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Responsible Learning Analytics for Identifying and Supporting Academically At-Risk Students in Secondary Schools

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ABSTRACT
Learning analytics may help secondary schools identify students who need additional support, but prediction alone does not improve educational outcomes. This integrative review synthesizes 289 publications on predictive modeling, educational measurement, student support, fairness, privacy, and implementation. The analysis examines predictive validity, data quality, fairness and bias, intervention design, privacy and consent, and implementation capacity. The evidence shows that early-warning systems fail when missing or delayed data distort risk estimates, subgroup performance is hidden by aggregate accuracy, alerts lack actionable explanations, or schools lack resources to respond. Ethical implementation also requires proportionate data use, professional review, student recourse, and monitoring for unintended effects. The paper contributes a prediction-to-support framework that separates risk estimation from intervention decisions and outcome evaluation. It also specifies indicators and propositions for testing whether learning analytics produces timely, fair, and effective academic support.

KEYWORDS: learning analytics; at-risk student; early warning; academic performance; student prediction; secondary school; machine learning

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1 Introduction

Learning analytics may help secondary schools identify students who need additional academic support, but prediction alone does not improve outcomes. Attendance, assessment histories, engagement records, behavior reports, and contextual variables may reveal patterns associated with risk. Studies have applied machine-learning methods to academic-performance prediction and early-warning systems across different educational settings [1-6]. Their results establish the technical feasibility of prediction, yet they also show that performance depends on the available variables, population, outcome definition, and evaluation design. A model developed in one setting may not retain accuracy or calibration elsewhere.

The educational purpose of an early-warning system is intervention, not classification. An alert must reach an appropriate professional, support a reasonable interpretation, and lead to assistance suited to the student's needs. Research on virtual learning environments and predictive models illustrates the growing range of data sources used to identify risk [7-9]. Yet indicators may reflect limited connectivity, disability, family responsibilities, school resources, or prior disadvantage rather than lack of effort. Schools therefore need safeguards against stigmatizing labels and automatic high-consequence decisions.

Data quality creates further difficulty. Missing attendance, inconsistent assessment practices, delayed records, and changing course structures may distort risk estimates. Aggregate accuracy may conceal poor performance for particular schools or student groups. Studies linking learning barriers, facilities, leadership, participation, and other institutional factors to academic performance demonstrate that student outcomes arise from multiple interacting conditions [10-15]. Predictive validity should therefore be examined alongside subgroup error, calibration, temporal stability, and the operational meaning of each variable.

Responsible implementation requires privacy, proportionality, professional review, and student recourse. Schools should collect only information needed for defined support purposes, restrict access, document model changes, and monitor unintended effects. Explanations must help practitioners distinguish actionable conditions from proxies or correlations. Evaluation should also test whether interventions improve attendance, learning, progression, or wellbeing rather than reporting model accuracy alone. Research on machine-learning prediction and model-agnostic interpretation supports transparent examination of influential factors, although explanation does not remove the need for educational judgment [16-19].

This review asks which mechanisms support valid risk identification, how schools should govern fairness and privacy, and which conditions convert alerts into timely assistance. It synthesizes 289 publications through six dimensions: predictive validity, data quality, fairness and bias, intervention design, privacy and consent, and implementation capacity. The paper contributes a prediction-to-support framework that separates risk estimation from professional review, intervention selection, monitoring, and outcome evaluation. It also specifies indicators and propositions for testing whether learning analytics produces fair and beneficial academic support across students and operating conditions [3,5,7,16].

2 Learning Analytics Student Risk and Intervention Evidence

2.1 Predictive Validity

Predictive validity depends on whether attendance, assessment, and engagement indicators forecast a clearly defined outcome early enough for support. Attendance often provides a stable signal, but its meaning varies across timetable, transport, health, and recording practices. Assessment history offers direct academic information yet may identify difficulty only after substantial failure. Digital engagement adds timeliness but excludes learning completed offline and reflects course design as much as student behavior. Models should report discrimination, calibration, precision, recall, and lead time using data from a later cohort or different school. A model that ranks students accurately but overstates absolute risk may misallocate limited support. Validation must therefore address both statistical performance and the intervention decision attached to each threshold [1-4].

