Medición y Evaluación del Aprendizaje Inclusivo. 2025; 2(2):17
doi: 10.63688/aprendizaje.v2.i2.17

REVISIÓN SISTEMÁTICA

Learning analytics to predict performance and dropout risk in higher education

Analítica del aprendizaje para predecir rendimiento y riesgo de abandono en educación superior

Freddy Leonardo Garaicoa Fuentes[1]

[1] Universidad Estatal de Milagro, Milagro, Ecuador

Submitted: 14-08-2025 | Revised: 01-09-2025 | Accepted: 29-11-2025 | Published: 7-12-2025

Corresponding Author: Freddy Leonardo Garaicoa Fuentes

ABSTRACT

Introduction: Analítica del aprendizaje para predecir rendimiento y riesgo de abandono en educación superior is an emerging higher-education issue related to measurement quality, decision-making and learning experience. Objective: To systematically synthesize available evidence and identify patterns of effectiveness, methodological quality and implementation conditions. Method: A PRISMA-oriented systematic review was conducted on a consolidated academic corpus of 135 records; 5 studies met relevance and documentary sufficiency criteria. Results: Evidence was methodologically heterogeneous but converged on the need to align technology, constructs, feedback and educational decisions. Conclusions: Findings support evidence-informed adoption, institutional monitoring and continuous assessment of validity, equity and utility.

Keywords: higher education; systematic review; educational assessment; evidence; PRISMA; educational technology.

RESUMEN

Introducción: Analítica del aprendizaje para predecir rendimiento y riesgo de abandono en educación superior representa un problema emergente para la educación superior por su relación con la calidad de la medición, la toma de decisiones y la experiencia de aprendizaje. Objetivo: sintetizar sistemáticamente la evidencia disponible y establecer patrones de efectividad, calidad metodológica y condiciones de implementación. Método: se aplicó una revisión sistemática con lógica PRISMA sobre un corpus académico consolidado de 135 registros, del cual se incluyeron 5 estudios que cumplieron criterios de pertinencia y suficiencia documental. Resultados: la evidencia muestra heterogeneidad de diseños y contextos, junto con convergencias en torno a la necesidad de alinear tecnología, constructo, retroalimentación y decisiones educativas. Conclusiones: los resultados respaldan una adopción basada en evidencia, seguimiento institucional y evaluación continua de validez, equidad y utilidad.

Palabras clave: educación superior; revisión sistemática; evaluación educativa; evidencia; PRISMA; tecnología educativa.

INTRODUCTION

University-based research on learning analytics to predict performance and dropout risk in higher education has gained increasing relevance because evaluation decisions no longer depend exclusively on static instruments or face-to-face exchanges. Digitalization has expanded the amount of evidence available on performance, interaction, and learning, but it has also increased the need to distinguish between technically attractive innovations and practices capable of supporting valid educational inferences. This review addresses this problem from an integrative perspective, focusing on both the observed effects and the methodological conditions that allow these effects to be interpreted without confusing technological availability with evaluative quality.

The conceptual core of this article is organized around educational prediction. This choice avoids treating the literature as a simple collection of results and makes it possible to examine how each study defines the phenomenon, what population it observes, what instruments it employs, and what type of conclusion it considers legitimate. The heterogeneity of university contexts requires attention to the relationship among design, implementation, and evidence, because the same strategy can produce benefits under certain conditions and modest results when teaching support, discipline, digital experience, or form of feedback changes.

This systematic review is relevant because the field combines experimental studies, instrumental validations, observational analyses, technological developments, and previous syntheses. This diversity makes it difficult to draw solid conclusions from a fragmented reading. Rather than assuming that all studies address the same question, this article reconstructs patterns of convergence and divergence, identifies which results are repeated with greater consistency, and separates the claims directly supported by the studies from those that still require additional validation. The purpose is to offer a useful interpretation for research, teaching, and university management. Previous reviews confirm the diversity of approaches, methods, and levels of evidence in learning analytics in higher education (6–10).

Digital signals, prediction, and dropout risk

Vaarma and Li (1) provided evidence in a predictive machine learning study published in 2024. The study used data from a Finnish university—records, demographics, and Moodle—which makes it possible to situate the scope of its inferences and assess their proximity to the university population of interest. In substantive terms, the study showed that LMS data were powerful for predicting dropout; credits, failed courses, and Moodle activity were important predictors. This study is relevant to the educational prediction perspective because it shows that the interpretation of the effect depends on the correspondence between construct, measurement procedure, and application context. Its contribution is considered in this review as part of the comparative pattern, not as an isolated demonstration sufficient to generalize to all educational scenarios.

