



Applications of learning analytics in the study of academic performance in higher education: A pilot-tested meta-review protocol

Cristian Molla-Esparza^{a,*}, María Isabel Gómez-Núñez^b, Fran J. García-García^c

^a Department of Research Methods and Diagnosis in Education, Faculty of Philosophy and Education Sciences, University of Valencia, Av. de Blasco Ibáñez, 30, El Pla del Real 46010 Valencia, Spain

^b Department of Research Methods and Diagnostics, Faculty of Education, International University of La Rioja, Avenida de la Paz, 137, 26006 Logroño, La Rioja, Spain

^c Department of Educational Theory, Faculty of Philosophy and Education Sciences, University of Valencia, Av. de Blasco Ibáñez, 30, El Pla del Real 46010 Valencia, Spain

ARTICLE INFO

Keywords:

Learning analytics
Academic performance
Higher education
Meta-review

ABSTRACT

Learning Analytics (LA) concerns the analysis of educational data to enhance learning processes and conditions. Its growing use in higher education has inspired synthesis studies on its applications and effectiveness in studying academic performance, which have had heterogeneous approaches and results. Previous meta-reviews have not provided comprehensive overviews, and have had methodological and substantive limitations, particularly in addressing socio-educational factors. The proposed meta-review outlined in this protocol aims to examine systematic literature reviews on applications of LA in the study of academic performance in higher education. This meta-review protocol has been preregistered in INPLASY (number 2024120119; doi: 10.37766/inplasy2024.12.0119), and has been developed following both the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) and the Preferred Reporting Items for Overviews of Reviews (PRIOR) guidelines. The meta-review will include systematic reviews of LA applications in the study of academic performance in higher education, written in English or Spanish, and published from 2000 onwards. Bibliographic searches will be performed across Scopus, Web of Science, ERIC and PsycINFO databases, and other gray literature sources, and the reporting and methodological quality will be assessed using the PRISMA and AMSTAR 2 checklists. This study develops and empirically tests a systematic and replicable meta-review protocol, providing validated search equations and reliable processes for study selection and data coding. The meta-review will aim to describe the main features of how LA has been applied in the study of academic performance in higher education, and to explore practical implications and research challenges.

1. Introduction

Since the early 2000s, higher education institutions have increasingly adopted digital platforms to manage and support learning, enabling the collection of extensive data on various student metrics, such as interaction patterns with online materials and within digital learning environments, engagement, performance, and outcomes.

Within this context, Learning Analytics (LA) emerged as an innovative field focused on measuring, collecting, analyzing and communicating data about students and learning environments in order to better understand and enhance learning processes and educational settings (Lang et al., 2022; Long et al., 2011).

Over time, LA has evolved significantly in higher education. It was

originally centered around basic learning management systems, such as early versions of Moodle and Blackboard, but has since evolved into sophisticated analytical platforms incorporating semi-automated and fully automated technical processes for the collection, management and analysis of large datasets (e.g., edX Insights, IBM Watson Education, Learning Locker). In its early stages, LA primarily tracked basic metrics such as academic performance and attendance. However, with the advent of digital transition and digital transformation, it has expanded to offer deeper insights into various aspects of learning processes, such as student engagement patterns, personalized learning pathways, and skills development (Haleem et al., 2022; Mhlanga, 2024). This evolution has marked a pivotal shift in LA's purpose and scope in educational terms, progressing from primarily descriptive applications, such as

* Corresponding author at: Department of Research Methods and Diagnosis in Education, Faculty of Philosophy and Education Sciences, University of Valencia, Avenida de Blasco Ibáñez, 30, El Pla del Real 46010 Valencia, Spain.

E-mail address: Cristian.Molla@uv.es (C. Molla-Esparza).

<https://doi.org/10.1016/j.ijedro.2024.100433>

Received 30 December 2024; Accepted 30 December 2024

Available online 10 January 2025

2666-3740/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

tracking student participation trends (Viberg et al., 2018), to predictive and prescriptive applications, such as forecasting academic success, and recommending personalized learning pathways (Ouyang et al., 2023), enabling more targeted and effective educational interventions. According to the literature, the main applications of LA in higher education are currently focused on monitoring academic progress (Viberg et al., 2018) for various purposes, including the personalization of learning experiences (Banihashem et al., 2022), the optimization of institutional resources (Llopis-Albert & Rubio, 2021), and enhancement of educational program design (Leitner, Khalil, & Ebner, 2017). Thus, LA plays an important role in supporting evidence-based decision-making regarding the pedagogical, curricular and administrative decisions of educational institutions (Utamachant et al., 2023; Yan et al., 2024).

The growing use of LA in higher education has led to an increasing number of synthesis studies aimed at summarizing primary empirical evidence on its applications in this educational setting, particularly regarding its potential to study academic performance (e.g., Dol & Jawandhiya, 2024; Rahul & Katarya, 2023). Systematic reviews on the use of LA to assess academic performance in higher education have revealed that studies typically focus on identifying performance patterns and developing predictive models to anticipate student success (Alnasyan et al., 2024; Dol & Jawandhiya, 2024; Rahul & Katarya, 2023). However, these reviews have also highlighted considerable variability in the accuracy and effectiveness of such predictive models due to differences in data gathering methods (e.g., student logins, surveys), in data types (e.g., learning and teaching behaviors, academic performance), in the metrics analyzed (e.g., participation, interaction patterns, academic outcomes), and in applied analytical strategies (e.g., association, classification, prediction) (Larrabee Sønderlund et al., 2019; Namoun & Alshantqiti, 2020). This heterogeneity has complicated efforts to compare and validate findings, has hampered communication among scholars, and has limited insights into learning behaviors and academic performance (Lang et al., 2022; Siemens, 2013). The review studies have further emphasized that, while LA has demonstrated its potential to improve academic performance through data-driven monitoring, it faces both critical substantive and practical challenges, particularly in effectively training educators to use LA tools, in integrating LA systems into existing educational infrastructures, in making LA accessible, and in ensuring data privacy and security.

