addressing academic issues. Furthermore, the existing domain-based literature reviews rarely or only to some extent rely on established frameworks to guide the review of a domain, which, according to Paul et al. (2021), helps authors maximise clarity and coverage. For example, the interrogative framework consisting of what, why, where, when, who, and how (5W1H) (Lim, 2020) has only been used to some extent in recent literature reviews (Banihashem et al., 2023; de Oliveira et al., 2021; Foster & Francis, 2020). Foster & Francis (2020) and de Oliveira et al. (2021) only addressed the where, how, and what questions, while Banihashem et al. (2023) neglected the where and when questions. Although one of the first domain-based systematic literature reviews (Nunn et al., 2016) provided an overview of LA issues in higher education by covering the antecedents, decisions, and outcomes of the Antecedents, Decisions, and Outcomes (ADO) framework proposed by Paul & Benito (2018), it only included literature published up to 2016. As significant gaps remain, this study examines empirical and theoretical studies published after 2011 to understand the antecedents, decisions, and outcomes of LA in higher education. In particular, the review focuses on teaching staff, as the adoption of LA at the institutional level remains limited. Despite this, many teachers independently attempt to implement LA within their courses (Gedrimiene et al., 2020) and are often neglected in the literature, yet their perspectives and practices are frequently underrepresented in the existing literature (Hernández-de-Menéndez et al., 2022). As teachers play an important role in interpreting LA data to improve student achievement and curriculum design, their first-hand experience and understanding of classroom dynamics are invaluable in applying insights from LA tools.

The main objective of this review is to highlight a topic that has gained importance as the share of the education market has increased significantly in recent years due to the growing awareness and understanding of LA and artificial intelligence. It is also expected to grow at a compound annual growth rate of 10.49% during the forecast period from 2022 to 2027 (Statista, 2024). In this context, the paper proceeds as follows. The second section describes the methodology used in this study. The third section provides an overview of studies on journals, publication distributions, and investigated regions. In section four, we summarise our findings through the lens of the ADO framework. In the final section, we make concluding remarks and outline future research directions.

2 Methodology

To address the research gaps, a systematic literature review was conducted. The main aim of this research is to systematise and summarise the empirical research in this area published between 2011 and 2024. Before the systematic review, we conducted a broad search using the terms "learning analytics*" AND "higher education" to familiarise ourselves with the scope of the literature, identify main keywords and develop the exclusion criteria. To ensure minimal researcher bias and support reproducibility, a transparent procedure proposed by Paul et al. (2021) was adapted.

To maintain a high standard for the studies analysed, only empirical, peer-reviewed academic research was included. Scopus was chosen as the search engine as it covers a broader range of subject areas and categories compared to WOS, allowing researchers to more effectively find the journals most relevant to their area of enquiry (Paul et al., 2021), and it has the largest abstract database (Schotten et al., 2017). Based on the main keywords identified (see Table 1), we conducted our search in May 2024. The search resulted in 634 entries.

The screening of the articles was carried out in two stages, as applying the ADO framework to all 634 articles would have been too time-consuming. In the first stage, the titles and abstracts were examined to decide whether the articles should be considered for further analysis. The articles that (1) did not focus on teachers' perspective, (2) focused only on the specific use of LA – case study, (3) were conceptual or review articles, and (4) focused on the design or evaluation of LA tools rather than their use were excluded from the list. In the second screening phase, the full text of 51 articles was screened, and the ADO framework (Paul & Benito, 2018) was used to code articles in terms of antecedents, decisions, and outcomes. In this purification phase, 16 papers were excluded as they focused more on design analytics or mainly reflected the perspective of students or institutions.

Before the evaluation, the snowball technique was used to identify additional relevant studies by examining the reference sections of each selected paper. This approach led to the inclusion of 4 more articles, bringing the total number of relevant articles used for further analysis to 39.

To understand LA antecedents, decisions, and outcomes in higher education from the teaching staff perspective, we used a two-stage analysis (Tranfield et al., 2003) to obtain relevant information for our review: (1) general characteristics of the included studies, (2) teachers' use of LA at the course/classroom level, (3) antecedents specific to teachers' LA use, (4) the outcomes of teachers' LA use. In the first phase, some of the data used for the descriptive analysis were exported from the Scopus search results, while the remaining data were collected manually. In the second stage, an in-depth qualitative synthesis of the included studies was conducted. This process involved dividing the studies into ADO categories, analysing the results within each ADO category and synthesising the results of all studies (Petticrew & Roberts, 2006).

To obtain a theoretically meaningful, robust classification of antecedents, decisions, and outcomes of LA use, we used an inductive-deductive approach to content analysis (Tranfield et al., 2003). First, an inductive approach was applied to identify antecedents, decisions, and outcomes of LA use from teachers' perspectives, reported in previous studies. Then, a theory-based approach was employed to synthesise them into meaningful constructs.

3 Overview of included studies

First, a descriptive summary of the characteristics of the included studies is provided. This summary includes aspects such as the date of publication, the regions analysed and the journals in which the studies were published.

