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EXPLORING THE EFFECTIVENESS OF MACHINE LEARNING-BASED EARLY WARNING SYSTEMS IN EDUCATION: A SCOPING REVIEW

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ABSTRACT

Early Warning Systems (EWS) and learning analytics have become key tools in education for identifying and supporting students at risk of academic failure or dropout. This scoping review synthesises current evidence on the effectiveness and implementation of academic EWS across school and higher education settings. Guided by the PRISMA-ScR framework, searches of Google Scholar, ERIC, SAGE, and Frontiers databases yielded 26 studies, with 20 meeting the inclusion criteria. Data were charted according to context, methodology, system characteristics, and outcomes. Thematic analysis identified five major themes: advancements in predictive analytics, increasing reliance on learning analytics for real-time monitoring, incorporation of multidimensional risk indicators, the critical role of timely and sustained intervention, and the importance of institutional readiness and staff capacity. Overall, findings show that machine learning–driven EWS can predict academic risk with high accuracy; however, their success depends on how effectively institutions act on predictions. Rapid intervention, educator engagement, and coherent institutional processes were consistently linked to positive outcomes, whereas ethical considerations remain essential to responsible implementation. The review highlights the promise of EWS while underscoring the need for integrated, well-supported intervention ecosystems.

Keywords: *Early warning systems, learning analytics, machine learning, academic risk, student intervention, retention, predictive analytics.*

INTRODUCTION

Background

The increasing complexity of educational environments has intensified the need for early and accurate identification of students at risk of academic failure or disengagement. Traditional monitoring approaches such as teacher referral, manual grade reviews, or end-of-term assessments often detect academic issues too late for meaningful intervention (Bowers & Zhou, 2019). In response, educational institutions worldwide have turned to Early Warning Systems (EWS) and learning analytics-based intervention models to improve detection precision and

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support timely intervention. These systems leverage student data which includes academic performance, attendance, behavioural patterns, socio-emotional indicators, and digital engagement metrics, to predict risk and trigger support mechanisms.

Advances in machine learning and artificial intelligence have further accelerated the development of highly accurate predictive models capable of analysing large, multidimensional datasets (Cao & Mai, 2025; Stark, 2024). Empirical studies demonstrate that machine learning-based EWS can achieve prediction accuracies between 85% and 99%, significantly outperforming traditional linear models or single-indicator approaches (Alsariera et al., 2022; Bai & Cai, 2018). Meanwhile, learning analytics systems extract behavioural data from digital platforms to offer real-time, course-level insights that allow educators to respond proactively to academic risk (Macfadyen & Dawson, 2010; Okubo et al., 2017).

Parallel to technological advancements, research increasingly highlights the importance of multi-dimensional risk factors, including socio-economic conditions, family environments, and relational dynamics, in predicting dropout or academic struggle (Korkmaz & Aydin, 2025; Vasconcelos et al., 2023). As a result, contemporary EWS models increasingly integrate holistic indicators to capture the complexity of student experiences.

Despite rapid progress in the field, there remains substantial variability in system design, implementation quality, and intervention effectiveness across contexts. Questions persist regarding how effectively these systems support actionable intervention, how educators interpret and use predictive outputs, and what conditions enable successful implementation.

This scoping review synthesises existing research to map the landscape of machine learning-based and learning analytics-driven early warning systems and to understand their effectiveness in facilitating academic intervention across school and higher education settings.

Research Objective

The objective of this scoping review is to explore and synthesise current evidence on the effectiveness, implementation, and impact of academic early warning systems, particularly those using machine learning, AI, and learning analytics, in predicting academic risk and supporting intervention for students in schools and higher education institutions.

Research Questions

This scoping review was done in order to answer the following questions:

1. How effective are academic early warning systems in providing intervention for students in schools and higher educational institutions?

2. What factors strongly influence use, interpretation and trust of machine learning-based early warning systems?

3. How can multidimensional student data be integrated into early warning systems to enhance predictive accuracy?

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METHODOLOGY

As shown in Figure 1, this scoping review followed the PRISMA-ScR (Tricco et al., 2018) guidelines and adopted the methodological framework proposed by Arksey and O'Malley (2005), further refined by Levac et al. (2010). Stages of the review process consisted of identifying the research question, identifying relevant studies, selecting the studies, charting the data and finally collating, summarising and reporting the results.