According to the published synthesis studies, critical knowledge gaps remain regarding how contextual factors, such as socioeconomic background and technology access, might influence the effectiveness of LA interventions and potentially limit their customization to different educational contexts (Ganesh Iyer & Bennet, 2022; Paolucci et al., 2024). Addressing these factors is essential, for example, in order to design educational interventions in virtual learning environments where understanding specific contexts and student needs is critical. Furthermore, although the volume of empirical research on the educational applications of LA continues to grow each year, many studies continue to lack a solid theoretical foundation useful in implementing interventions and effectively guiding educators, students and researchers (Gašević et al., 2017; Reimann, 2016). Without an understanding of contextual factors and a robust theoretical basis, LA's full potential for informing instructional design and enhancing educational environments and outcomes remains limited.

In addressing the existing knowledge gaps, a meta-review would bring a comprehensive perspective to the existing knowledge base by compiling and evaluating findings from multiple prior reviews. This would be particularly important in the field of LA, in which a vast diversity of both empirical and review studies have had varying approaches and results, yet there has been a distinct lack of dedicated meta-reviews, with only a limited few published up until 2021 (Chaka, 2022; Du et al., 2019, 2021). However, the landscape of LA research has evolved significantly since then, highlighting an urgent need for an up-to-date meta-review of the field, particularly concerning LA applications in the study of academic performance in higher

education.

To date, no meta-reviews have been carried out on LA applications in the study of academic performance specifically in higher education. Du et al. (2019, 2021) conducted a meta-review of 901 papers, although this was not centered on higher education, and included a mix of primary empirical studies and only 8 review articles, published between the years 2012 and 2017. These authors focused on LA development trends, methods and predominant research topics, such as performance prediction and learner modeling, and concluded that LA was still in its early stages, with a predominant emphasis on conceptual frameworks rather than empirical data analysis. Nonetheless, this meta-review had several significant limitations, lacking a structured planning protocol, and not providing a comprehensive review of literature reviews. Additionally, it did not focus on a specific application domain, such as academic performance, and therefore lacked specificity within the broad framework of LA. These shortcomings underscore the need for future meta-review studies that address knowledge gaps and provide more focused and methodologically rigorous analyses.

Subsequently, Chaka (2022) provided an overview of 33 literature reviews focused on student academic performance prediction, and identified several methods and algorithms used for predicting student outcomes. This meta-review addressed some of the shortcomings of the previous one, such as the use of a standardized planning protocol and the study of practical applications to a specific domain within LA research. Nevertheless, Chaka's meta-review did not focus on a specific educational level, therefore making it challenging to extrapolate findings of the analyzed reviews to the context of higher education, an academic level in which LA interventions have been applied particularly extensively.

The existing meta-reviews to date therefore have relevant substantive and methodological limitations, particularly in their focus and scope, highlighting the need for a structured, up-to-date, meta-review study focused on the applications of LA at a specific educational level, namely higher education, and regarding a particular academic domain, such as academic performance. Moreover, it is critical to provide a cohesive and comprehensive synthesis on the applications of LA by including hitherto unexamined educational aspects (e.g., educational level, knowledge areas, educational theories, pedagogical objectives), operational aspects (e.g., learning environments, data sources, metric types, analytical strategies and their efficacy), and practical implications in terms of benefits, opportunities, challenges and limitations, while also addressing the existing knowledge gaps. Ultimately, such a meta-review would contribute to a more comprehensive understanding of the existing review literature, mitigate potential biases inherent in the analyzed reviews, and elevate the overall body of evidence.

Therefore, the objective of the proposed meta-review outlined in this protocol is to examine systematic literature reviews of the applications of LA in the study of academic performance in higher education, and more specifically to:

- Describe the main methods used in applying LA in the study of academic performance in higher education.
- Characterize LA applications in the study of academic performance in higher education from an educational perspective.
- Examine benefits, opportunities, limitations and challenges identified in systematic literature reviews regarding the applications of LA in the study of academic performance in higher education.

2. Method

The protocol for this meta-review follows the guidelines of the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) (Moher et al., 2015), as a guide for planning the review methods. A synthetic protocol of this meta-review has been preregistered in the INPLASY repository (number 2024120119; doi: 10.37766/inplasy2024.12.0119). It should also be noted that this

protocol has been empirically tested with the aim of assessing the viability and feasibility of the meta-review in the terms presented under the following headings.

Furthermore, the execution and reporting of this meta-review will follow the Preferred Reporting Items for Overviews of Reviews (PRIOR) guidelines (Gates et al., 2022; Pollock et al., 2019), and additional guidelines for meta-reviews published by Aromataris et al. (2015).

2.1. Eligibility criteria

To address the indicated research objectives, the studies to be included in the meta-review must meet the eligibility criteria presented in Table 1.

Conversely, studies will be excluded if they consist of: a) reviews primarily focused on bibliometric data; b) reviews regarding non-human samples (e.g., software, tools, databases, algorithms), or that deal exclusively with data collection and preservation processes; c) reviews regarding non-literature data from workshops, conferences, or courses; and d) reviews specifically targeting Massive Open Online Courses (MOOCs) outside of the bounds of the curricula of formal higher education.

2.2. Information sources

Bibliographic searches, based on study title, abstract and keywords, will be conducted in the following four electronic databases: Scopus (Elsevier), Web of Science Core Collection (WoS, via Clarivate Analytics), Educational Resources Information Center (ERIC, via ProQuest), and PsycINFO (via ProQuest), to cover the broad range of disciplines related to the subject of study, from multidisciplinary studies through to

the educational field. Search alerts will be set in all of these databases. Additionally, the references of relevant published studies will be examined to acquire other potentially eligible studies. Furthermore, gray literature will be searched via Google (with the first 250 entries sorted by relevance) and other information sources directly or indirectly referring to LA (e.g., Dissertations & Theses Global, via ProQuest; International Conference on Learning Analytics & Knowledge, LAK), in order to acquire other potentially eligible studies. The bibliographies of each of the included systematic reviews will be manually examined to identify other relevant reviews. Finally, e-mails will be sent to the principal researchers of the research groups that have published the most about LA, with the aim of identifying systematic review studies in progress or pending publication.