Table 1: Results following the adapted SPAR-4-SLR protocol

Stage	Sub-stage	Criterion	Action
Assembling	Identification	Domain	Learning analytics in higher education: the teacher perspective.
		Source type	English peer-reviewed papers in academic journals.
		Source quality	Scopus
	Acquisition	Search mechanism	Scopus search engine
		Search period	From 2011, when SoLAR was established.
		Search keywords	"learning analytics" AND ("higher education" OR "tertiary education" OR "University" OR "College" OR "Faculty") AND ("educator" OR "teacher" OR "class" OR "course")
		Total number of articles	634
Arranging	First purification	Articles excluded	583
		Articles included	51
	Organization	Organization framework	ADO
	Second purification	Articles excluded	16
		Articles included	35
	Identification of additional relevant studies	Articles included (snowball technique)	4
Assessing	Evaluation	Analysis method	descriptive and content
		Agenda proposal method	best practices, gaps
	Reporting	Reporting conventions	Summarization (visualisations) and discussion

Figure 1 illustrates the distribution of publications by year. Up to three papers on LA adoption and use of teaching at the course level were published up to 2018, with no publications in 2014 and 2017. Since 2018, the number of publications has increased, reaching nine in 2020. Thereafter, however, the number of publications has declined. The declining number of publications in recent years can be attributed to the emerging trend towards big data, where researchers have shifted their focus to individual projects that use specific predictive analyses.

Teachers' perspectives on the adoption and use of LA were mainly analysed in European countries, followed by North America and Oceania (see Figure 2). Of the seven international studies, five collected data from South America, North America and Oceania. At the national level, most studies were conducted in Australia. Australia was also involved in international studies, with countries such as Chile, Canada and the United States indicating that their researchers were actively collaborating with their counterparts in the Americas. While several studies have been conducted in Europe, particularly in the United Kingdom and Spain, our research did not find comprehensive international studies across multiple European countries.