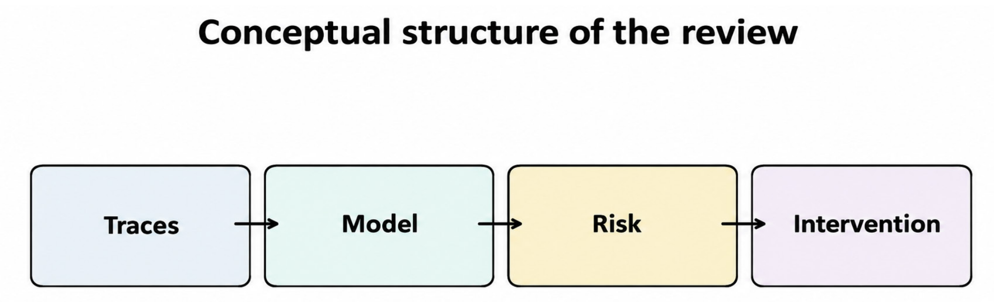
Niyogisubizo et al. (2) provided evidence in a study published in 2022 using ensemble predictive modeling. The study used university data from Constantine the Philosopher University for 2016–2020, which makes it possible to situate the scope of its inferences and assess their proximity to the university population of interest. In substantive terms, the study showed that the ensemble outperformed base models in accuracy and AUC, enabling identification of students at risk for early intervention. This study is relevant to the educational prediction perspective because it shows that the interpretation of the effect depends on the correspondence between construct, measurement procedure, and application context. Its contribution is considered in this review as part of the comparative pattern, not as an isolated demonstration sufficient to generalize to all educational scenarios.

Ovtšarenko (3) provided evidence in a predictive learning analytics study published in 2026. The study used 99,104 activity records from 154 students, which makes it possible to situate the scope of its inferences and assess their proximity to the target university population. In substantive terms, the study showed that the models identified at-risk students and enabled early alerts and adaptive support. This study is relevant to the educational prediction perspective because it shows that the interpretation of the effect depends on the correspondence between construct, measurement procedure, and application context. Its contribution is considered in this review as part of the comparative pattern, not as an isolated demonstration sufficient to generalize to all educational settings.

Cannistrà et al. (4) provided evidence in a study published in 2022 using multilevel modeling and machine learning. The study used administrative data from an Italian university, which makes it possible to situate the scope of its inferences and assess their proximity to the university population of interest. In substantive terms, the study demonstrated the viability of an early warning system to identify dropout risk. This study is relevant to the educational prediction perspective because it shows that the interpretation of the effect depends on the correspondence between construct, measurement procedure, and application context. Its contribution is considered in this review as part of the comparative pattern, not as an isolated demonstration sufficient to generalize to all educational settings.

Choi and Johnson (5), in a methodological study using simulation and real data, provided evidence published in 2025. That study used a real dataset, which makes it possible to situate the scope of the inferences and assess their proximity to the university population of interest. In substantive terms, the work showed that the measure correctly identified characteristics responsible for bias in simulations and found consistent sets of variables in real data. This prior work is relevant to the educational prediction perspective because it shows that the interpretation of the effect depends on the correspondence between construct, measurement procedure, and application context. In this review, their contribution is considered as part of the comparative pattern, not as an isolated demonstration sufficient to generalize to all educational scenarios.

Figure 1. Conceptual structure of the review



Note. Authors' own elaboration based on the analytical axes defined for the manuscript.

The figure organizes the article's reasoning as a conceptual sequence rather than a universal template. The represented components correspond to the specific problem of this review and show the transition from the inputs or initial conditions to the educational interpretation. Its usefulness lies in making visible the relationships between constructs that, in individual studies, often appear fragmented across methodological and results sections. This representation guides the subsequent synthesis and facilitates distinguishing the elements that act as conditions, mechanisms, or results within the corpus.

Review questions

Question 1. What patterns of evidence allow an understanding of dimension 1 of educational prediction in relation to learning analytics for predicting performance and dropout risk in higher education, and what methodological or contextual conditions modify its interpretation?