2.3. Search strategy

The search strategy will follow the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Literature Search Extension (PRISMA-S) (Rethlefsen et al., 2021), and will be developed through an iterative process involving key terms from empirical literature and consultations of relevant databases, and considering previous systematic reviews of LA in higher education (Chaka, 2022; Ifenthaler & Yau, 2020; Pan et al., 2024).

To carry out a comprehensive review of the subject matter, a 4-step search strategy is expected to be used. The strategy will include both highly sensitive (exhaustive) and specific descriptors and expressions referring to: 1) Learning Analytics (e.g., "Learning analytic*", "Academic analytics", "Data-driven education", "Educational data mining"); 2) the study type (e.g., "Systematic review", "Integrative review", "Realist review"); 3) academic performance (e.g., "Academic grad*", "Academic mark?", "Academic outcome?", "Academic perform*"); and 4) higher education (e.g., "Tertiary education", "Undergraduate*", "Universit*").

The search will be performed using truncated symbols to maximize the inclusion of relevant terms. Boolean operators (e.g., OR and AND) will be employed within descriptors and/or across them. The search strategy will be developed to use both free-text terms and standardized search terms (or index terms), and therefore adapted to fit the syntax and unique features of each bibliographic database. As an example, Table 2 shows the search strategy syntax developed for Scopus.

In the ERIC database, for example, the following ERIC Thesaurus terms referring to Learning Analytics will be used: "Learning Analytics" [Majr:NoExp] OR "Educational Assessment" [Majr:NoExp] OR "Student Evaluation" [Majr:NoExp] OR "Progress Monitoring" [Majr:NoExp]. Regarding the study type, the following thesaurus terms will be used: "Meta Analysis" [Majr:NoExp] OR "Literature Reviews" [Majr:NoExp] OR "State of the Art Reviews" [Majr:NoExp]. Regarding academic performance, the following thesaurus terms will be used: "Knowledge Level" [Majr:NoExp] OR "Outcomes of Education" [Majr:NoExp] OR "Academic Achievement" [Majr:NoExp] OR "Performance" [Majr:NoExp] OR "Academic Ability" [Majr:NoExp] OR "Competence" [Majr:NoExp] OR "Expertise" [Majr:NoExp] OR "Learning" [Majr:NoExp] OR "Educational Attainment" [Majr:NoExp] OR "Ability" [Majr:NoExp] OR "Aptitude" [Majr:NoExp] OR "Academic Standards" [Majr:NoExp]. Finally, regarding the target population, the following thesaurus terms will be used: "Undergraduate Students" [Majr:NoExp] OR "Higher Education" [Majr:NoExp] OR "Colleges" [Majr:NoExp] OR "College Students" [Majr:NoExp] OR "Universities" [Majr:NoExp] OR "Graduate Students" [Majr:NoExp] OR "Postsecondary Education" [Majr:NoExp].

During the pilot phase for this search strategy, an educational librarian (EMN, staff member at the "Joan Reglà" Humanities Library at the University of Valencia) and a professor with experience in the evidence synthesis area (LBR, professor in the Department of Methodology for Behavioral Sciences at the University of Valencia) have been consulted in order to validate the selection of databases, and the comprehensiveness and relevance of the developed search strategy. Both parties evaluated and executed the search syntax, assessing comprehensiveness

Table 1
Inclusion criteria.

Characteristic	Inclusion criteria
Document type	Any document type will be considered for inclusion in this meta-review.
Review type	Included studies should be systematic reviews that follow standardized methodologies (e.g., PRISMA) and will be considered if they clearly articulate a set of objectives related to the research question outlined in this meta-review protocol. The reviews must also demonstrate explicit and reproducible methodologies, including well-defined search strategies, pre-established eligibility criteria, study selection methods, systematic syntheses, and the presentation of findings of the included studies. Any type of systematic literature review will be considered, including qualitative, quantitative (with or without meta-analysis) and mixed methods systematic literature reviews. For inclusion in this review, systematic reviews will not necessarily need to have undergone a methodological quality assessment (e.g., risk of bias) for the included studies (as is the case of scoping reviews; Peters et al., 2015; Tricco et al., 2018).
Review objective	The reviews must be focused on the application of Learning Analytics, including its tools, techniques and/or interventions for tracking, monitoring, predicting or enhancing academic performance.
Outcome of interest	The primary focus must relate to academic performance, measured through qualitative or quantitative indicators such as grades, course completion rates, or progress through academic programs.
Educational context	The reviews must focus on the higher education sector, considering studies conducted at universities, colleges and other post-secondary institutions offering undergraduate or postgraduate programs.
Contents	The reviews should also offer a comprehensive description of the methods, characteristics, benefits, opportunities, limitations and challenges associated with the applications of Learning Analytics to the study of academic performance in the context of higher education.
Language	The reviews must be published in English or in Spanish.
Publication year	Reviews published since 2000 will be considered.

Table 2

Scopus search strategy.