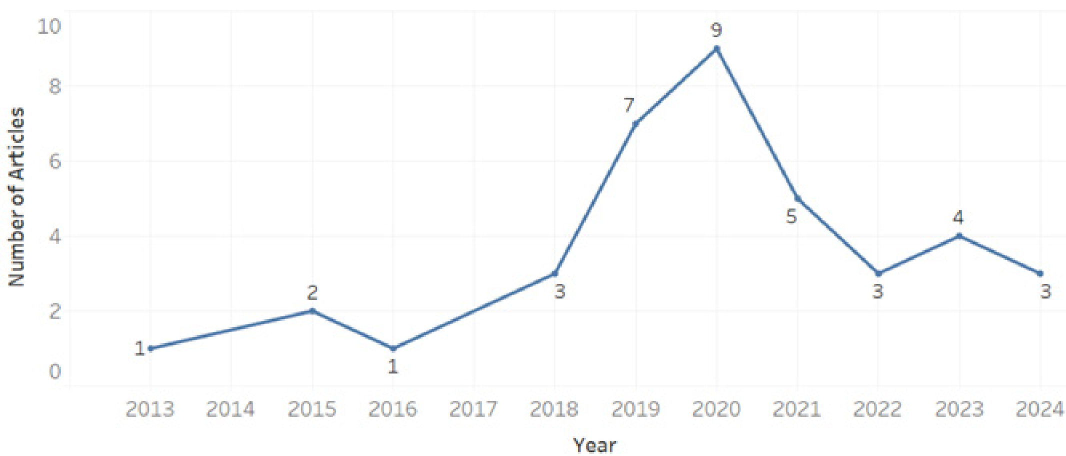

Figure 1: Distribution of publications per year

Figure 2: Investigated regions

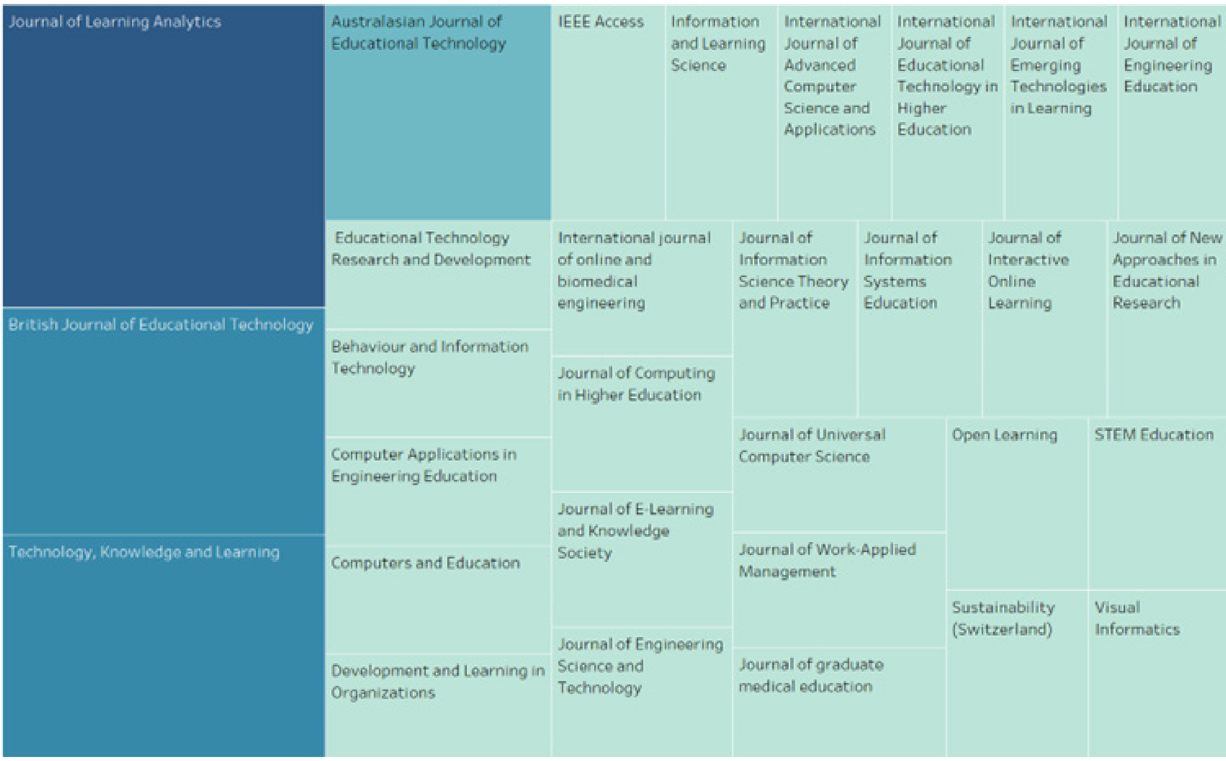

Figure 3: Articles distributed over journals

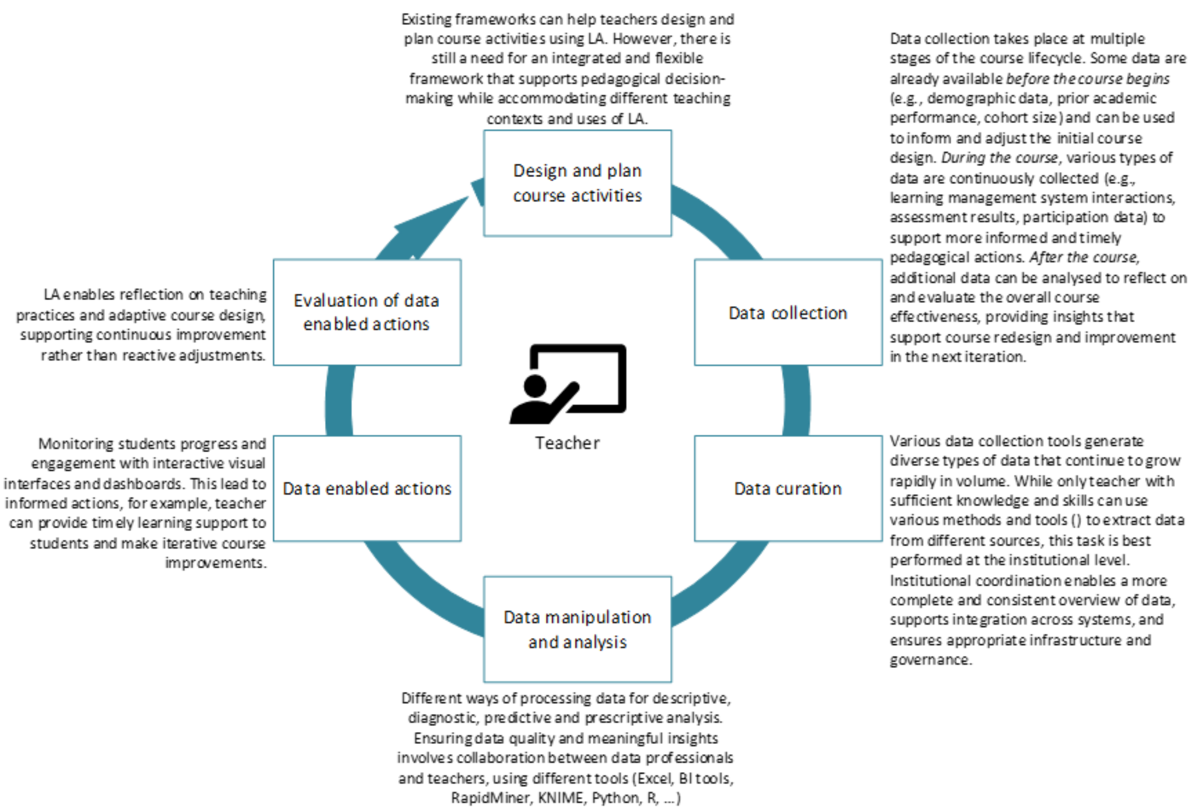

Figure 4: Synthesis of findings on teachers' use of LA

The distribution of publication journals (see Figure 3) indicates that the research in this area is spread across a large number of journals. Journal of Learning Analytics, British Journal of Educational Technology, Technology, Knowledge and Learning, and Australian Journal of Educational Technology are somewhat more strongly represented in this area. 26 journals featured only one article. Most of these 26 journals belong to the fields of education, information technology, and engineering.