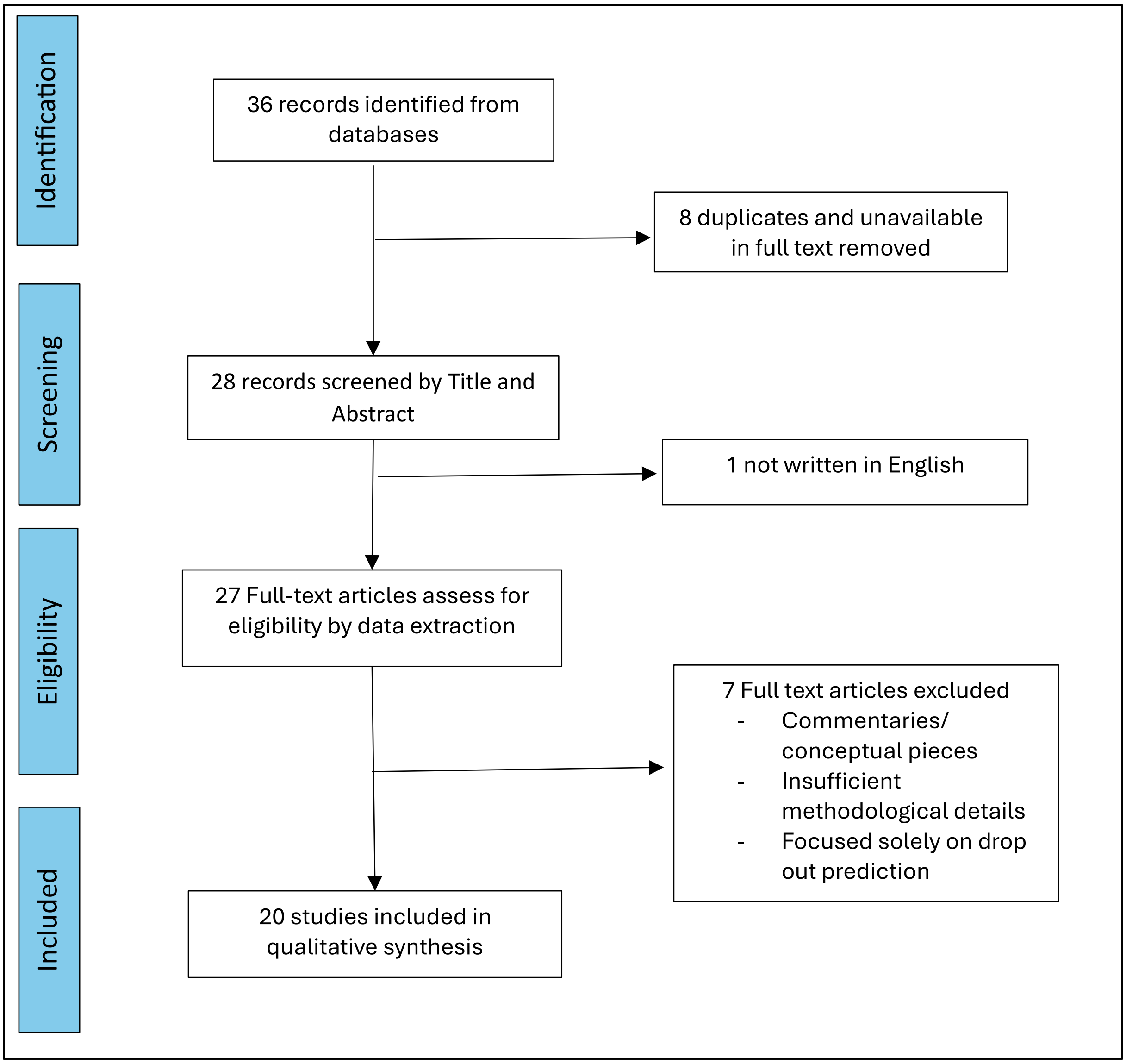

Figure 1: PRISMA Flow Diagram

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Search Strategy

A comprehensive literature search was conducted across Google Scholar, ERIC (Education Resources Information Center), SAGE Journals and the Frontiers journal database. The following Boolean search string was used:

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("early warning system*" OR "early alert system*" OR "predictive analytic*"
OR "learning analytic*" OR "academic risk" OR "student success prediction"
OR "dropout prevention" OR "at-risk student*" OR "student intervention")
AND ("school*" OR "higher education" OR "university" OR "college")
AND ("academic performance" OR "student retention" OR "student success")
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The search included peer-reviewed journal articles, conference papers and doctoral dissertations published between 2010 and 2025. Only studies written in English were considered.

Inclusion and Exclusion Criteria

Studies were included if they:

a) Examined academic early warning systems (EWS), early alert systems, or learning analytics-based intervention systems used to identify and support at-risk students

b) Reported empirical data, including quantitative, qualitative or mixed-method designs

c) Were conducted in school or higher education contexts

d) Addressed academic monitoring, prediction or intervention as part of student success or retention efforts

Studies were excluded if they:

a) Were written in languages other than English

b) Were duplicate publications or unavailable in full text

c) Were commentaries, conceptual papers or policy briefs without empirical evidence

d) Focused exclusively on dropout prediction without any monitoring or intervention component

Study Selection

The database search initially generated several thousand records. After applying inclusion and exclusion criteria and screening by titles and abstracts, 36 full-text articles were retrieved for detailed review.

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Of these,

a) n = 1 was written in a language other than English

b) n = 8 were duplicates or unavailable in full text

c) n = 3 were commentaries or conceptual pieces with insufficient methodological detail

d) n = 4 focused solely on dropout prediction without intervention mechanisms

Ultimately, 20 studies were included in the final analysis. The study selection process is illustrated in the PRISMA flow diagram (Figure 1).