2.2 Data Quality

Data quality problems enter learning analytics before model training. Missing attendance may reflect device failure or inconsistent teacher practice; assessment scales may change across subjects; engagement records depend on platform use. Imputation and aggregation may hide these differences. Schools should document provenance, missingness, coding changes, and the time at which each variable becomes available. Leakage occurs when a predictor contains information recorded after the intended prediction point. Quality checks should compare groups, schools, terms, and data-collection methods. A complex model trained on unstable records will reproduce administrative variation with high confidence. Reliable early warning begins with consistent definitions, auditable transformations, and a prediction timeline aligned with real support decisions [5-8].

2.3 Fairness and Bias

Fairness requires examination of errors and consequences across student groups. Equal overall accuracy does not prevent one group from receiving more false alarms or missed identifications. Differences may arise from structural inequity, measurement bias, unequal access to digital systems, or variation in outcome prevalence. Schools should report group-specific calibration, false-positive and false-negative rates, sample sizes, and uncertainty, while protecting privacy. Fairness metrics involve trade-offs and should follow an explicit educational objective. Sensitive attributes should not be removed reflexively because they are needed to detect unequal performance. The appropriate response may involve data improvement, threshold revision, additional human review, or changes to the intervention, rather than a mathematical adjustment alone [9-12].

2.4 Intervention Design

Intervention usefulness is the test of an early-warning system. Risk scores have limited value when schools lack timely, acceptable, and resourced responses. Each alert should connect to a support pathway, responsible staff member, review period, and closure rule. The system should distinguish academic, attendance, wellbeing, and access needs instead of presenting one unexplained risk category. Evaluation should compare contact, uptake, service completion, academic progress, and unintended effects against a credible baseline. Randomized or phased implementation offers stronger evidence where ethical and feasible. A reduction in predicted risk does not establish benefit if students receive stigmatizing labels, unnecessary surveillance, or support unrelated to the cause of difficulty [13-16].

2.5 Privacy and Consent

Explainability should help educators understand the basis and limits of a prediction without presenting association as cause. Feature rankings, local explanations, and counterfactual examples answer different questions and may conflict when variables are correlated. Explanations need stable definitions, plain language, uncertainty, and a clear distinction between modifiable and non-modifiable factors. Teachers and counsellors should test whether the explanation improves review accuracy and support selection. Students also need an appropriate route to question data and decisions. An explanation is inadequate when it merely makes a complex model look precise. Its value lies in supporting accountable judgment, error detection, and a proportionate response [17-20].

2.6 Implementation Capacity

Governance defines who collects data, approves models, reviews alerts, contacts students, and evaluates outcomes. Schools should limit data to educational purposes, control access, document retention, monitor drift, and provide correction and appeal routes. Model updates require version records and renewed validation because enrollment patterns, curricula, and data systems change. Oversight should include educators, safeguarding staff, technical specialists, and student representation suited to the setting. Audit measures should cover access, overrides, unresolved alerts, group disparities, and intervention capacity. Responsible learning analytics is a managed educational process, not a prediction service operating outside professional judgment [21-23].

2.7 Weaknesses in Early-Warning Evidence

The strongest evidence on learning analytics for identifying academically at-risk students identifies interacting mechanisms rather than a single dominant tool. Results depend on the fit among the decision problem, data quality, implementation capacity, user behavior, and the consequence of error. Studies that isolate one performance indicator therefore provide only partial support for practice.

Learning-analytics studies differ because they predict different events, use different observation windows, and apply alerts to different student groups. Accuracy, calibration, fairness, intervention uptake, and educational benefit represent separate outcomes. The synthesis therefore evaluates prediction and the support process together.

Prediction studies emphasize accuracy while providing less evidence on calibration, subgroup error, temporal validity, intervention uptake, and student outcomes. A risk alert has limited value when a school lacks timely, appropriate, and adequately resourced support.