4 Synthesis of findings

4.1 Teachers' use of learning analytics

Existing studies investigate LA either from a solution-oriented perspective, focusing on specific technologies and their applications, or from a process-oriented perspective, emphasising broader teaching and learning practices. To summarise these findings, a theory-based approach was employed to develop a model that links the process-oriented LA perspective with data sources and analytical tools, providing a coherent structure to support the pedagogical use of LA (see Figure 4).

LA implementation represents a complex, multi-stakeholder endeavour aimed at supporting educators in addressing questions related to student learning (Tsai & Gašević, 2017). While institutional support is important, teachers remain central actors, as they directly apply LA insights to improve teaching practices and learning outcomes (Naujokaitienė et al., 2020). Accordingly, several frameworks have been proposed to assist teachers in structuring course objectives and planning learning activities supported by LA. However, as noted by Kaliisa, Kluge, et al. (2022), existing frameworks reflect diverse learning theories and pedagogical assumptions, suggesting that LA can serve different pedagogical purposes to varying extents. Some frameworks focus on supporting teachers in collecting, representing, analysing, interpreting, and acting upon LA outputs (Arthars et al., 2019; Bakharia et al., 2016; Wise & Jung, 2019), while others emphasise the mapping of learner characteristics and course-related data derived from learning management systems (LMS) and other sources (Gunn et al., 2017). Taken together, these perspectives highlight the need for an integrated and flexible framework that supports pedagogical decision-making while accommodating different teaching contexts and uses of learning analytics.

By properly structuring the course objectives and activities, teachers can determine in advance what data about the students is useful to them and when they want to collect it (van Leeuwen, 2019). Some data can be collected before the course begins, such as demographic data, cohort size, etc. This data can be collected from student information systems, learning platforms, questionnaires, public data, etc. There are several methods for collecting data throughout the course. The most convenient way is to use LMS features, such as digital fingerprint (connection time, access and use of resources provided by the teacher, participation in forums, …) (Cobo-Rendon et al., 2021; Cui et al., 2020; Deng et al., 2019), assessment results, and quiz results (Cui et al., 2020; Deng et al., 2019; Dietz-Uhler & Hurn, 2013). More advanced approaches utilise Web 2.0 tools, including social media and virtual environments (Cambruzzi et al., 2015), as well as modern devices such as eye trackers and smartphones (Saar et al., 2017). Data can also be collected after the course has ended. Post-course data collection can include metrics such as resource utilisation data, student evaluations, grades, pass rates, failure rates, and retention rates. This data provides valuable insight into the effectiveness of the course and the overall student learning experience. However, several issues with data collection have been reported. Firstly, the data is often available but not readily accessible (Hilliger et al., 2020). In addition, advanced methods of data collection require expensive equipment, significant human resources, and raise ethical concerns (Bellini et al., 2019; Godínez et al., 2024; Thoma et al., 2020; van Leeuwen, 2019).

The use of various data collection tools generates diverse types of data, including structured, unstructured, visual, non-visual, historical, and real-time data. The volume of this diverse data continues to grow rapidly and should ideally, but not necessarily, be accessible in one place for analysis. While individual teachers with sufficient knowledge and skills can use various methods and tools to extract data from different sources, such as student data, LMS, assessment tools, etc., and load it into a single repository (Alachiotis et al., 2019), this task is best performed at the institutional level. At this level, it is essential not only to establish infrastructure for big data but also to implement comprehensive data governance policies (Godínez et al., 2024; Thoma et al., 2020). This approach provides a more comprehensive and coherent view of the data. Before various analyses can be carried out, datasets must first be cleaned and prepared from their raw state. Microsoft Excel and Google Sheets are the most accessible tools, with a handful of languages available for those with programming skills, Python being considered the most suitable (Slater et al., 2017). Once the data is properly prepared, the next step is to perform the various analyses. For the basic descriptive and diagnostic analyses, the reporting functions in LMS and other educational tools can be used. For creating advanced reports, various LMS plugins or other tools such as Microsoft Excel and Power BI can be used to create a dashboard that visualises the frequency of login, clickstream pattern, time spent in an online learning environment, and students' assessment scores and ranking compared to their peers (Deng et al., 2019). However, to fully understand how students interact with the course, their engagement, motivation, performance, and weaknesses, specialised tools are required. These tools include those for text mining and social network analysis that can process specific types of data (Kaliisa, Mørch, et al., 2022; Muñoz-Merino et al., 2023; Nguyen et al., 2020). The information obtained from the descriptive analysis serves as the basis for the predictive analysis (Cobos & Ruiz-Garcia, 2021). Tools such as RapidMiner, Orange, and Weka provide a wide range of algorithms (e.g., artificial neural networks, random forest, gradient boosting, decision tree) and modelling frameworks to model student performance and predict the likelihood of course dropout or failure. Prescriptive analytics then builds on predictive analytics, providing various possibilities for interventions in the student learning process.