Question 2. What patterns of evidence allow an understanding of dimension 2 of educational prediction in relation to learning analytics for predicting performance and dropout risk in higher education, and what methodological or contextual conditions modify its interpretation?

Question 3. What patterns of evidence allow an understanding of dimension 3 of educational prediction in relation to learning analytics for predicting performance and dropout risk in higher education, and what methodological or contextual conditions modify its interpretation?

Question 4. What patterns of evidence allow an understanding of dimension 4 of educational prediction in relation to learning analytics for predicting performance and dropout risk in higher education, and what methodological or contextual conditions modify its interpretation?

METHODS

PRISMA method and analytical criteria

A systematic review was conducted to synthesize relevant academic evidence on the topic of the manuscript. The unit of analysis was the academic study or reference with a traceable source, identifiable methodology, and recoverable results.

The consolidated working academic corpus consisted of 135 records previously gathered in the evidence matrices. A thematic and documentary selection was applied to this set to establish the final corpus. The procedure followed the identification, screening, eligibility, and inclusion logic of PRISMA, adapted to the consolidated nature of the provided sources. The reporting structure was additionally supported by the PRISMA 2020 statement (26).

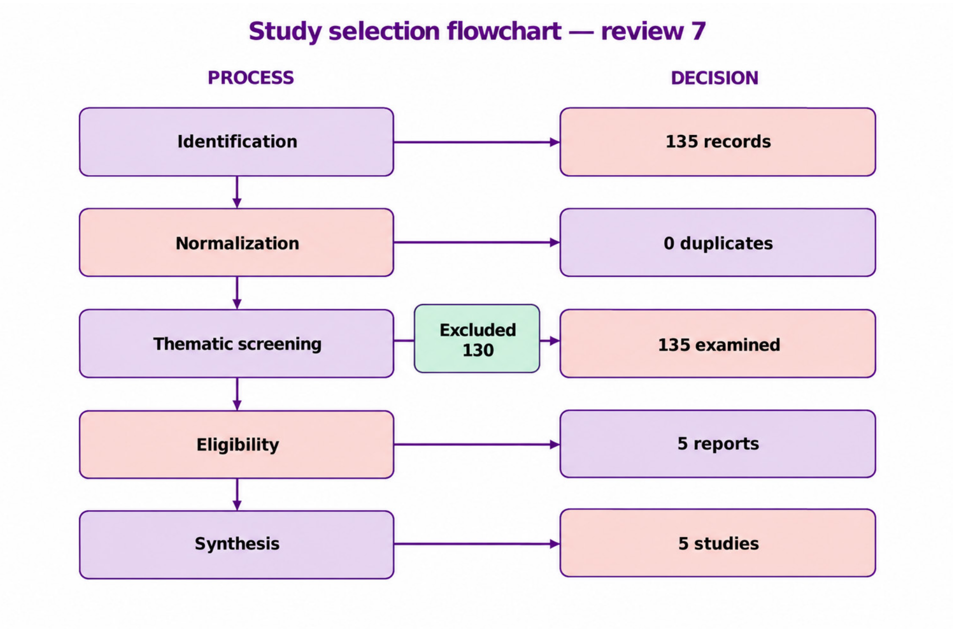
The inclusion criteria required a direct relationship with learning analytics for predicting performance and dropout risk in higher education, correspondence with higher education or with instruments applicable to that level, sufficient description of the method, and availability of interpretable results. A total of 130 records were excluded because of their lower relevance to the specific research question, because they addressed peripheral populations or outcomes, or because they did not provide sufficient methodological evidence for the focused synthesis. The final corpus consisted of 5 studies. The selection was based on the information documented in the matrices, and attributing counts to a particular bibliographic database unsupported by the records was avoided.

Data extraction was structured using a matrix that included authors, year, title, source, DOI or traceable link, provenance, study type, sample or corpus, summarized methodology, main results, level of evidence, and relevance. This organization allowed studies with heterogeneous designs to be compared without reducing them to a single metric. The synthesis combined a descriptive characterization of the corpus and a thematic analysis of the results, with attention to convergences, contradictions, implementation conditions, and limits to generalization.