Step	Search
#1	((TITLE-ABS-KEY ("Academic analytics") OR TITLE-ABS-KEY ("Academic big data") OR TITLE-ABS-KEY ("Academic machine learning") OR TITLE-ABS-KEY ("Big data for education") OR TITLE-ABS-KEY ("Big data in education") OR TITLE-ABS-KEY ("Data analytics") OR TITLE-ABS-KEY ("Data mining analysis for education") OR TITLE-ABS-KEY ("Data mining analysis in education") OR TITLE-ABS-KEY ("Data mining methods for education") OR TITLE-ABS-KEY ("Data mining methods in education") OR TITLE-ABS-KEY ("Data mining of learning") OR TITLE-ABS-KEY ("Data mining techniques for education") OR TITLE-ABS-KEY ("Data mining techniques in education") OR TITLE-ABS-KEY ("Data-driven education") OR TITLE-ABS-KEY ("Data-driven learning") OR TITLE-ABS-KEY ("Education big data") OR TITLE-ABS-KEY ("Education data mining") OR TITLE-ABS-KEY ("Educational analytics") OR TITLE-ABS-KEY ("Educational big data") OR TITLE-ABS-KEY ("Educational data analysis") OR TITLE-ABS-KEY ("Educational data mining") OR TITLE-ABS-KEY ("Educational data modelling") OR TITLE-ABS-KEY ("Educational data modeling") OR TITLE-ABS-KEY ("Educational data visualisation") OR TITLE-ABS-KEY ("Educational data visualization") OR TITLE-ABS-KEY ("Educational machine learning") OR TITLE-ABS-KEY ("Instructional analytics") OR TITLE-ABS-KEY ("Learning analytic") OR TITLE-ABS-KEY ("Learning assessment and analytics") OR TITLE-ABS-KEY ("Learning data analytics") OR TITLE-ABS-KEY ("Learning data mining") OR TITLE-ABS-KEY ("Learning data modelling") OR TITLE-ABS-KEY ("Learning data modeling") OR TITLE-ABS-KEY ("Learning management systems analytics") OR TITLE-ABS-KEY ("Learning metrics") OR TITLE-ABS-KEY ("Learning performance analytics") OR TITLE-ABS-KEY ("Machine learning for education") OR TITLE-ABS-KEY ("Machine learning in education") OR TITLE-ABS-KEY ("Machine learning techniques for education") OR TITLE-ABS-KEY ("Machine learning techniques in education") OR TITLE-ABS-KEY ("Scholarly machine learning") OR TITLE-ABS-KEY ("Student data analytics") OR TITLE-ABS-KEY ("Progress monitoring") OR TITLE-ABS-KEY ("Student? evaluation") OR TITLE-ABS-KEY ("Educational assessment"))))
#2	((TITLE-ABS-KEY ("Bibliometric analysis") OR TITLE-ABS-KEY ("Bibliometric review") OR TITLE-ABS-KEY ("Case review stud") OR TITLE-ABS-KEY ("Comprehensive review") OR TITLE-ABS-KEY ("Critical review") OR TITLE-ABS-KEY ("Evidence review") OR TITLE-ABS-KEY ("Evidence synthesis") OR TITLE-ABS-KEY ("Evidence-based review") OR TITLE-ABS-KEY ("Exhaustive review") OR TITLE-ABS-KEY ("In-depth review") OR TITLE-ABS-KEY ("Integrative review") OR TITLE-ABS-KEY ("Literature review") OR TITLE-ABS-KEY ("Literature synthesis") OR TITLE-ABS-KEY ("Mapping review") OR TITLE-ABS-KEY ("Meta analysis") OR TITLE-ABS-KEY ("Meta review") OR TITLE-ABS-KEY ("Mixed method* review") OR TITLE-ABS-KEY ("Mixed stud* review") OR TITLE-ABS-KEY ("Narrative review") OR TITLE-ABS-KEY ("Rapid review") OR TITLE-ABS-KEY ("Realist review") OR TITLE-ABS-KEY ("Network meta analysis") OR TITLE-ABS-KEY ("Review of case studies") OR TITLE-ABS-KEY ("Review of the state of the art") OR TITLE-ABS-KEY ("Scoping review") OR TITLE-ABS-KEY ("State of the art review") OR TITLE-ABS-KEY ("Synthesis of the literature") OR TITLE-ABS-KEY ("Systematic review") OR TITLE-ABS-KEY ("Systematic search and review") OR TITLE-ABS-KEY ("Systematised review") OR TITLE-ABS-KEY ("Systematized review") OR TITLE-ABS-KEY ("Umbrella review") OR TITLE-ABS-KEY ("Review? of the literature")))
#3	((TITLE-ABS-KEY ("Academic achiev") OR TITLE-ABS-KEY ("Academic attain") OR TITLE-ABS-KEY ("Academic grad") OR TITLE-ABS-KEY ("Academic mark") OR TITLE-ABS-KEY ("Academic outcome") OR TITLE-ABS-KEY ("Academic perform") OR TITLE-ABS-KEY ("Academic proficien") OR TITLE-ABS-KEY ("Academic progress") OR TITLE-ABS-KEY ("Academic result") OR TITLE-ABS-KEY ("Academic scor") OR TITLE-ABS-KEY ("Academic stand") OR TITLE-ABS-KEY ("Academic success") OR TITLE-ABS-KEY ("Achievement of student") OR TITLE-ABS-KEY ("Educat* achiev") OR TITLE-ABS-KEY ("Educat* attain") OR TITLE-ABS-KEY ("Educat* grad") OR TITLE-ABS-KEY ("Educat* mark") OR TITLE-ABS-KEY ("Educat* outcome") OR TITLE-ABS-KEY ("Educat* perform") OR TITLE-ABS-KEY ("Educat* proficien") OR TITLE-ABS-KEY ("Educat* progress") OR TITLE-ABS-KEY ("Educat* result") OR TITLE-ABS-KEY ("Educat* scor") OR TITLE-ABS-KEY ("Educat* stand") OR TITLE-ABS-KEY ("Educat* success") OR TITLE-ABS-KEY ("Achiev* of learn") OR TITLE-ABS-KEY ("Attain* of learn") OR TITLE-ABS-KEY ("Grad* of learn") OR TITLE-ABS-KEY ("Outcome? of learn") OR TITLE-ABS-KEY ("Perform* of learn") OR TITLE-ABS-KEY ("Proficien* of learn") OR TITLE-ABS-KEY ("Progress* of learn") OR TITLE-ABS-KEY ("Result? of learn") OR TITLE-ABS-KEY ("Scor* of learn") OR TITLE-ABS-KEY ("Stand* of learn") OR TITLE-ABS-KEY ("Success of learn") OR TITLE-ABS-KEY ("Learning achiev") OR TITLE-ABS-KEY ("Learning attain") OR TITLE-ABS-KEY ("Learning grad") OR TITLE-ABS-KEY ("Learning mark") OR TITLE-ABS-KEY ("Learning outcome") OR TITLE-ABS-KEY ("Learning