Using interactive visual interfaces and dashboards, teachers can monitor students' progress and engagement (Cambruzzi et al., 2015; Cohen, 2018) as well as anticipate potential performance issues. By knowing the course activities, they can make appropriate interventions and improvements (Naujokaitienė et al., 2020). For informed and timely interventions, teachers can use frameworks such as the Analytics4Action Framework (Rienties et al., 2016), which guides the selection of appropriate interventions. Alternatively, instead of relying solely on existing frameworks, teachers can leverage prescriptive analytics to determine an optimal course of action (Susnjak, 2024). Integrating these approaches allows for continuous monitoring, iterative course improvement, and proactive support, ultimately enhancing both teaching effectiveness and student learning experiences.

LA could serve as a crucial reflective tool to improve teaching practise and enable adaptive rather than reactive teaching approaches (Kaliisa, Mørch, et al., 2022). According to Wise & Jung (2019), LA can not only lead to simple course adjustments, but teachers can also reflect on their teaching practises and course design, which affects the continuity of the LA cycle.

4.2 Antecedent specific to the teacher's LA use

Teachers are increasingly recognising the value of LA as they discover its potential to improve educational outcomes. After initial scepticism and unfamiliarity, LA tools are now gaining traction due to case studies (Alachiotis et al., 2019; De Laet et al., 2020; Deng et al., 2019; Mahmoud et al., 2020; Qazdar et al., 2023) and other research highlighting their positive effects (Bamiah et al., 2018; Cobos & Ruiz-Garcia, 2021; Kaliisa, Mørch, et al., 2022; Naujokaitienė et al., 2020; West et al., 2016), which emphasise their positive effects. The literature (Bamiah et al., 2018; Bart et al., 2020; Bellini et al., 2019; Cambruzzi et al., 2015; de Freitas et al., 2015; De Laet et al., 2020; Dietz-Uhler & Hurn, 2013; Dollinger et al., 2019; Godínez et al., 2024; Herodotou et al., 2021; Hilliger et al., 2020; Kaliisa, Mørch, et al., 2022; Muljana & Luo, 2021; Muñoz-Merino et al., 2023; Olney et al., 2021; Thoma et al., 2020; West et al., 2016) identifies several antecedents that influence the extent to which LA tools are adopted and used effectively in educational institutions.

Several prerequisites are often mentioned in the literature to facilitate the effective use of LA. These include appropriate policies regulating data access, the availability of suitable data analytic tools, training on the use of LA, and sufficient information on the use of LA. Distance learning facilitates the collection of sensitive data and the profiling of students to predict and identify learning behaviour. The Open University (OU) has been instrumental in addressing these concerns by developing the first policy on the ethical use of LA in 2014, which has influenced global standards (Bart et al., 2020). Despite this progress, teachers and students are often unaware of the specifics of data collection and consent processes, emphasising the need for greater transparency and data governance. Ethical principles, such as transparency, student control over data, security, and accountability, are essential for ensuring the protection of user data (Godínez et al., 2024). The growing volume of educational data requires a balance between the use of data and the protection of student privacy (Bellini et al., 2019). This balance requires teachers to be well-informed about their responsibilities and the legal implications of using student data. Therefore, institutions must foster a culture of privacy and data literacy to effectively address these challenges (West et al., 2016).

Many studies emphasise the potential of LA tools, but their successful use depends heavily on the support of teachers (Godínez et al., 2024). Teachers are the main actors who access and interpret LA data, draw conclusions about student performance, support them and improve curriculum design. However, the transition to deep and personalised learning requires major changes in the educational infrastructure (de Freitas et al., 2015). A responsive and flexible infrastructure is needed to support dynamic and adaptable learning contexts, as Gibson (2012) suggests. In addition, teachers need access to appropriate tools and resources to effectively integrate LA into their practise (Bart et al., 2020; Dollinger et al., 2019; Mahmoud et al., 2022; Muljana & Luo, 2021). Despite technological advancements, many universities continue to face challenges in integrating data to gain a comprehensive understanding of educational processes and service quality. This emphasises the need for institutions to become more flexible and build partnerships with different stakeholders that will help them implement LA (de Freitas et al., 2015).

LA in education faces major challenges due to the shortage of qualified staff and the high cost of recruiting professionals (Bamiah et al., 2018). Teachers, as key stakeholders in the effective use of LA, need professional development to improve their data literacy and technical skills. Studies have shown that teachers who do not engage in continuous professional development often struggle to interpret and act on data insights (Bart et al., 2020). For example, even after initial training, teachers reported difficulties in understanding the functions of dashboards and interpreting data (Herodotou et al., 2021). To address these issues, institutions need to invest in continuous and practical training programmes. These programmes should include case studies and good LA practises to improve teacher understanding and promote usage (Muñoz-Merino et al., 2023; West et al., 2016). In addition, informal professional development opportunities such as online courses and social media groups can provide teachers with flexible learning opportunities to improve their LA skills (Muljana & Luo, 2021; West et al., 2018).