The review retains six dimensions because each represents a separate point of failure: predictive validity, data quality, fairness and bias, intervention design, privacy and consent, and implementation capacity. Negative and inconsistent findings define moderators and limits rather than being discarded. This approach supports propositions that later studies may confirm, refine, or reject.

2.8 Intervention Synthesis and Ethical Gaps

Evidence relevant to learning analytics for identifying academically at-risk students spans several research traditions, but those traditions do not provide equal forms of support. Direct domain studies establish the focal problem. Measurement and methodological studies clarify how constructs should be assessed. Governance and implementation studies identify controls and operating conditions. Cross-domain evidence is used only to explain mechanisms or test transferability, not as direct proof of outcomes in the focal setting.

A valid early-warning claim requires a defined outcome, prediction horizon, baseline model, intervention capacity, and record of what followed an alert. Evaluation should reveal false positives, missed students, subgroup error, delayed support, and cases where staff overrode the model. Educational benefit cannot be inferred from prediction alone.

The synthesis therefore treats predictive validity, data quality, fairness and bias, intervention design, privacy and consent, and implementation capacity as linked requirements. The framework predicts weak results when one requirement advances while another remains underdeveloped. This configuration logic explains why technically competent interventions may fail after implementation and why favorable pilot results may not persist at scale.

Risk estimates identify statistical patterns rather than causes or fixed student traits. Schools should use them to trigger review and support, never as automatic grounds for exclusion, punishment, or reduced academic opportunity.

Future studies should preregister the student population, outcome, observation window, features, threshold, comparison model, and intervention protocol. Reporting should include calibration, subgroup errors, alert burden, support uptake, and student outcomes. Multi-term validation would show whether performance survives cohort and policy changes.

Table 1. Evidence integration map for learning analytics for identifying academically at-risk students

Evidence domain	References	Role in synthesis
Predictive validity	[1-48]	Defines the focal construct and its principal outcome.
Data quality	[49-96]	Clarifies mechanisms, competing explanations, and performance conditions.
Fairness and bias	[97-144]	Informs measurement validity, comparison criteria, and analytical design.
Intervention design	[145-192]	Tests contextual transfer, implementation capacity, and operational constraints.
Privacy and consent	[193-240]	Supports governance, assurance, accountability, privacy, and risk controls.
Implementation capacity	[241-289]	Informs cross-domain interpretation, boundary conditions, and future validation.

3 Responsible Analytics Review Method

3.1 Review questions and student-support outcomes

The study used a conceptual and methodological review because the research questions concern mechanisms, interactions, measurement, and implementation rather than a pooled treatment effect. The analytical corpus comprised 289 publications spanning conceptual, empirical, methodological, and institutional work relevant to secondary schools using attendance, assessment, engagement, and contextual information to identify students who may need support. Eligibility required a clear connection to at least one research question, identifiable methods or conceptual reasoning, and enough detail to evaluate the claim advanced.

Screening excluded duplicates, vendor claims, prediction studies without educational relevance, and reports lacking enough information to assess model or intervention quality. Evidence on validity, data quality, fairness, intervention design, privacy, and implementation was retained. Findings were grouped by prediction target and school context.

3.2 Coding models interventions and safeguards

Extraction recorded the student population, prediction target, time horizon, features, model, baseline, performance measure, subgroup analysis, intervention, governance control, and limitation. Appraisal examined leakage, calibration, fairness, temporal validation, consent, and whether alerts led to documented support.

Open coding identified recurring problems and mechanisms. Axial coding organized relationships among inputs, processes, controls, outputs, and outcomes. Integrative coding consolidated the evidence into six dimensions: predictive validity, data quality and missingness, fairness, intervention design, privacy and consent, implementation capacity. Negative cases and inconsistent findings were retained to identify moderators, failure modes, and limits to transfer. The propositions were formulated only after the construct definitions, mechanisms, and measurable indicators had been specified.

3.3 School context and evidence limits

The framework does not establish that any one model or intervention will transfer across schools. Prospective validation must assess both prediction quality and support outcomes. The synthesis therefore reports mechanisms, trade-offs, and testable propositions rather than universal effects. Future validation should use preregistered measures, transparent sampling, subgroup analysis, sensitivity tests, and longitudinal outcome assessment where feasible.