Charting the Data

Data was systematically extracted from the included studies using a standardised data charting template. The purpose of this stage was to capture relevant information that aligned with the research question and supported thematic analysis. The following categories were used for data charting:

a) Full reference – citation of the study, including year the study was published

b) Country or context – geographical location and educational setting of where the study was conducted (school or higher learning institutions)

c) Research aims or purpose – statement of what the study set out to do

d) Research design or methodology – methodological approach (e.g. qualitative, quantitative or mixed-methods, review-based) including number, type and characteristics of sample

e) Type or nature of early warning system – description of the system: data-based, predictive model, dashboard, AI, learning analytics tool, etc.

f) Key findings – summary of main findings; how effective the system was, student outcomes, implementation success

g) Implications and recommendations – for practice, policy and future research

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Table 1: Data Charting

No	Full Reference	Country / Context	Research Aim / Purpose	Research Design / Methodology	Type / Nature of Early Warning System	Key Findings	Implications / Recommendations
1	Stark, J. T. (2024). Enhancing Algorithmic Early Warning Systems with Dynamic Selection to Predict High School Graduation Outcomes *(Doctoral dissertation, University of Nevada, Reno).*	United States / K-12 Education / High School level	To enhance data-driven Early Warning Systems (EWS) by integrating advanced machine learning algorithms and a wider range of student-level variables to more accurately predict high school graduation outcomes and identify at-risk students.	Quantitative predictive study using student-level administrative data analysed with multiple machine learning models.	Algorithmic Early Warning System (EWS) leveraging predictive modeling and AI-based data analysis for student risk identification.	Random Forest and AutoML models achieved the highest predictive accuracy (97–99%) across grades 10–12. The inclusion of diverse variables improved model performance, enabling dynamic selection at the student level and earlier identification of risk.	Educational institutions can improve intervention, timing and precision by adopting AI-driven EWS models. Future research should explore linking dynamically selected variables to intervention design, and expanding the model to earlier grade levels.
2	Liu, Y., Wang, W., & Xu, E. (2025). The effectiveness of learning analytics-based interventions in enhancing students' learning effect: A meta-analysis. *SAGE Open 15*(2).	China / schools and higher education contexts	To examine the efficacy of interventions based on learning analytics in improving learning outcomes	Meta-analysis of 34 empirical and quasi-experimental studies published between 2012 and 2021 in English and Chinese using systematic literature search, coding of study characteristics and statistical analysis of effect sizes.	Learning analytics-based interventions employing learning analytics technology to collect and analyze data from learners and their contexts to serve as early warning, monitoring and personalized support functions	Learning analytics interventions had a moderate positive effect on learning outcomes, particularly for knowledge acquisition. Effects were stronger in higher education settings.	Learning analytics should support monitoring and feedback practices. Interdisciplinary collaboration can strengthen intervention design and effectiveness.
3	Cao, W., & Mai, N. (2025). Predictive Analytics for Student Success: AI-Driven Early Warning Systems and Intervention Strategies for Educational Risk Management. *Educational Research*	USA / higher education context	To examine the current state of AI-driven predictive analytics and early warning systems (EWS) for student success	Systematic and integrative literature review of peer-reviewed articles, applied research studies and implementation case reports on predictive analytics and EWS	AI-driven EWS employing algorithms such as Random Forest, Gradient Boosting, SVM and Deep Learning for prediction	Predictive models reliably identified at-risk students earlier than traditional approaches. Personalised interventions were more effective than generic support.	EWS should combine predictive accuracy with human-led interventions. Longitudinal studies are needed to assess sustained impact.

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	and Human Development, 2(2), 36-48.						
4	Bowers, A. J., & Zhou, X. (2019). Identifying students at risk using prior performance versus a machine learning algorithm. *Educational Researcher, 48*(5), 273–283.	United States / High School context	To compare traditional early warning indicators based on prior student performance with modern machine learning algorithms in identifying students at risk of dropping out	Quantitative study using longitudinal school data; applied logistic regression, random forest, and gradient boosting machine learning models to predict dropout risk.	Data-driven predictive Early Warning System (EWS) using prior academic and behavioral data compared with machine learning–based EWS models.	Machine learning algorithms showed marginally higher predictive accuracy but offered earlier and more nuanced risk identification compared to traditional EWS methods.	Schools can enhance existing EWS by integrating machine learning models for more precise, earlier detection. Policymakers should support ethical AI adoption and cross-validation across diverse school settings.
5	Sepanik, S., Zhu, P., Shih, M. B., & Commins, N. (2021). First-year effects of early indicator and intervention systems in Oregon. *U.S. Department of Education, Institute of Education Sciences* (REL 2021–097).	Oregon, United States / High School districts	To examine the first-year impacts of district-level implementation of Early Indicator and Intervention Systems (EIIS) on attendance, discipline, course progression, and academic performance.	Quantitative comparative interrupted time series (CITS) design using administrative data from 65 EIIS districts and 29 matched comparison districts.	State-funded Early Indicator and Intervention System (EIIS) integrating multiple indicators—attendance, behavior, and course performance—to identify and support at-risk students.	EIIS adoption reduced chronic absenteeism by 3.9 percentage points in its first year but had limited effects on academic performance and disciplinary infractions.	Encourages continued investment in data-based EIIS for long-term outcomes. Policymakers should provide implementation guidance, infrastructure, and training. Future studies should assess multi-year effects.
6	Macfadyen, L. P., & Dawson, S. (2010). Predictive identification of at-risk students using learning management system data. *The International Review of Research in Open and Distributed Learning, 12*(2), 17–26.	Canada / Higher Education context	To explore how Learning Management System (LMS) data can be used to predict student academic risk and identify students requiring early intervention.	Quantitative correlational study analyzing LMS activity logs and academic performance data across multiple university courses.	Learning analytics–based Early Warning System using LMS data (logins, downloads, forum participation) to predict performance.	LMS engagement patterns strongly predicted final grades; early online activity effectively identified at-risk learners before midterm evaluations.	Encourages using LMS data for proactive risk detection. Policies should integrate analytics into academic monitoring. Future research should test scalability and cross-course applicability.
7	Cabezas, F., Burgos, L., Darrigol, J., & Zúñiga, M. (2024). Implementation of an	South America / Higher Education (Health Sciences)	To develop and implement an Early Alert System (EAS) that identifies	Quantitative quasi-experimental design comparing experimental and	Early Alert System using big data and quiz-based cognitive skill tracking to	The EAS improved approval rates and enhanced collaboration among	Recommends integrating EAS tools for real-time feedback and data-