A well-developed infrastructure for LA, clear guidelines for data management and targeted professional development seem to be the most important prerequisites for the effective use of LA. However, these are not the only prerequisites, as the existing literature also emphasises other factors such as performance expectancy, effort expectancy, social effect, and perceived risks. A recent study emphasises that teachers who find LA useful for their teaching are more likely to engage with these technologies and use them effectively (Herodotou et al., 2021). For example, Masiello et al. (2024) highlight that LA dashboards are designed to improve teachers' pedagogical decisions by providing actionable insights based on student data. When teachers understand and expect these tools to have a positive impact on their learning outcomes, their willingness to adopt and integrate LA into their practise increases. Similarly, research by Mohseni et al. (2023) shows that co-designing user-friendly dashboards tailored to teachers' needs can increase their expected performance. By involving teachers in the design process, dashboards are more likely to meet their practical needs, increasing their confidence in using LA tools to support their teaching.

If teachers feel that using LA tools requires minimal effort, they are more likely to use them. Mohseni et al. (2023) emphasise that the design and usability of LA dashboards play a key role in shaping teachers' effort expectancy. Their study shows that teachers are more likely to use LA tools when dashboards are intuitive and user-friendly. Similarly, Herodotou et al. (2021) indicated that the perceived ease of use of LA tools has a direct impact on teachers' engagement with these tools. If teachers perceive LA tools as intuitive and easy, they are more likely to integrate them consistently into their lessons. Additionally, teachers' attitudes towards technology and their previous experience with digital tools also influence their expected effort. Those who are more comfortable with technology tend to perceive LA tools as less intimidating and easier to use.

A supportive environment, organisational culture, and participation in professional learning communities promote teachers' willingness and ability to integrate LA into their classroom practise. Support from colleagues and administrators can have a significant impact on whether teachers adopt institutional educational tools. When teachers feel supported and encouraged by colleagues and supervisors, they are more willing to experiment with and adopt new technologies, including LA tools (Bart et al., 2020; De Laet et al., 2020; Kaliisa, Mørch, et al., 2022; Muljana & Luo, 2021). The organisational culture of a university can influence the willingness of teachers to use LA. In environments that foster innovation, encourage the use of technology, and maintain a positive attitude towards change, teachers are more inclined to use LA tools (Mahmoud et al., 2022). Additionally, participation in professional learning communities, where teachers can share their experiences, challenges, and successes with LA, can have a positive impact on the adoption of these tools. Professional learning communities provide a support network for collaborative problem solving and make the use of LA less challenging (Muljana & Luo, 2021; West et al., 2018).

The perceived risks have a significant impact on teachers' acceptance and use of LA in education. These risks include concerns about privacy and security as well as the potential misuse of student data (Bamiah et al., 2018; Dietz-Uhler & Hurn, 2013; Dollinger et al., 2019; Godínez et al., 2024). Research shows that teachers are wary of the ethical implications and negative consequences of using LA tools, which can affect their willingness to integrate these technologies into their teaching practise (Bart et al., 2020). In addition, issues such as the accuracy and reliability of analytics-based findings also contribute to teachers' scepticism and hesitation (Kaliisa, Mørch, et al., 2022).

To summarise, several models are particularly relevant to the study of LA adoption (Cobo-Rendon et al., 2021; Herodotou et al., 2021; Kaliisa, Mørch, et al., 2022; Muljana & Luo, 2021; Olney et al., 2021). These models are primarily grounded on the Theory of Diffusion of Innovations and examine the role of innovation, communication, social systems and time in the context of adoption (Rogers, 1995). In contrast, the Technology Acceptance Model (TAM) (Davis, 1989) and the Universal Technology Adoption and Use Theory (UTAUT) (Venkatesh et al., 2003) focus on individual characteristics that influence the adoption of specific technologies, such as perceptions, beliefs, and attitudes. In addition, the Concerns-Based Model of Acceptance (CBAM) addresses faculty concerns in the context of P-20 education (Hall, 1979), while the Academic Resistance Model emphasises the critical importance of examining staff responses to change over time and understanding their reactions to change initiatives that occur from the bottom up (Piderit, 2000).

4.3 Outcomes of teachers' LA use

From a teacher's perspective, LA can change teaching methods, course recommendations, and improve the overall educational experience through data-driven insights and personalised learning paths. A key benefit is the ability to tailor courses to the individual learner needs, increasing engagement and performance (Alachiotis et al., 2019; Cobos & Ruiz-Garcia, 2021; Ifenthaler et al., 2018; Q. Nguyen et al., 2018; West et al., 2018). For example, by analysing learners' past behaviour and performance patterns, teachers can predict future performance and identify at-risk learners and thus implement timely interventions to reduce dropout rates (Bart et al., 2020; Dietz-Uhler & Hurn, 2013; Kaliisa, Mørch, et al., 2022; West et al., 2016).

Teachers also use LA to monitor absences in real time and improve attendance, as demonstrated by the use of dashboards and big data analytics at Purdue University (Bamiah et al., 2018). Additionally, teachers at the University of Wollongong employ visual analytics to understand student interactions in discussion forums, which in turn enables them to tailor teaching strategies to student needs (Daniel & Butson, 2013). This holistic data use supports more informed decisions regarding course content and teaching methods, fostering an environment that promotes active learning and student retention (West et al., 2016). It also reduces the time spent identifying students who need support and engaging in follow-up communication (Honson et al., 2024).