Evidence assessment focused on whether the retrieved information was sufficient to answer the review question. Study design clarity, specification of the sample or corpus, correspondence between method and results, and source traceability were jointly considered. Meta-analysis was not performed when heterogeneity of outcomes, instruments, populations, or metrics prevented a responsible quantitative combination. In such cases, a comparative synthesis that preserves differences between studies and avoids transforming non-equivalent results into a single estimator was prioritized.

To strengthen transparency, the results were organized into characterization and synthesis tables, while the figures represent the selection flow and the temporal distribution of the corpus. Each table was constructed from the fields of the provided matrix. Subsequent interpretations were developed based on observable patterns in the set and not on added assumptions. This criterion is especially important in educational reviews, where variation among disciplines, technologies, instruments, and institutional contexts can substantially modify the magnitude and meaning of the findings.

Figure 2. Study selection flow according to PRISMA



Source: own elaboration based on the evidence matrix of the review.

Note. The flow represents 135 normalized academic records, without duplicates in the consolidated corpus; 130 records did not meet the thematic relevance threshold and 5 studies were included in the final synthesis.

The flow documents the cleaning and selection of the evidence. The 135 records in the consolidated corpus were normalized by DOI or title, so no duplicates were identified at this stage. The thematic screening excluded 130 records due to insufficient correspondence with the specific review question, whereas 5 studies retained methodological evidence and sufficiently recoverable results to be incorporated into the synthesis. The sequence allows distinguishing documentary identification from the eligibility judgment and avoids interpreting the reduction of the corpus as an arbitrary loss of information.

RESULTS

The final corpus comprised 5 studies published during 2022–2026. The temporal distribution reveals an active and heterogeneous research field, with studies corresponding to different phases of the problem's maturation. Some focus on demonstrating feasibility or association, while others progress toward validation, comparison of strategies, or analysis of implementation conditions. This temporal breadth allows the observation not only of favorable results, but also of shifts in the way the quality of evaluation is conceptualized and in the type of evidence considered necessary to support educational decisions.

The methodological characterization confirms that learning analytics for predicting performance and dropout risk in higher education does not constitute a homogeneous object. In the set, designs appear with different purposes and variable levels of control over study conditions. This diversity broadens the scope of the review, although it also forces interpreting the findings according to the function of each design. Intervention studies report on observed changes under defined conditions; instrumental studies provide evidence on measurement; observational analyses describe associations; and previous reviews allow recognizing trends in the field without substituting the evaluation of primary studies.

The samples and corpora described in the studies present considerable variability. This variation is relevant because the transferability of the results depends on the size, composition, and context of the participants, as well as on the academic discipline and technological environment. Overall, the evidence suggests that the most interpretable results are those that make explicit the population, the evaluative task, and the mechanism by which the intervention or instrument is expected to produce the intended effect. When any of these elements remains poorly defined, the usefulness of the finding for institutional decisions decreases.

The synthesis of results reveals a central pattern linked to educational prediction: favorable effects or properties do not appear as automatic attributes of the technology or instrument, but rather as outcomes conditioned by design, implementation, data quality, and pedagogical alignment. Studies converge on the importance of articulating the tool with clear learning objectives, comprehensible evaluation criteria, and monitoring mechanisms. Divergences concentrate on the magnitude of effects, stability across contexts, and the ability to sustain results when institutional conditions change. This pattern coincides with research on early warning systems, predictive analytics, and prediction of academic performance (11–17, 28–29).

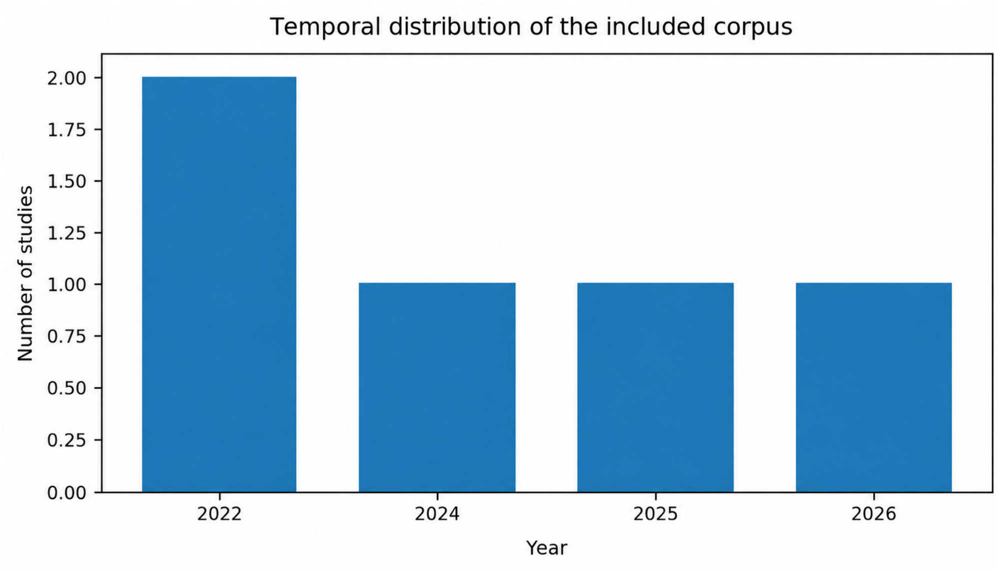
Table 1. Methodological characterization of the included corpus