4 Analytics Findings and Intervention Analysis

4.1 Responsible for early-warning framework

Table 2. Comparative dimensions and evaluation rules

Dimension	Operational definition	Primary indicators	Decision risk
Predictive validity	The observable capability represented by predictive validity in the proposed model.	calibration; sensitivity; specificity; lead time	Weak validity or unmeasured outcome
Data quality and missingness	The observable capability represented by data quality and missingness in the proposed model.	missingness; timeliness; label reliability; drift	Inconsistent interpretation or control
Fairness	The observable capability represented by fairness in the proposed model.	subgroup calibration; error disparity; access to support	Misleading average or hidden failure
Intervention design	The observable capability represented by intervention design in the proposed model.	uptake; response time; treatment effect; burden	Delay, overload, or unstable response
Privacy and consent	The observable capability represented by privacy and consent in the proposed model.	purpose limitation; access; correction; transparency	Misuse, exclusion, or weak accountability

Dimension	Operational definition	Primary indicators	Decision risk
Implementation capacity	The observable capability represented by implementation capacity in the proposed model.	caseload; review delay; staff capacity; fidelity	Learning failure or unsupported scaling

Responsible learning analytics requires predictive validity, reliable data, fairness assessment, effective interventions, privacy protection, and implementation capacity. A precise risk score has little educational value when no timely support follows. Fairness analysis must examine both prediction errors and the distribution of interventions because biased support decisions may persist even when aggregate accuracy appears acceptable. Table 2 therefore links model performance to student support and accountable use [112-116].

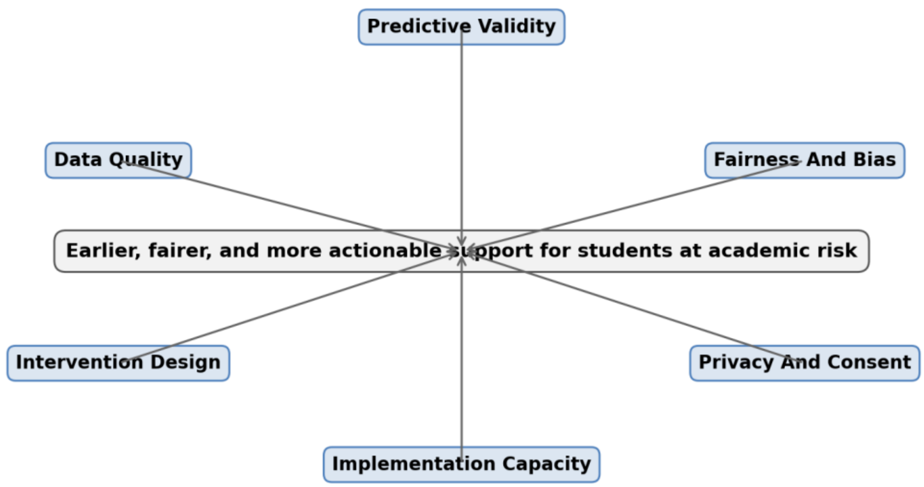

Figure 1. Integrated analytical framework.

Figure 1 shows how data quality, prediction, fairness, intervention design, privacy, and implementation capacity jointly shape student support. Evidence from interventions should refine model features, thresholds, review rules, and service capacity. The framework evaluates whether alerts lead to timely and equitable support. [117]

4.2 Prediction errors intervention gaps and harm

Predictive value depends on the decision horizon and intervention opportunity. A model that identifies risk after recovery options have narrowed offers limited practical benefit. [118-120]

Missing data is often informative. Absence may reflect disengagement, exclusion, mobility, or system failure, so simple imputation can remove meaningful risk signals or create bias. [121-125]

Fairness requires more than equal average accuracy. Thresholds, error costs, calibration, support availability, and subgroup treatment must be assessed together. [126-129]

Intervention effectiveness is separate from model accuracy. Identification improves outcomes only when schools provide timely, suitable, and sufficiently resourced support. [130-132]

Privacy and consent require purpose limitation, understandable communication, correction routes, and control over access to sensitive student information. [133-135]

Implementation capacity constrains threshold choice. Over-sensitive alerts can overwhelm counselors, delay review, and reduce attention to the highest-risk cases. [136-140]

4.3 Propositions for prediction and support

P1: Intervention lead time mediates the relationship between predictive accuracy and student outcome improvement.