Various institutions have started to use LA for specific purposes. For example, Northern Arizona University uses the Performance Grading System (GPS) to identify students at risk of dropping out, while Austin Peay State University's Degree Compass system predicts student performance and makes study recommendations. Similarly, Purdue University uses Course Signals to examine behaviour and identify at-risk students (Bamiah et al., 2018). These implementations demonstrate the potential of LA to improve teaching effectiveness and ultimately contribute to better educational outcomes (Deng et al., 2019).

Overall, implementing LA at the course level lays the foundation for continuous improvement across the institution. By using data to enhance personalisation, early intervention, instructional quality, resource allocation, and support services, institutions can achieve better student outcomes, higher retention and graduation rates, and an overall improved performance and reputation (Tsai et al., 2020). This approach also reduces the time and effort required to identify students in need of support and to coordinate appropriate interventions, allowing staff to focus on proactive, data-informed decision-making across courses and programs. Moreover, it supports the adaptation of curricula to evolving industry demands driven by digital technologies, fostering more agile and responsive higher education institutions (Honson et al., 2024; West et al., 2018).

5 Discussion

This literature review reveals a decline in publications dealing with the use of LA by teachers. This decline appears to be related to the advent of big data, as recent publications have shifted to advanced LA projects. These projects often utilise machine learning and deep learning models to predict key academic outcomes beyond the course level. In these contexts, teachers are usually only mentioned as stakeholders and primarily as users of pre-built dashboards that help identify specific learning issues and predict outcomes (Herodotou et al., 2021). Teachers' perspectives on the use of LA have been studied in Europe, North America, and Oceania, with Australia playing a significant role in promoting international research collaboration and contributing notable findings. Therefore, institutions and researchers in the field of LA should seek opportunities for international research collaboration to promote innovation and improve educational practise globally (Kurniati et al., 2022). By pooling resources and knowledge, international partnerships can advance the development and application of LA in different educational contexts, enriching the overall understanding and effectiveness of LA tools. In addition, researchers should continue to draw on knowledge, methods and perspectives from various disciplines to deepen the understanding of LA. This approach can help address complex educational challenges by integrating different perspectives and methods (Ouhaichi et al., 2023).

The content analysis revealed that most of the articles in our sample used a descriptive research approach. For example, Dollinger et al. (2019) show the use of the LA tool over six years at several Australian universities, and Cobos & Ruiz-Garcia (2021) present the effectiveness of weekly feedback on learner interaction and performance in a learning system. Another dominant approach is theory-based research. Different theories explain different aspects of LA, such as the LA cycle (Arthars et al., 2019; Wise & Jung, 2019) and the acceptance and use of technology (Cobos & Ruiz-Garcia, 2021; Herodotou et al., 2021; Muljana & Luo, 2021; Olney et al., 2021). Although theoretical developments in this area are evident, interpretative methods of data collection (e.g., interviews, focus groups) are most commonly used (Bart et al., 2020; Godínez et al, 2024; Honson et al., 2024; Kaliisa, Mørch, et al., 2022; Naujokaitienė et al., 2020), followed by experiment (Cagliero et al., 2019; Cambruzzi et al., 2015; Deng et al., 2019) and survey (Cobo-Rendon et al., 2021; West et al., 2018). Only a few studies used mixed methods for data collection (De Laet et al., 2020; Herodotou et al., 2021; Hilliger et al., 2020), highlighting the need for more frequent use of approaches that combine qualitative and quantitative methods to gain a deeper understanding of complex learning environments.

To systematically summarise the solution-oriented and process-oriented findings, an LA cycle was adapted from the existing literature (Arthars et al., 2019; Drachsler & Kalz, 2016; Ndukwe & Daniel, 2020). The first step in this cycle is the structuring of course objectives and the planning of activities for the use of LA tools, for which various frameworks have been developed to support teachers. Despite the variety of frameworks available, more comprehensive guidelines on which framework or combination of frameworks to use are needed, along with clear instructions on specific actions to take and their timing (Kaliisa, Kluge, et al., 2022). Properly structuring course objectives and activities enables teachers to determine useful data and optimal collection times, which is the second step in this cycle. During this process, ethics must be prioritised (Bamiah et al., 2018; Bellini et al., 2019; Dollinger et al., 2019). The various data collected should ideally be organised and managed in a way that meets the needs and interests of the teachers. Although experienced teachers can perform this task, it is more effective when implemented at an organisational level (Godínez et al., 2024; Thoma et al., 2020). Although not mandatory, this step provides a better overview of the available data, facilitating subsequent data manipulation and analysis. Before conducting analyses, data sets must be cleaned and prepared using accessible tools such as Microsoft Excel or programming languages like Python (Slater et al., 2017). Basic descriptive and diagnostic analyses can be performed using the LMS reporting features, while more advanced reports and dashboards can be created using plug-ins and tools such as Microsoft Excel and Power BI (Deng et al., 2019). Predictive and prescriptive analytics, on the other hand, require more specialised tools and advanced knowledge to make predictions and informed interventions. The easiest way for teachers to use predictive and prescriptive analytics is through interactive dashboards provided by their institutions. However, the availability of these tools is limited, and many teachers indicated that they are unsure how to use them effectively (Herodotou et al., 2021). Alternatively, teachers with limited LA experience can use frameworks to help select the most appropriate interventions (Kaliisa, Kluge, et al., 2022). Regardless of the method, teachers need to systematically engage with LA to make informed decisions during the course and to reflect on and continuously improve their teaching practises. As such, LA can serve as an important tool for proactive pedagogical approaches.