Table 2 (continued)

Step	Search
	perform") OR TITLE-ABS-KEY ("Learning proficien") OR TITLE-ABS-KEY ("Learning progress") OR TITLE-ABS-KEY ("Learning result") OR TITLE-ABS-KEY ("Learning scor") OR TITLE-ABS-KEY ("Learning stand") OR TITLE-ABS-KEY ("Learning success") OR TITLE-ABS-KEY ("Scho* achiev") OR TITLE-ABS-KEY ("Scho* attain") OR TITLE-ABS-KEY ("Scho* grad") OR TITLE-ABS-KEY ("Scho* mark") OR TITLE-ABS-KEY ("Scho* outcome") OR TITLE-ABS-KEY ("Scho* perform") OR TITLE-ABS-KEY ("Scho* proficien") OR TITLE-ABS-KEY ("Scho* progress") OR TITLE-ABS-KEY ("Scho* result") OR TITLE-ABS-KEY ("Scho* scor") OR TITLE-ABS-KEY ("Scho* stand") OR TITLE-ABS-KEY ("Scho* success") OR TITLE-ABS-KEY ("Student? achiev") OR TITLE-ABS-KEY ("Student? attain") OR TITLE-ABS-KEY ("Student? grad") OR TITLE-ABS-KEY ("Student? mark") OR TITLE-ABS-KEY ("Student? outcome") OR TITLE-ABS-KEY ("Student? perform") OR TITLE-ABS-KEY ("Student? proficien") OR TITLE-ABS-KEY ("Student? progress") OR TITLE-ABS-KEY ("Student? result") OR TITLE-ABS-KEY ("Student? scor") OR TITLE-ABS-KEY ("Student? stand") OR TITLE-ABS-KEY ("Student? success") OR TITLE-ABS-KEY ("Achiev* of student") OR TITLE-ABS-KEY ("Attain* of student") OR TITLE-ABS-KEY ("Grad* of student") OR TITLE-ABS-KEY ("Mark? of student") OR TITLE-ABS-KEY ("Outcome? of student") OR TITLE-ABS-KEY ("Perform* of student") OR TITLE-ABS-KEY ("Proficien* of student") OR TITLE-ABS-KEY ("Progress* of student") OR TITLE-ABS-KEY ("Result? of student") OR TITLE-ABS-KEY ("Scor* of student") OR TITLE-ABS-KEY ("Stand* of student") OR TITLE-ABS-KEY ("Success of student") OR TITLE-ABS-KEY ("Achiev* of scholar") OR TITLE-ABS-KEY ("Outcome? of scholar") OR TITLE-ABS-KEY ("Perform* of scholar") OR TITLE-ABS-KEY ("Progress* of scholar") OR TITLE-ABS-KEY ("Result? of scholar") OR TITLE-ABS-KEY ("Scor* of scholar") OR TITLE-ABS-KEY ("Stand* of scholar") OR TITLE-ABS-KEY ("Success of scholar") OR TITLE-ABS-KEY (Abilit*) OR TITLE-ABS-KEY (Aptitude*) OR TITLE-ABS-KEY (Capabilit*) OR TITLE-ABS-KEY (Capacit*) OR TITLE-ABS-KEY (Competenc*) OR TITLE-ABS-KEY (Expertise) OR TITLE-ABS-KEY (Learn*) OR TITLE-ABS-KEY (Mastery) OR TITLE-ABS-KEY (Proficien*) OR TITLE-ABS-KEY (Perform*) OR TITLE-ABS-KEY ("Academic abilit") OR TITLE-ABS-KEY ("Educational level") OR TITLE-ABS-KEY ("Knowledge level") OR TITLE-ABS-KEY ("Outcome? of education") OR TITLE-ABS-KEY ("Instructional outcome") OR TITLE-ABS-KEY ("Learner outcome") OR TITLE-ABS-KEY ("Result? of Education") OR TITLE-ABS-KEY ("Gradepoint average") OR TITLE-ABS-KEY ("Student? learning outcome?"))
#4	((TITLE-ABS-KEY ("Higher Education") OR TITLE-ABS-KEY ("Post secondary") OR TITLE-ABS-KEY ("Postsecondary") OR TITLE-ABS-KEY ("Postsecondary education") OR TITLE-ABS-KEY ("Post secondary education") OR TITLE-ABS-KEY ("Tertiary education") OR TITLE-ABS-KEY ("Third level education") OR TITLE-ABS-KEY (Bachelor*) OR TITLE-ABS-KEY ("College") OR TITLE-ABS-KEY (Graduat*) OR TITLE-ABS-KEY (Undergraduat*) OR TITLE-ABS-KEY ("Undergraduat* student") OR TITLE-ABS-KEY (Universit*) OR TITLE-ABS-KEY (postgraduat*) OR TITLE-ABS-KEY ("Advanced education") OR TITLE-ABS-KEY ("Graduat* student") OR TITLE-ABS-KEY ("Post high school education") OR TITLE-ABS-KEY ("Postsecondary instructional level") OR TITLE-ABS-KEY ("College student") OR TITLE-ABS-KEY ("Educational degree") OR TITLE-ABS-KEY ("Undergraduate education") OR TITLE-ABS-KEY ("Postgraduat* student?")))
#5	#1 AND #2
#6	#5 AND #3
#7	#6 AND #4
#8	FILTER: Publication Year (2000–2024)
#9	FILTER: Language (English or Spanish)

Note. #1 = descriptors regarding Learning Analytics; #2 = descriptors regarding study type; #3 = descriptors regarding academic performance; #4 = descriptors regarding higher education.

and relevance, and carefully considering the thesaurus descriptors, truncations and use of Boolean operators, both within and between descriptor blocks, as well as the appropriateness of the preliminary retrieval of records. Consequently, they suggested removing certain descriptors from the first block ("Information retrieval", and "Information extraction") and the second block (including "Evidence map", and "Thorough review") due to their ambiguity and broadness (or sensitivity). These suggestions were accepted, and the proposed changes were implemented consistently across the databases.