Validation of this proposition requires a defined unit of analysis and prespecified indicators. Researchers should report the proposed mechanism, competing explanations, subgroup results, and uncertainty. Core indicators include calibration; sensitivity; specificity; lead time. [141-145]

P2: Informative missingness moderates the validity of models trained on administrative records.

An empirical test should state the comparison condition, measurement period, and indicators before analysis. Reporting should include null results, alternative explanations, and sensitivity to key assumptions. Core indicators include missingness; timeliness; label reliability; drift. [146-149]

P3: Subgroup calibration reduces unequal treatment when a common risk threshold is used.

Researchers should test this relationship with transparent measures and a credible baseline. The analysis should distinguish the proposed pathway from confounding influences and report variation across relevant groups. Core indicators include subgroup calibration; error disparity; access to support. [150-152]

P4: Intervention fidelity mediates the effect of risk identification on academic recovery.

Assessment should link the proposition to observable process and outcome measures. A defensible test reports effect size, uncertainty, adverse results, and the conditions under which the relationship weakens. Core indicators include uptake; response time; treatment effect; burden. [153-156]

P5: Transparent correction and appeal processes strengthen student trust in learning analytics.

Prospective evaluation is preferable because it fixes the prediction, intervention, and outcome windows in advance. Results should include implementation fidelity, competing mechanisms, and sensitivity checks. Core indicators include purpose limitation; access; correction; transparency. [157-159]

P6: Counselor capacity moderates the relationship between alert sensitivity and effective support.

Testing should combine quantitative outcomes with process evidence explaining how the proposed relationship operated. Replication across settings is needed before treating the proposition as general. Core indicators include caseload; review delay; staff capacity; fidelity. [141-145]

4.4 Safeguarded implementation and monitoring

Table 3. Staged implementation and evaluation pathway

Stage	Required action	Decision output
1 Diagnose	Define decision, unit, baseline, users, and failure costs	Approved problem statement and baseline

Stage	Required action	Decision output
2 Govern	Assign owners, definitions, access, review, and escalation	Accountable operating design
3 Prepare	Assess data quality, workflow fit, capacity, and safeguards	Readiness evidence and test plan
4 Pilot	Test normal cases, edge cases, subgroup effects, and failure recovery	Pilot results with uncertainty
5 Scale	Expand only when reliability, usability, equity, and workload thresholds are met	Controlled implementation
6 Learn	Monitor outcomes, drift, exceptions, complaints, and corrective action	Revised rules and sustained learning

Implementation starts by mapping the support process and confirming available services. A baseline model is validated across groups and time, followed by a limited human-reviewed pilot. Thresholds and workflows are revised from alert and intervention evidence before any expansion.

5 Conclusion for Responsible Student Support

This conceptual and methodological review developed a prediction-to-intervention pathway that connects model performance with triage, review, support assignment, monitoring, and appeal. Its central finding is that earlier, fairer, and more effective student support depends on the interaction of predictive validity, data quality and missingness, fairness, intervention design, privacy and consent, implementation capacity, rather than on one tool, metric, or control.

The review joins predictive validity, data quality, fairness, intervention design, privacy, and staff capacity in one accountable support process. The framework evaluates an analytics system through both model behavior and the timeliness and distribution of help offered to students.

Schools should begin with a support decision, an available intervention, and a clearly defined student outcome. Pilots should test data quality, threshold burden, subgroup errors, staff interpretation, student communication, appeals, and the capacity to respond to every alert.

The framework does not establish that any one model or intervention will transfer across schools. Prospective validation must assess both prediction quality and support outcomes. Future research should test the propositions prospectively, compare alternative specifications, report null and adverse outcomes, and examine whether benefits persist after initial implementation.

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