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	early alert system in quizzes of a high complexity subject in higher education: Improvement of student performance and teacher perception. *Education and Information Technologies, 29*, 19321–19341.		weaknesses in students' cognitive skills in a complex first-year university course.	control groups using quiz analytics and faculty perception surveys analyzed with Power BI.	identify learning gaps and support early interventions.	teachers; experimental groups showed better cognitive skill mastery and course performance.	driven interventions. Policymakers should promote faculty training and collaborative implementation. Future studies should measure long-term impact across subjects.
8	Sattar, T., Javed, S., & Hussain, N. (2022). The role of stakeholders' participation, goal directness, and learning context in enhancing educational outcomes. *Journal of Educational Research, 25*(3), 145–160.	Pakistan / Higher Education context	To investigate how stakeholder participation, goal orientation, and learning context contribute to improving institutional learning outcomes and early identification of learning gaps.	Quantitative correlational study using survey data and structural equation modeling to analyze stakeholder engagement and learning variables.	Institutional framework emphasizing collaborative early warning and goal-aligned learning models integrating stakeholder feedback for monitoring performance.	Stakeholder engagement positively influenced goal clarity and student learning outcomes. A strong learning context moderated these relationships, highlighting participative approaches as key to sustained improvement.	Encourages institutions to design participatory systems where teachers, administrators, and parents collaborate in monitoring progress. Future research can explore longitudinal impact of stakeholder-driven learning analytics.
9	Borna, M.-R., Saadat, H., Hojjati, A. T., & Akbari, E. (2024). Analyzing click data with AI: Implications for student performance prediction and learning assessment. *Frontiers in Education, 9*, 1421479.	Iran / Online Learning context (Open University UK dataset)	To evaluate the effectiveness of AI-based models, including Random Forest, XGBoost, and RNNs, in predicting academic performance and identifying at-risk and high-achieving students using LMS click data.	Quantitative study applying machine learning and deep learning models to the Open University Learning Analytics Dataset (OULAD) of 32,000+ students; evaluated with precision, recall, and F1-scores.	AI-driven Early Warning System using LMS clickstream data for predictive modeling and adaptive learning assessment.	Random Forest achieved highest accuracy (78.68%) for dropout prediction; deep learning models closely followed. Predicting high achievers remained complex, indicating limits of behavioral data alone.	Highlights AI's potential in inclusive learning assessment. Recommends combining behavioral and motivational factors for more precise predictions. Future studies should ensure ethical AI deployment in education.
10	Vasconcelos, A. N., Freires, L. A., Loureto, G. D. L., Fortes, G., Costa, J. C. A., Torres, L. F. F.,	Brazil / Secondary Education context	To develop and validate the IAFREE relational model—a multidimensional tool for assessing	Mixed-methods research including scale development, content validation, pilot study, and	Relational Early Warning System model (IAFREE) capturing five relational	The validated IAFREE-12 scale demonstrated strong psychometric reliability and	Supports embedding relational measures in EWS to capture non-academic dropout risks. Policies should