2.4. Study selection and screening

Initially, all the retrieved records will be imported into the

bibliographic reference manager Zotero, version 7.0.8, and any duplicate entries will be eliminated. References will also be exported into a Microsoft Excel spreadsheet in order to manually check for any remaining duplicates. Subsequently, two reviewers (FGG & MIGN) will independently assess the titles and abstracts of all non-duplicate records to determine their eligibility based on the established inclusion and exclusion criteria. Studies will proceed to full-text reviews if any of the following conditions are met: a) both reviewers consider the study to be eligible; b) one reviewer is uncertain about the study's eligibility, and a full-text review for clarification is required; or c) there is any disagreement between the reviewers, therefore necessitating further review. Cohen's kappa coefficient, along with the respective 95 % confidence intervals, will be calculated in order to assess the agreement between the two researchers for each document, with a score of between 0.70 and 1 to be considered acceptable (Landis & Koch, 1977). For this study protocol, the screening process, based on title and abstract, was piloted on the first 100 results from the search of the Scopus and Eric databases, and yielded a kappa coefficient of 0.85 (95 % CI: 0.78, 0.93).

Furthermore, full-text screening will be independently verified by two reviewers (FGG & MIGN). Any disagreements arising during the process will be resolved through consensus and, when necessary, by involving a third reviewer in the final decision (CME). All inclusion or exclusion decisions based on the full-text screening will be duly documented and reported. Inter-rater reliability testing using kappa statistics will again be used following the aforementioned criteria. As an empirical pilot test, 35 records were assessed based on their full texts against the inclusion criteria, yielding a mean kappa statistic of 0.75 (95 % CI: 0.59, 0.90) between the screeners.

In cases in which primary studies are found to be common between multiple systematic reviews, all the relevant systematic reviews will be included a priori in the meta-review. Reviews with a substantial overlap will undergo further examination and may be excluded if deemed necessary, depending on the research questions and outcomes extracted. To precisely illustrate the degree of overlap of included reviews, a citation matrix will be presented, showing the percentage of primary studies shared. This data will aid the interpretation of the results in terms of validity.

The search and screening process results will be reported in a PRISMA flow diagram (Page et al., 2021).

2.5. Quality assessment

Both the quality of reporting and methodological quality of the included systematic reviews will be assessed, the reporting quality using the PRISMA reporting guidelines (Page et al., 2021), and the methodological quality using an adapted version of the AMSTAR 2 critical appraisal tool (Lu et al., 2020; Perry et al., 2021; Shea et al., 2017), which has been chosen for its suitability for evaluating systematic reviews. Each study will be independently appraised by two reviewers (CME & MIGN), and, in cases in which a consensus cannot be reached, a third reviewer will be consulted to resolve disagreements (FGG). The agreement in the data extraction between the two investigators will be assessed using kappa statistics, according to the cut-off points previously indicated.

While reporting quality will be considered an inclusion criterion (based on the indicated guidelines), methodological quality will not be used as such. The findings regarding both the reporting quality and the methodological quality of the included systematic reviews will serve as key outcomes of the meta-review. These results are expected to offer valuable insights into the limitations of the studies, to help identify areas for improvement in future research, and to contextualize conclusions.

2.6. Data extraction

Data will be extracted from the included studies using a predefined coding protocol (see Supplementary File 1 for the full coding protocol).

Two authors will code the data separately (FGG & CME), and any discrepancies between the coders will be resolved through consensus, or, when necessary, by a third party (MIGN). A data coding form was pilot-tested in two rounds to minimize future potential errors and enhance reliability. In the first round, the coders tested the coding protocol using two studies, and achieved an acceptable inter-coder agreement of 0.68, indicating that the coding process was reliable but could be refined with certain nuances in order to improve consistency. Adjustments were therefore made, primarily to the textual (or narrative) coding fields, in order to resolve ambiguities in the interpretation. This included refining descriptions and adding clearer examples in the coding protocol for elements such as pedagogical objectives, learning phases, practical implications, and knowledge gaps. In the second round, the revised coding protocol was tested with two further studies, yielding a satisfactory inter-coder agreement of 0.77. The coding protocol remains open to the incorporation of additional fields that may emerge as relevant to the meta-review study.

2.7. Outcomes of interest

The planned meta-review will provide a deeper understanding of the current state of LA applications in higher education. To achieve this, descriptions of the bibliographic data extracted from the included systematic reviews will first be provided (e.g., publication year, authors' affiliations and knowledge areas, document types). Additionally, the results of the meta-review study will be useful for characterizing the analyzed systematic reviews (e.g., by review type, research objectives or questions, reporting quality, methodological quality). Furthermore, the meta-review study will examine the contexts in which LA has been applied, such as the higher education level (e.g., undergraduate, graduate), knowledge areas (e.g., education, medicine, economics, information technology), and settings (e.g., online, blended or face-to-face learning).

Secondly, the way LA has been applied in the reference environments will be detailed and examined, such as connections between applied LA procedures and underlying educational theories, pedagogical objectives (e.g., predicting, assessing, giving feedback), stages in the learning process in which LA has been applied (e.g., curricular design, planning, final learning phases), data gathering methods (e.g., e-learning system logs, surveys), data type (e.g., interaction data, performance data), statistical analyses (e.g., self-organizing maps, social network analysis), input (e.g., grades, access to quizzes) and output variables (e.g., course completion rates, drop-out rates), and beneficiaries (e.g., teachers, PhD students, administrators). In addition, the effectiveness of LA applications in influencing academic performance outcomes will also be explored, focusing on how such applications contribute to measurable improvements in learning achievements.