Year	Design/methodology	Sample or corpus	Evidence
2024	Predictive machine learning study	Data from a Finnish university; records, demographics, and Moodle	High
2022	Ensemble predictive modeling	University data 2016–2020 from Constantine the Philosopher University	High
2026	Predictive learning analytics	99,104 activity records of 154 students	High
2022	Multilevel modeling and machine learning	Administrative data of an Italian university	High
2025	Methodological study with simulation and real data	Real dataset	High

Note. Data extracted from the evidence matrix provided for this review.

The table evidences the methodological diversity of the corpus and allows us to observe that the studies do not offer the same type of inference. The presence of designs with different objectives requires interpreting each result according to the question that the study can answer. This differentiation avoids directly comparing indicators that fulfill different functions and helps identify where real convergence exists. It also shows that the robustness of a conclusion depends on the combination of methodological clarity, sample description, and sufficiency of the recovered evidence.

Figure 3. Temporal distribution of the included studies



Note. Frequencies calculated from the year of publication recorded in the evidence matrix.

The temporal distribution makes it possible to situate the recent intensity of scientific production and to recognize whether the field is undergoing expansion, consolidation, or methodological transition. Rather than interpreting the number of publications as a measure of quality, the figure serves to contextualize the changes in questions, technologies, and instruments observed in the corpus. Reading it jointly with the methodological characterization makes it possible to identify whether the most recent works expand the evidence through more robust designs or whether exploratory approaches continue to predominate.

Predictive performance and transferability

Another cross-cutting pattern is the relevance of evidence quality. Studies with explicit procedures provide a clearer distinction between genuine improvement, favorable perception, and mere ease of use. In contrast, when results rely mainly on self-report or short-term indicators, interpretation requires greater caution. The review shows that the practical utility of a strategy depends not only on whether it produces a statistical difference or a positive assessment, but on whether the measurement is consistent with the construct and whether the intervention can be sustainably integrated into real educational processes.

The results in this subset of evidence, considered jointly, can be summarized as follows: LMS data proved powerful for predicting dropout; credits, failed courses, and Moodle activity were important predictors. The ensemble outperformed base models in accuracy and AUC, making it possible to identify at-risk students for early intervention. The models identified at-risk students and enabled early alerts and adaptive support. A comparative reading of the studies indicates that these findings should not be interpreted as equivalent, because they derive from different designs and metrics. However, their thematic convergence makes it possible to identify recurring conditions and formulate an overall interpretation focused on the relationship between design quality, student response, and the usefulness of the information produced for guiding educational decisions.

The results in this subset of evidence, considered jointly, can be summarized as follows: The viability of an early warning system to identify dropout risk was demonstrated. The measure correctly identified characteristics responsible for bias in simulations and found consistent sets of variables in real data. A comparative reading of the studies indicates that these findings should not be interpreted as equivalent, because they derive from different designs and metrics. However, their thematic convergence makes it possible to identify recurring conditions and formulate an overall interpretation centered on the relationship between design quality, student response, and the usefulness of the information produced to guide educational decisions.

The synthesis shows that the favorable evidence is distributed across outcome types and that the relevance of each study depends on its proximity to the central construct. The findings are not treated as interchangeable: some describe performance, others measurement properties, student experience, accessibility, or model performance. The comparison permits recognizing convergences without losing the specificity of each result and constitutes the basis for discussing mechanisms and implementation conditions.