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	Bittencourt, I. I., Cordeiro, T. D., & Isotani, S. (2023). Advancing school dropout early warning systems: The IAFREE relational model for identifying at-risk students. *Frontiers in Psychology, 14*, 1189283.		relational factors that predict school dropout risk in the Brazilian education system.	confirmatory factor analysis with 15,924 students.	dimensions—student-school, student-family, student-community, student-peer, and student-teacher relationships.	predictive capability. It filled a key gap by integrating social-relational data into dropout prediction models.	promote socio-relational monitoring alongside academic metrics. Future studies can adapt IAFREE cross-culturally.
11	Korkmaz, Ö., & Aydin, M. N. (2025). Detection of early school dropout in vocational and technical high schools in Turkey. *SAGE Open, 15*(3), 1–17.	Turkey / secondary education at a vocational and technical school in Istanbul	To identify the socio-economic, familial, and academic factors that contribute to early school dropout in Turkish vocational and technical high schools, and to evaluate the potential of machine learning models in accurately predicting students at risk of dropping out.	Quantitative predictive analysis using survey data of 220 students between 2023 and 2024. Variables include personal, socio-economic, familial, and academic factors	Machine learning–based early warning model for detecting students at risk including Decision Tree, Random Forest, Gradient Boosting, AdaBoost, Logistic Regression, Naïve Bayes, Neural Networks, etc.	Socio-economic and family factors were stronger predictors of dropout than academic variables. Machine learning models effectively captured complex risk patterns.	AI-driven EWS should monitor socio-economic stressors in real time. Family-focused interventions are essential.
12	Alsariera, Y. A., Baashar, Y., Alkawsi, G., Mustafa, A., Alkahtani, A. A., & Ali, N. (2022). Assessment and evaluation of different machine learning algorithms for predicting student performance. *Computational Intelligence and Neuroscience, 2022*, Article 4151487.	Saudi Arabia, Malaysia and Yemen / various educational levels focusing on higher education and high school contexts	To systematically assess and evaluate existing research on machine learning (ML) algorithms used for predicting student academic performance, identifying the key predictive features, accuracy levels, and research gaps between 2015 and 2021	Systematic literature review using PICO framework on combined keywords from various databases on 39 empirical studies from 2015 to 2021	Machine learning prediction models including Artificial Neural Networks (ANN) Decision Tree (DT) Support Vector Machine (SVM) K-Nearest Neighbor (KNN) Naïve Bayes (NB) Linear Regression (LinR)	Supervised machine learning models consistently outperformed traditional statistical methods. Multi-source data improved prediction accuracy.	Institutions should combine AI predictions with academic advising. Ethical and privacy issues must be addressed.
13	Okubo, F., Yamashita, T., & Ogata, H. (2017).	Japan / Higher education	To develop and test machine learning models for predicting	Quantitative predictive study using LMS and e-book	Machine learning-based early warning system (EWS) within	Reliable predictions were possible as early as 20–30% into a	Early interventions can be implemented well before midterm.

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	Predicting at-risk students at different percentages of course length for early intervention using machine learning models. *International Journal of Learning Analytics and Artificial Intelligence for Education (iJAI), 9*(3), 1–17.		"at-risk" students at different stages of a course completion so that early interventions can be implemented effectively.	learning behaviour data.	an e-book and LMS platform. Machine learning algorithms tested: Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), k-Nearest Neighbors (k-NN)	course. Engagement and quiz performance were key predictors.	Behavioural metrics should form core EWS indicators.
14	Alalawi, K., Athauda, R., & Chiong, R. (2025). An extended learning analytics framework integrating machine learning and pedagogical approaches for student performance prediction and intervention. *International Journal of Artificial Intelligence in Education, 35*(3), 1239–1287.	Australia – tertiary (higher education)	To develop and evaluate an extended Learning Analytics Intervention (LAI) framework that enables academics to pilot learning analytics interventions (LAIs) without requiring institutional-level infrastructure, and to integrate pedagogical approaches for effective student interventions	Design: Mixed-methods Participants: Academics and students across six tertiary-level courses Data Collection: Historical continuous assessment data, course results, and academic interviews Analyses: Predictive model evaluation, statistical tests, and thematic analysis of interviews	Learning Analytics–based Early Warning System that predicts students "at risk of failure" using course-specific machine learning models	The framework enabled accurate early risk prediction and effective targeted interventions. Student outcomes and academic acceptance improved.	Self-service learning analytics systems can increase adoption. Pedagogical integration enhances intervention effectiveness.
15	Bai, Z.-J., & Cai, G.-Q. (2018). A study on academic early-warning system based on machine learning. *Advances in Social Science, Education and Humanities Research, 183*, 257–262. Atlantis Press.	China – higher education (Xiamen University of Technology)	To improve the existing academic early-warning system at Xiamen University of Technology by introducing a machine learning–based mathematical model using multiple indicators to provide more accurate and timely academic risk predictions.	Applied system development and validation study using institutional academic data.Tools: Python programming for model development and validation	Multi-indicator academic early-warning system integrating family, academic, attendance, and behavioral data. Machine learning based (KNN and decision tree algorithms). Predicts five warning levels (focus, junior, intermediate, senior, super).	The multi-indicator ML model accurately classified students into risk levels. Integrating diverse indicators improved prediction quality.	Institutions should integrate fragmented data systems. EWS must be paired with structured student support.