Teachers are increasingly recognising the value of LA in significantly improving educational outcomes. However, there are several factors that influence the adoption of LA tools (Bamiah et al., 2018; Bart et al., 2020; Bellini et al., 2019; De Laet et al., 2020; Dollinger et al., 2019; Godínez et al., 2024; Herodotou et al., 2021; Hilliger et al., 2020; Muljana & Luo, 2021; Muñoz-Merino et al., 2023; Olney et al., 2021; Thoma et al., 2020). As primary interpreters of LA data, teachers need access to suitable tools, resources, and ongoing professional development to effectively enhance student achievement and inform curriculum design (Godínez et al., 2024; Herodotou et al., 2021). The successful integration of LA requires a responsive educational infrastructure and a supportive organisational culture that encourages innovation and the use of technology (Mahmoud et al., 2022; West et al., 2018). In addition, concerns about privacy, security, and the accuracy and reliability of LA findings affect teachers' acceptance and use of these tools (Dollinger et al., 2019; Godínez et al., 2024; Kaliisa, Mørch, et al., 2022). To utilise LA effectively, institutions need to invest in robust infrastructure, clear data management guidelines, and targeted professional development that addresses both technical and ethical aspects of LA use (Bamiah et al, 2018; Bart et al, 2020; Mahmoud et al, 2022; West et al, 2018). Overall, the inclusion of models such as TAM, UTAUT, and education-focused adoption models such as CBAM can help to promote wider and more effective adoption of LA in educational institutions by exploring the decision points of individuals at the interface between the organisation and the technological innovation. As predominantly qualitative methodological approaches were utilised when building on the theoretical lenses of these models to gain a more comprehensive understanding, future research should aim to collect quantitative data from a large cohort of teachers to explore how factors such as age, gender, experience, and social influence affect adoption.

LA tools are gaining acceptance due to case studies and research highlighting their positive effects (Alachiotis et al., 2019; Bamiah et al., 2018; Cobos & Ruiz-Garcia, 2021; De Laet et al., 2020; Deng et al., 2019; Kaliisa, Mørch, et al., 2022; Mahmoud et al., 2020; Naujokaitienė et al., 2020; Qazdar et al., 2023; West et al., 2016). Regardless, there is a need for more case studies that demonstrate clear performance outcomes. These case studies should highlight successful implementations of LA and provide well-documented approaches and practical insights that can facilitate the adoption of LA at individual and institutional levels. To obtain generalisable and transferable results, future LA research must also place a stronger methodological focus on large-scale, longitudinal, and experimental research designs. Future studies should also explore the development of teacher-centred dashboards and the long-term effects of LA on student learning and retention. Moreover, research examining cross-cultural and international contexts could reveal how local practices and organisational cultures shape the adoption and use of LA. The research gaps identified in this review offer multiple opportunities for further research.

6 Conclusion and outlook

Building an integrated LA system that effectively meets the needs of higher education institutions is a vision shared by many education stakeholders around the world. As higher educational institutions advance their efforts to implement LA, it is crucial to recognise that teachers are not only end users but also important contributors to this transformation process. Recent trends in big data and predictive analytics have largely relegated teachers to the passive role of users of pre-built dashboards, often neglecting their direct involvement in the LA process. To truly realise the potential of LA, it is essential to actively engage teachers, address their specific needs, and ensure their meaningful participation in the development and implementation of LA.

This literature review adapted the SPAR-4-SLR protocol to identify 39 papers and the ADO framework to categorise studies accordingly. The combination of SPAR-4-SLR and ADO provides a transparent methodology that other researchers could replicate or extend. Furthermore, it facilitates a structured synthesis and systematic comparison of findings across studies. While this approach provides a good balance between structure and clarity, it carries the risk of oversimplifying complex studies that do not fit neatly within the ADO framework and can be time-consuming.

Although evidence of teacher involvement in LA was found, a higher level of teacher engagement was expected. The literature review provides insights into how teachers use LA tools and frameworks, the challenges they encounter, and their perceptions of the outcomes associated with these tools. The findings highlight the need for institutional strategies that support teacher training, promote ethical data use, and foster collaboration among stakeholders to maximise the impact of LA.

Finally, it is worth noting that this review has several limitations. First, our search was limited to the Scopus database. While Scopus covers a wide range of subject areas and categories, it is possible that some important articles from other databases were overlooked. Second, we focused exclusively on articles in which teachers were explicitly mentioned as participants. Consequently, relevant findings from studies examining the perspectives of stakeholders more broadly may have been missed. Third, we only considered fully available English articles published in peer-reviewed journals and excluded conference papers. This exclusion may have led to the omission of relevant research presented at conferences, which often showcase the latest developments in the field. Additionally, the rapid evolution of LA technologies means that some of the latest findings may not be captured in this review. Addressing these limitations in future literature reviews could lead to a more comprehensive understanding of the role of teachers in LA implementation.

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