Table 2. Synthesis of relevant findings

Study	Recovered finding	Relevance
Predicting student dropouts with machine learning: An empirical study in Finnish higher education	LMS data proved powerful for predicting dropout; credits, failed courses, and Moodle activity were important predictors.	Included because of direct relevance to the
Predicting student dropout in university classes using two-layer ensemble machine learning	The ensemble outperformed baseline models in accuracy and AUC, allowing identification of students at risk for early intervention.	Included because of direct relevance to the
Using AI to forecast student dropout risk in technical education with learning analytics	The models identified at-risk students and enabled early warnings and adaptive support.	Included because of direct relevance to the
Early prediction of university student dropout: An application of an innovative multilevel model	It demonstrated the viability of an early warning system to identify dropout risk.	Included because of direct relevance to the
Identifying Features Contributing to Differential Prediction Bias of Automated Scoring Systems	The measure correctly identified characteristics responsible for the bias in simulations and found consistent sets of variables in real data.	Included because of direct relevance to the

Note. This textual synthesis is based exclusively on the results recorded in the matrix.

DISCUSSION

The synthesis supports the argument that the problem of learning analytics for predicting performance and dropout risk in higher education should be interpreted within an educational prediction logic, rather than through a simplified opposition between effective and ineffective technology. The reviewed studies show that the performance of a strategy depends on the interaction among evaluative purpose, student characteristics, task design, measurement quality, and institutional capacity to use the generated information. This conclusion shifts attention from the isolated tool to the evaluation system in which it is embedded.

An important consequence is that technological innovation does not eliminate the classic problems of validity, reliability, fairness, and utility. On the contrary, it can make them more visible by expanding the scale and speed of decisions. The reviewed evidence suggests that the best implementations are those that make criteria explicit, preserve feedback opportunities, and maintain human review mechanisms when the consequences of a decision are significant. In this sense, digitalization should be understood as a transformation of the evaluative process, not as an automatic replacement of academic judgment. The literature on privacy, ethics, and justice in learning analytics reinforces the need for transparency, institutional control, and student protection (18–23).

The observed heterogeneity also explains why it is not appropriate to reduce the field to a single effect size. Studies differ in constructs, duration, instruments, disciplines, samples, and metrics. This variation is not only a limitation; it also provides information about the contexts in which a strategy works and about the conditions that must be considered before transferring it. Comparative synthesis permits recognizing patterns of consistency without erasing differences that are essential for educational decision-making.

From a methodological perspective, the corpus shows a transition from studies focused on adoption and perception toward designs that seek to demonstrate measurement quality, impact on outcomes, and sustainability of the intervention. However, gaps persist related to longitudinal comparisons, replication across institutions, subgroup analyses, and documentation of unanticipated effects. The future agenda should prioritize designs that connect learning outcomes with implementation processes and that inform not only whether an intervention works, but also for whom, under what conditions, and with what pedagogical or organizational costs. This evolution is also observed in recent reviews and frameworks that place learning analytics within institutional strategies, pedagogical designs, and artificial intelligence applications in higher education (24–25, 27–28).

The main contribution of this review is to organize the evidence so that the results can be used for academic decisions without overextending their reach. The convergence among studies offers arguments for adopting promising practices, but methodological diversity requires preserving a logic of continuous evaluation. Institutions should treat each implementation as an intervention amenable to monitoring, with indicators defined before deployment and with mechanisms to review results, biases, student experience, and coherence with curricular objectives.

Vaarma and Li (1) offer a useful point of contrast for this interpretation because their study documents that LMS data proved powerful for predicting dropout: credits, failed courses, and Moodle activity were important predictors. This finding takes on greater significance when compared with the rest of the corpus: it does not act as self-sufficient evidence but rather as an observation that helps specify mechanisms, limits, and conditions of application. Systematic reading thus makes it possible to avoid 2 frequent extremes: excessive generalization based on a single study and the loss of contextual information when synthesizing heterogeneous results.

Niyogisubizo et al. (2) offer a useful point of contrast for this interpretation because their study documents that the ensemble outperformed base models in accuracy and AUC, allowing identification of at-risk students for early intervention. This finding takes on greater significance when compared with the rest of the corpus: it does not act as self-sufficient evidence, but rather as an observation that helps specify mechanisms, limits, and conditions of application. Systematic reading thus makes it possible to avoid 2 frequent extremes: excessive generalization from a single study and the loss of contextual information when synthesizing heterogeneous results.