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16	Embarak, O. H., & Hawarna, S. (2024). Enhancing student success with XAI-powered RADAR: An automated AI-driven system for early detection of at-risk students. *Procedia Computer Science, 231*, 151–160.	United Arab Emirates (UAE) – school district dataset; developed and piloted in collaboration with the Higher Colleges of Technology and Hamdan Bin Mohammed Smart University.	To design and implement an automated system, RADAR (Rapid Analysis and Detection of At-risk students with Artificial intelligence-based Response), that leverages Explainable Artificial Intelligence (XAI) to accurately detect at-risk students	Quantitative pilot study involving development and testing of an XAI-based EWS.	RADAR (Rapid Analysis and Detection of At-risk students with Artificial intelligence-based Response)	The system achieved high prediction accuracy and provided interpretable risk explanations. Multi-factor data improved detection precision.	Explainable AI can support transparent decision-making. Larger-scale validation and ethical safeguards are required.
17	Schroeder, M. N., & Murphy, J. A. (2025). Blending early warning and remediation processes to facilitate student success. *American Journal of Pharmaceutical Education, 89*(3), 101420.	United States / Higher Education (health professions education)	To describe early-warning and remediation strategies and to evaluate their impact on student success indicators such as attrition rates, on-time graduation rates, and remediation pass rates.	Institutional evaluative study using early-warning, remediation, and graduation data.	Digital tracking and advising tool built in Qualtrics where the faculty report low grades (< C) for early identification of at-risk students	Combining early warning with structured remediation reduced attrition and increased on-time graduation.	EWS should be integrated with academic and non-academic supports. Faculty engagement is critical for system effectiveness.
18	Kustitskaya, T. A., Kytmanov, A. A., & Noskov, M. V. (2022). Early student-at-risk detection by current learning performance and learning behavior indicators. *Cybernetics and Information Technologies, 22*(1), 117–133.	Russia / Higher Education (university-level blended learning course)	To develop an approach to timely student-at-risk detection, which could serve as a basis for the development of an early warning system.	Quantitative pilot study using learning analytics data and machine learning classifiers involving 179 + 75 students' attendance, quiz scores, e-test performance and persistence indicators (using number of attempts) to compare three machine learning models	A Bayesian Network Classifier (BNC)-based Early Warning System (EWS) integrated into the university's blended learning course	Bayesian models enabled early and accurate identification of at-risk students. Early feedback improved engagement and performance trends.	Continuous assessment data should support early detection. Institution-wide EWS expansion is recommended.
19	Hyatt, V. (2015). The relationship between participation in an academic	United States – Middle school (K–12)eighth-grade	To examine the relationship between participation in an Academic	Quantitative causal-comparative study using archival academic records.	An early academic warning and support system designed to assist students	Students participating in academic intervention programs achieved	Schools should implement data-driven academic intervention

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	intervention program and performance in coursework for at-risk eighth-grade middle school students *(Doctoral dissertation, University of Central Florida).*	students attending middle schools	Intervention Program (AIP) and course performance among at-risk eighth-grade middle school students.		identified as academically at risk before entering high school.	higher course grades. Early structured support mitigated academic risk.	programs. Longitudinal impacts should be examined.
20	McMahon, B. M., & Sembiante, S. F. (2019). Re-envisioning the purpose of early warning systems: Shifting the mindset from student identification to meaningful prediction and intervention. *Review of Education, 7*(3), 1–34.	United States – K–12 education context (elementary to high school levels).	To critically review and reconceptualize the purpose of Early Warning Systems (EWS) in education.	Systematic literature review and conceptual analysis of K–12 EWS research.	Conceptual and analytical redefinition of EWS at student-level, using data-driven early warning systems in K–12 education	Effective EWS require multi-domain indicators and direct links to intervention. Many existing systems lack theoretical grounding.	EWS should shift from identification to intervention-oriented models. Early, malleable indicators should guide personalised support.

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Summarising and Reporting the Findings

Lastly, the charted data was analysed to identify key themes and the findings were summarised to present a structured, evidence-based overview.

A thematic analysis approach was adopted to identify recurring qualitative patterns across the studies, focusing on the effectiveness of early warning systems at identifying, predicting and intervening with at-risk students. This process involved comparing results across different educational contexts, system designs and methodological approaches to determine common strengths, limitations and implementation factors.

FINDINGS

A total of 20 articles were included in this review. To provide an overview of the reviewed studies, a data charting table is presented in Table 1. This table summarises the key characteristics of each study, including the full reference, context, research purpose, research design, nature of early warning system, key findings and implications. The table serves as a foundation for understanding the scope and focus of the included studies, which inform the thematic findings discussed in the subsequent sections.

Thematic Findings

Across the reviewed studies, several key themes emerged concerning the design, implementation and impact of academic early warning systems (EWS) and related predictive analytics frameworks across school and higher education contexts. These themes highlight an evolving landscape of data-driven educational risk management, emphasising the balance between technological precisions and human-centered intervention.

1. Advancements in Predictive Analytics and Machine Learning Accuracy

A strong and recurring theme across studies is the increasing sophistication of predictive models used in early warning systems. Multiple studies (Stark, 2024; Cao & Mai, 2025; Alsariera et al., 2022; Bai & Cai, 2018) reported high accuracy levels (85–99%) using machine learning algorithms such as Random Forest, Gradient Boosting, and Neural Networks in identifying at-risk students. This demonstrates significant progress from earlier, rule-based systems toward AI-driven, dynamic selection models that can process large, multi-source datasets. These models enable earlier and more precise identification of academic risk, sometimes as early as 20–30% into a course (Okubo et al., 2017). However, these studies also caution that predictive precision must be paired with meaningful human-led intervention to produce tangible improvements in student outcomes.