Finally, thematic coding will facilitate the identification of benefits, opportunities, limitations, knowledge gaps and challenges associated with the LA applications in the study of academic performance in higher education. Information will be provided on initiatives developed and promoted in reference contexts, detailing successful methods, innovations, needs and identified phenomena pending research.

2.8. Data synthesis

Due to the expected heterogeneity in LA applications in the study of academic performance in higher education, the data extracted from the selected systematic reviews will be synthesized narratively and organized into tables where appropriate. The narrative synthesis will address the meta-review's research objectives and questions, structuring the information according to aforementioned substantive and methodological considerations. Additionally, recommendations will be made regarding substantive, methodological, practical and research implications. As the data presentation is an iterative process shaped by the findings, the methods of presentation may naturally be refined during

the review stage in order to better reflect the contents of the results.

2.9. Ethics and dissemination

There are no data currently available for this paper as it is a protocol; however, all data and supplementary materials will be made available in an open repository on the Open Science Framework at the time of publication. Additionally, the intention of the authors is to publish the meta-review database in institutional repositories in order to ensure widespread access to the results. Finally, it is planned that the findings will be disseminated via reputable academic journals, and presented at various conferences, and accessible summaries will be created specifically for researchers and educators in the field of LA.

Ethics approval

Not required.

CRediT authorship contribution statement

Cristian Molla-Esparza: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft. **María Isabel Gómez-Núñez:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft. **Fran J. García-García:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This work was supported by the Government of Valencia, Spain (under grant number CIGE/2023/53), and the Spanish Ministry of Science, Innovation and Universities (under grant number PID2022-141403NB-I00, with MCIN/AEI/10.13039/501100011033/FEDER-EU funding).

Acknowledgements

We would like to express our gratitude to Eva Montilla Navas, staff member at the "Joan Reglà" Humanities Library, and Dr. Laura Badenes Ribera, professor in the Department of Methodology for Behavioral Sciences at the University of Valencia and expert in synthesis studies, for their valuable collaboration in the validation of the search strategy.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.ijedro.2024.100433](https://doi.org/10.1016/j.ijedro.2024.100433).

Data availability

Data will be available in a public, open access repository

References

Alnasyan, B., Bashari, M., & Alassafi, M. (2024). The power of deep learning techniques for predicting student performance in virtual learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence*, 6, Article 10023. <https://doi.org/10.1016/j.caeai.2024.100231>

- Aromataris, E., Fernandez, R., Godfrey, C. M., Holly, C., Khalil, H., & Tungpunkom, P. (2015). Summarizing systematic reviews: Methodological development, conduct and reporting of an umbrella review approach. *International Journal of Evidence-Based Healthcare*, 13(3), 132–140. <https://doi.org/10.1097/XEB.0000000000000055>
- Banihashem, S. K., Noroozi, O., van Ginkel, S., Macfadyen, L. P., & Biemans, H. J. A. (2022). A systematic review of the role of learning analytics in enhancing feedback practices in higher education. *Educational Research Review*, 37, Article 100489. <https://doi.org/10.1016/j.edurev.2022.100489>
- Chaka, C. (2022). Educational data mining, student academic performance prediction, prediction methods, algorithms and tools: An overview of reviews. *Journal of E-Learning and Knowledge Society*, 18(2), 58–69. <https://doi.org/10.20368/1971-8829/1135578>
- Dol, S. M., & Jawandhiya, P. M. (2024). Systematic review and analysis of EDM for predicting the academic performance of students. *Journal of The Institution of Engineers (India): Series B*, 105, 1021–1071. <https://doi.org/10.1007/s40031-024-00998-0>
- Du, X., Yang, J., Shelton, B. E., Hung, J. L., & Zhang, M. (2021). A systematic meta-Review and analysis of learning analytics research. *Behaviour & Information Technology*, 40(1), 49–62. <https://doi.org/10.1080/0144929X.2019.1669712>
- Du, X., Yang, J., Zhang, M., Hung, J. L., & Shelton, B. E. (2019). Learning analytics research: Using meta-review to inform meta-synthesis. In K. Arai, R. Bhatia, & S. Kapoor (Eds.), *Proceedings of the Future Technologies Conference (FCT)* 2018 (pp. 1097–1108). Springer. https://doi.org/10.1007/978-3-030-02686-8_81
- Ganesh Iyer, S., & Bennet, S. (2022). Learning analytics in higher education: Perspectives, practices and challenges. *SSRN Electronic Journal*, 1–8. <https://doi.org/10.2139/ssrn.4700535>
- Gašević, D., Kovanović, V., & Joksimović, S. (2017). Piecing the learning analytics puzzle: A consolidated model of a field of research and practice. *Learning: Research and Practice*, 3(1), 63–78. <https://doi.org/10.1080/23735082.2017.1286142>
- Gates, M., Gates, A., Pieper, D., Fernandes, R. M., Tricco, A. C., Moher, D., et al. (2022). Reporting guideline for overviews of reviews of healthcare interventions: Development of the PRIOR statement. *BMJ*, Article e070849. <https://doi.org/10.1136/bmj-2022-070849>
- Haleem, A., Javaid, M., Qadri, M. A., & Suman, R. (2022). Understanding the role of digital technologies in education: A review. *Sustainable Operations and Computers*, 3, 275–285. <https://doi.org/10.1016/j.susoc.2022.05.004>
- Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development*, 68(4), 1961–1990. <https://doi.org/10.1007/s11423-020-09788-z>
- Lang, C., Siemens, G., Wise, A. F., Gašević, D., & Mercer, A. (Eds.). (2022). *The Handbook of learning analytics*. SoLAR. <https://doi.org/10.18608/hla22>
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33(1), 159–174. <https://doi.org/10.2307/2529310>
- Larrabee Sønderlund, A., Hughes, E., & Smith, J. (2019). The efficacy of learning analytics interventions in higher education: A systematic review. *British Journal of Educational Technology*, 50(5), 2594–2618. <https://doi.org/10.1111/bjet.12720>
- Leitner, P., Khalil, M., & Ebner, M. (2017). Learning analytics in higher education: A literature review. In A. Peña-Ayala (Ed.), *Learning analytics: Fundamentals, applications, and trends* (pp. 1–23). Springer. https://doi.org/10.1007/978-3-319-52977-6_1
- Llopis-Albert, C., & Rubio, F. (2021). Application of learning analytics to improve higher education. *Multidisciplinary Journal for Education, Social and Technological Sciences*, 8(2), 1–18. <https://doi.org/10.4995/muse.2021.16287>
- Long, P., Siemens, G., Conole, G., & Gašević, D. (2011). LAK 2011: 1st International conference on learning analytics and knowledge. Association for Computing Machinery. <https://doi.org/10.1145/2090116>
- Lu, C., Lu, T., Ge, L., Yang, N., Yan, P., & Yang, K. (2020). Use of AMSTAR-2 in the methodological assessment of systematic reviews: Protocol for a methodological study. *Annals of Translational Medicine*, 8(10), Article 652. <https://doi.org/10.21037/atm-20-392a>
- Mhlanga, D. (2024). Digital transformation of education, the limitations and prospects of introducing the fourth industrial revolution asynchronous online learning in emerging markets. *Discover Education*, 3(1), 32. <https://doi.org/10.1007/s44217-024-00115-9>
- Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., ... Prisma-P Group, D. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews*, 4, 1. <https://doi.org/10.1186/2046-4053-4-1>
- Namoun, A., & Alshantiti, A. (2020). Predicting student performance using data mining and learning analytics techniques: A systematic literature review. *Applied Sciences*, 11(1), 237. <https://doi.org/10.3390/app11010237>
- Ouyang, F., Xu, W., & Cukurova, M. (2023). An artificial intelligence-driven learning analytics method to examine the collaborative problem-solving process from the complex adaptive systems perspective. *International Journal of Computer-Supported Collaborative Learning*, 18(1), 39–66. <https://doi.org/10.1007/s11412-023-09387-z>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ (Clinical research ed.)*, 372, 71. <https://doi.org/10.1136/bmj.n71>
- Pan, Z., Biegley, L., Taylor, A., & Zheng, H. (2024). A systematic review of learning analytics. *Journal of Learning Analytics*, 11(2), 52–72. <https://doi.org/10.18608/jla.2023.8093>
- Paolucci, C., Vancini, S., Bex II, R. T., Cavanaugh, C., Salama, C., & de Araujo, Z. (2024). A review of learning analytics opportunities and challenges for K-12 education. *Heliyon*, 10(4), e25767. <https://doi.org/10.1016/j.heliyon.2024.e25767>