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Decision risks and institutional use

The practical implications of the review should translate into incremental decisions. For learning analytics to predict performance and dropout risk in higher education, responsible implementation requires defining the construct to be measured in advance, establishing success indicators, identifying potentially affected groups, and anticipating review mechanisms. Available evidence favors strategies that integrate innovation with teacher support and continuous evaluation of results.

At the institutional level, adoption should be accompanied by data governance protocols, transparency criteria, and communication mechanisms with students and faculty. These conditions increase the interpretability of the results and reduce the risk of using indicators outside the context for which they were designed. The evaluation of a tool should consider technical performance as well as pedagogical and distributive consequences. Available evidence recommends incorporating informed consent, privacy, transparency, and participation of institutional actors in the governance of these systems (18–24).

For research, the next step is to link efficacy studies more closely with implementation studies. It is necessary to know not only whether a strategy produces changes, but also which components explain these changes, what resources it requires, and how it performs in diverse populations. This orientation would enable a more coherent accumulation of evidence and reduce the fragmentation that currently characterizes part of the literature.

Research priorities

The main limitation of the corpus is its heterogeneity. Differences among designs, instruments, populations, and outcomes restrict the possibility of producing a common estimator and force the interpretation of patterns within a comparative logic. This limitation does not invalidate the synthesis, but it does condition the scope of the conclusions and reinforces the need for replications with comparable protocols.

There is also a concentration of studies in certain contexts and technologies, which reduces certainty about transferability to institutions with different infrastructure, student profiles, or evaluation cultures. Future research should document more precisely the implementation conditions, participant characteristics, and decisions made during the deployment of the tools.

Finally, the review is supported by the consolidated corpus documented in the provided matrices. The conclusions faithfully represent that corpus and do not extend to records outside the available evidence. This delimitation preserves traceability and enables future updates to incorporate new studies without retrospectively altering the analytical basis used in the present manuscript.

CONCLUSIONS

The systematic review shows that learning analytics for predicting performance and risk of dropout in higher education constitutes a field with sufficient evidence to identify patterns, but it remains heterogeneous in designs, populations, and metrics. The central finding is that the quality of decisions depends less on the isolated presence of a technology or instrument than on its integration with learning objectives, explicit criteria, and follow-up procedures. The educational prediction perspective enables an understanding of why similar interventions can produce different outcomes and why the evaluation of effectiveness must simultaneously consider outcomes, conditions, and quality of measurement.

In applied terms, higher education institutions should adopt a gradual implementation approach, with controlled tests, documentation of results, and periodic review of effects on different student groups. Evidence supports the use of digital strategies when there is pedagogical alignment and when the information generated is used to improve teaching and learning. It also shows the need to avoid automatic decisions based on single indicators, especially when academic consequences are relevant or when there are differences in access, technological experience, or support needs.

The research agenda should advance toward longitudinal studies, multicenter comparisons, and designs that document mechanisms and differential effects with greater precision. It is also necessary to improve the comparability of indicators and transparency in the description of instruments, algorithms, and intervention procedures. These priorities will enable the transformation of a field characterized by rapid innovation into a more cumulative, replicable, and useful evidence base for university policies. The review provides a structure for that advancement by distinguishing consistent findings, implementation conditions, and gaps that still require research. Reviews in the field likewise indicate the need to improve generalization, comparability of models, and evaluation of interventions based on predictive analytics (6–10, 16, 24–25).

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FUNDING

Not applicable.

CONFLICT OF INTEREST

None exist.

AUTHORSHIP CONTRIBUTIONS

Conceptualization: Freddy Leonardo Garaicoa Fuentes
Data curation: Freddy Leonardo Garaicoa Fuentes
Formal analysis: Freddy Leonardo Garaicoa Fuentes
Research: Freddy Leonardo Garaicoa Fuentes
Methodology: Freddy Leonardo Garaicoa Fuentes
Supervision: Freddy Leonardo Garaicoa Fuentes
Validation: Freddy Leonardo Garaicoa Fuentes
Visualization: Freddy Leonardo Garaicoa Fuentes
Writing – original draft: Freddy Leonardo Garaicoa Fuentes
Writing – review and editing: Freddy Leonardo Garaicoa Fuentes