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2. Integration of Learning Analytics and Real-Time Monitoring

Several higher education studies (Macfadyen & Dawson, 2010; Cabezas et al., 2024; Alalawi et al., 2025) highlight the growing role of learning analytics (LA) in EWS design. These systems draw on LMS data such as login frequency, quiz scores, and engagement metrics to support real-time monitoring and adaptive feedback. The use of LA-enabled dashboards allows instructors to detect disengagement patterns and offer timely, individualised support. Evidence shows that students who received feedback or tutoring following early alerts had higher pass rates and improved academic performance. The integration of LA tools has thus shifted EWS from static, post-hoc monitoring to continuous, formative intervention systems that can be embedded within everyday teaching practice.

3. Multi-Dimensional Risk Factors and Contextual Variables

Beyond academic indicators, a growing body of research acknowledges the multi-dimensional nature of academic risk. Studies from Turkey (Korkmaz & Aydin, 2025) and Brazil (Vasconcelos et al., 2023) demonstrated that socio-economic, familial, and relational factors are strong predictors of dropout risk, often more so than academic variables alone. This broader, holistic approach incorporates student-school, student-family, and student-peer relationships into predictive models. Similarly, Embarak and Hawarna (2024) expanded the scope of early detection by integrating psychological and personality data through explainable AI, underscoring the importance of multi-modal data fusion in enhancing interpretability and inclusiveness. Together, these findings suggest a paradigm shift from purely academic risk models toward context-sensitive, socio-relational frameworks that capture the complex realities influencing student persistence.

4. Early Intervention and Timing of Support

Another prominent theme is the critical role of timing in the effectiveness of interventions. Studies (Cao & Mai, 2025; Okubo et al., 2017; Schroeder & Murphy, 2025) consistently report that earlier interventions that were identified usually within the first few weeks or even within 72 hours of risk identification were significantly more effective than delayed responses. Early feedback and structured remediation programs have been shown to improve retention, raise pass rates, and reduce attrition. For instance, Schroeder and Murphy (2025) demonstrated that combining early-warning data with systematic remediation reduced attrition by 10% and increased on-time graduation rates by a similar margin. These outcomes confirm that the true value of EWS lies not merely in detection, but in linking predictive insights with prompt, structured, and sustained intervention mechanisms.

5. Human-Technology Collaboration and Institutional Readiness

Several studies (McMahon & Sembiante, 2019; Sattar et al., 2022; Alalawi et al., 2025) emphasise that while predictive accuracy is essential, human interpretation and institutional culture ultimately

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determine the system's success. Faculty engagement, data literacy, and institutional support influence how well EWS outputs are translated into actionable strategies. A recurring challenge is the lack of staff training and integration across data systems, leading to fragmented implementation (Bai & Cai, 2018). Consequently, effective EWS deployment requires organisational readiness, professional development, and participatory design, where educators and administrators collaborate in decision-making. This highlights the growing recognition that technology must enhance instead of replacing human judgment in educational interventions.

6. Ethical, Privacy, and Equity Considerations

Although less frequently discussed, several authors (Alsariera et al., 2022; Embarak & Hawarna, 2024) raised concerns about ethical use, data privacy, and algorithmic bias in AI-based systems. The collection and analysis of sensitive academic and behavioral data require transparent governance structures to avoid potential misuse or unfair profiling of students. Explainable AI (XAI) frameworks, as proposed in RADAR, represent a promising direction toward ethical and interpretable prediction systems. Future research should continue to investigate equitable data practices and ensure that EWS deployment supports student empowerment rather than surveillance.

DISCUSSION

The findings of this review highlight rapid progress in the development and application of early warning systems, driven by technological advancements and deeper insights into student learning behaviour. Across the studies, several broader implications emerge for educational practice, institutional capacity building, and the ethical integration of predictive analytics in schools and universities.

1. Intervention Remains Uneven

Most reviewed studies reported high predictive accuracy, particularly those using machine learning models such as Random Forest, Gradient Boosting, or Neural Networks (Stark, 2024; Alsariera et al., 2022). These models can detect nuanced patterns and interactions between variables, often outperforming traditional methods (Bowers & Zhou, 2019). However, accuracy alone does not guarantee meaningful student support. As McMahon and Sembiante (2019) argue, the value of EWS lies not merely in identifying who is at risk but in guiding informed, timely, and contextually appropriate interventions. Recent research also highlights that while early warning systems often achieve high predictive performance, their translation into effective institutional practice remains uneven, as many models lack corresponding evaluation of intervention processes and outcomes, pointing to a gap between prediction and actionable support (Chang et al., 2025)

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2. Real-Time Feedback and Continuous Monitoring

Learning analytics-based systems demonstrated strong potential for early detection using behavioural engagement data, especially in higher education contexts. For example, Macfadyen and Dawson (2010) showed that LMS activity patterns can predict academic performance well before mid-term assessments. Similarly, Okubo et al. (2017) demonstrated accurate prediction even at 20% of course completion, allowing academically vulnerable students to receive support early in the semester.