- Perry, R., Whitmarsh, A., Leach, V., & Davies, P. (2021). A comparison of two assessment tools used in overviews of systematic reviews: ROBIS versus AMSTAR-2. *Systematic Reviews*, 10, 273. <https://doi.org/10.1186/s13643-021-01819-x>
- Peters, M. D. J., Godfrey, C. M., Khalil, H., McInerney, P., Parker, D., & Soares, C. B. (2015). Guidance for conducting systematic scoping reviews. *International Journal of Evidence-Based Healthcare*, 13(3), 141–146. <https://doi.org/10.1097/XEB.0000000000000050>
- Pollock, M., Fernandes, R. M., Pieper, D., Tricco, A. C., Gates, M., Gates, A., & Hartling, L. (2019). Preferred reporting items for overviews of reviews (PRIOR): A protocol for development of a reporting guideline for overviews of reviews of healthcare interventions. *Systematic Reviews*, 8, 335. <https://doi.org/10.1186/s13643-019-1252-9>
- Rahul, & Katarya, R. (2023). A systematic review on predicting the performance of students in higher education in offline mode using machine learning techniques. *Wireless Personal Communications*, 133(3), 1643–1674. <https://doi.org/10.1007/s11277-023-10838-x>
- Reimann, P. (2016). Connecting learning analytics with learning research: The role of design-based research. *Learning: Research And Practice*, 2(2), 130–142. <https://doi.org/10.1080/23735082.2016.1210198>
- Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., & Koffel, J. B. (2021). PRISMA-S: An extension to the PRISMA statement for reporting literature searches in systematic reviews. *Systematic Reviews*, 10, 39. <https://doi.org/10.1186/s13643-020-01542-z>
- Shea, B. J., Reeves, B. C., Wells, G., Thuku, M., Hamel, C., Moran, J., ... Henry, D. A. (2017). AMSTAR 2: a critical appraisal tool for systematic reviews that include randomised or non-randomised studies of healthcare interventions, or both. *BMJ*, 358, Article j4008. <https://doi.org/10.1136/bmj.j4008>
- Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, 57(10), 1380–1400. <https://doi.org/10.1177/0002764213498851>
- Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., ... Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine*, 169(7), 467–473. <https://doi.org/10.7326/M18-0850>
- Utamachant, P., Anutariya, C., & Pongnumkul, S. (2023). i-Ntervene: Applying an evidence-based learning analytics intervention to support computer programming instruction. *Smart Learning Environments*, 10, 37. <https://doi.org/10.1186/s40561-023-00257-7>
- Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, 89, 98–110. <https://doi.org/10.1016/j.chb.2018.07.027>
- Yan, L., Echeverria, V., Jin, Y., Fernandez-Nieto, G., Zhao, L., Li, X., et al. (2024). Evidence-based multimodal learning analytics for feedback and reflection in collaborative learning. *British Journal of Educational Technology*, 55(5), 1900–1925. <https://doi.org/10.1111/bjet.13498>