Recent research beyond the dataset supports this potential. Viberg et al. (2022) found that learning analytics interventions enhance self-regulated learning when paired with targeted feedback. Similarly, Fahd et al. (2022) demonstrated that early alerts in digital learning environments help instructors tailor instruction more effectively.

3. Multidimensional Data

Several studies emphasised the importance of including socio-emotional, relational, and contextual factors in early warning models (Vasconcelos et al., 2023; Korkmaz & Aydin, 2025). These models capture important non-academic factors that strongly predict dropout risk and student engagement. The shift toward multi-modal inputs including personality, family background, and psychological profiles moves EWS toward more holistic representations of student risk (Embarak & Hawarna, 2024). Recent research further indicates that integrating cognitive, affective, and metacognitive data can enhance predictive accuracy and provide deeper insight into students' learning processes, including how emotional and motivational variables intersect with academic behaviours (Kubsch et al., 2025). However, the increased complexity raises analytical, ethical, and logistical challenges, as institutions must balance the benefits of wide data inclusion with concerns about bias, privacy, and system transparency (Jin et al., 2024). Schools may lack the capacity to collect or manage such sensitive data reliably, raising concerns regarding privacy, informed consent, and potential misuse.

4. Early and Sustained Intervention

A further critical theme emerging from the review concerns the importance of early and sustained intervention in maximising the impact of early warning systems. The timing of support consistently surfaced as a determining factor in student outcomes. Cao and Mai (2025) demonstrated that intervention effectiveness increased by up to 67% when early alerts were acted upon within the first 72 hours, underscoring the need for rapid response mechanisms once risk is detected. Similarly, Schroeder and Murphy (2025) found that structured remediation processes significantly improved pass rates and reduced attrition within professional programmes, highlighting the value of systematic, ongoing academic support. These findings reinforce earlier research suggesting that rapid intervention, personalised assistance, and continuous follow-up are key elements of successful EWS implementations (Davis et al., 2019; Bruce et al., 2011). Collectively, the evidence makes clear that early identification alone is insufficient, and meaningful outcomes depend on timely, sustained, and well-coordinated intervention strategies.

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5. Human Factors, Institutional Readiness, and Staff Capacity

Closely related to the previous findings is the role of human factors, institutional readiness, and staff capacity, which emerged as foundational to the effectiveness of early warning systems. Beneres et al. (2021) states that AI systems tend to work autonomously and perform tasks without human intervention which can decrease the confidence and oversight needed on the task. Several studies emphasised that successful implementation requires strong institutional structures, including adequate staff training in data literacy, integrated data systems, strong leadership support, and clearly defined intervention protocols (Alalawi et al., 2025; McMahon & Sembiante, 2019). Without these elements, predictive analytics risk being underutilised, misinterpreted, or inconsistently applied across classrooms and departments.

As EWS rely heavily on educators and administrators to interpret data outputs and act upon them, the absence of professional development and shared institutional responsibility can undermine even the most sophisticated technological systems. Ultimately, the findings suggest that the success of early warning systems hinges not only on algorithmic accuracy or technological advancements but also on the preparedness, engagement, and collaborative capacity of the people using them.

CONCLUSION AND RECOMMENDATIONS

This scoping review provides a comprehensive overview of early warning systems and predictive analytics for student success across school and higher education contexts. Evidence shows that machine learning-based EWS offer strong predictive accuracy, and learning analytics systems successfully detect early behavioural patterns linked to academic risk. However, the effectiveness of these systems depends heavily on timely intervention, institutional readiness, and a balanced integration of human judgment and technology. There is a growing trend toward incorporating socio-relational and psychological variables, which enriches risk identification but raises additional considerations related to privacy and ethics. Overall, early warning systems hold significant promise but must be embedded within responsive, student-centered support structures to achieve meaningful impact.

Based on the synthesised evidence, several recommendations can guide the effective implementation and future development of early warning systems in education. For educational institutions, it is essential to strengthen staff capacity through sustained training in data literacy and intervention strategies, as educator expertise directly influences how predictive insights are interpreted and acted upon. Institutions should also work toward integrating multiple data sources from academic, behavioural, and socio-economic backgrounds into unified systems to enhance prediction accuracy while maintaining strong standards of data privacy and governance. Importantly, early warning systems must be paired with structured intervention protocols that prioritise timely, personalised support such as targeted tutoring, feedback loops, and consistent follow-up, ensuring that risk identification translates into meaningful action.

At the policy level, governments and regulatory bodies should establish clear ethical guidelines for the use of AI and predictive analytics in education, ensuring transparency, fairness,

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and the protection of vulnerable student populations. These guidelines should explicitly address issues of bias, data protection, and responsible use to prevent unintended harm. Finally, researchers play a crucial role in advancing the field by conducting longitudinal studies to assess long-term effectiveness, exploring explainable AI and multi-modal data to improve transparency and educator trust, and expanding research across culturally and socio-economically diverse settings. Such research will be vital for ensuring that early warning systems evolve into equitable, evidence-based tools that support student success across different educational contexts.

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