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Learning Analytics and Predictive Modeling in E-Learning Platforms for Early Identification of At-Risk Students

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Abstract

Early identification of at-risk students in e-learning platforms is often treated as a prediction problem, yet many studies do not carry this framing through to actionable early-warning decisions. A recurring gap is that risk indicators, predictive modeling, timing, interpretation, and intervention are seldom connected into a coherent decision logic that clarifies what can and cannot be concluded. This paper therefore presents a conceptual framework that defines at-risk and early, organizes learning management system signals, and situates modeling within a timing and interpretability layer that links to a response pathway. The framework is intended for literature synthesis and conceptual analysis rather than empirical benchmarking, and it makes explicit the boundary between cautious early-warning statements and stronger causal claims. Taken together, the contribution is a disciplined template for reporting predictive learning analytics in terms of practical usefulness, fairness, and intervention readiness, with attention to e-learning settings relevant to learning analytics researchers and online student-success practitioners.

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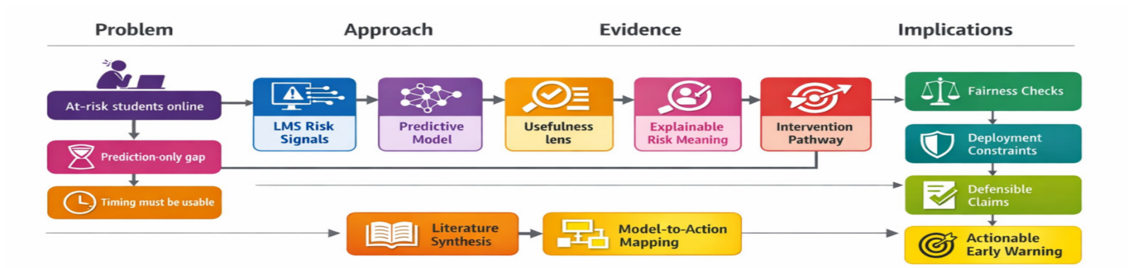

Graphical abstract

Introduction

Online and blended learning have expanded rapidly, and e-learning platforms now need to support diverse learners at scale. Recent syntheses in learning analytics and artificial intelligence in education report growing publication volume and a shift in priorities toward practical student support rather than prediction alone.[1, 2] The move to emergency remote teaching during COVID-19 further increased reliance on online study, which sharpened the need to identify emerging difficulty in time, before course failure or disengagement becomes difficult to reverse.[3] The pressures motivating early warning in e-learning are summarized in Fig. (1).

Early identification is educationally useful only when a risk flag arrives with enough time to act and when the reasons behind the flag can be interpreted and linked to a feasible support response. However, many published approaches still treat success prediction as the endpoint, which can yield high accuracy claims without clarifying who will act on the outputs, what information they require, and what interventions are realistic in a given platform context.[2] The decision points and information needs of typical instructors, support staff, and student-success leaders are summarized in Tab. (1).

This paper therefore situates predictive modeling as one component within a broader early-warning

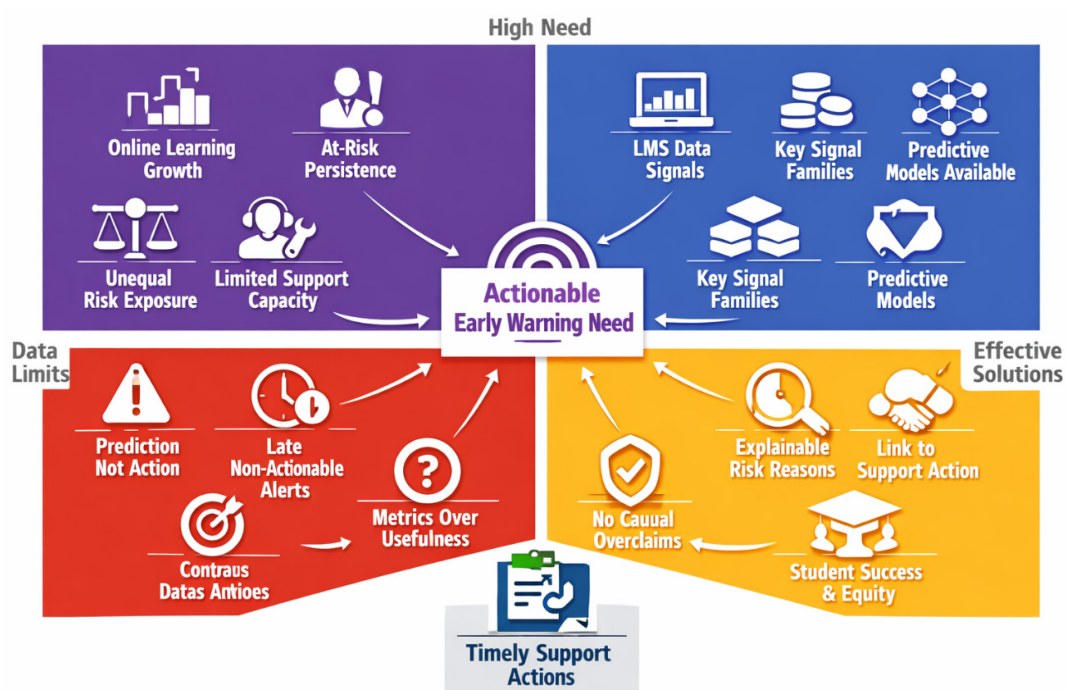

Fig. 1: Why early warning matters now

Table 1: Stakeholder decisions and information needs

Stakeholder	Decision Or Action	Information Needed
Online Instructor	Decide whether to reach out and what learning support to suggest	Risk flag with timing (early vs late), clear reasons or signals, suggested intervention options
Academic Support Staff	Prioritize which students need help first and choose a support response	Interpretable risk information, urgency based on timing, link from risk to a feasible intervention
Student Success Lead	Decide how the early-warning system should be used in practice	Practical usefulness criteria (timeliness, interpretability, intervention relevance), fairness considerations, clear limits on what claims the model supports
Learning Analytics Researcher	Choose signals and modeling approach consistent with actionable early warning	Common LMS signals, explainability needs, evaluation focus beyond prediction-only metrics, boundaries between early warning and causal claims

system that links platform signals, model outputs, timing, and interpretation to an intervention pathway. The central contribution is an **actionable early warning** framework that helps readers judge practical usefulness alongside predictive performance, and that clarifies boundaries between risk identification and stronger causal claims about what support will change outcomes.[3]

Early-Warning Problem Framing in E-Learning

Learner modeling traditions often report predictive performance while leaving decision timing and response pathways implicit.[4] However, early warning in e-learning is strongest when learning management system signals are interpreted within support workflows rather than treated as a standalone prediction task.[5] Fig. (2) differentiates major signal families by the time window in which risk flags can still enable help. Tab. (2) distils recurrent failure modes that turn accurate flags into non-actionable alerts.

Signal families in e-learning platforms

Risk identification in e-learning draws on signals recorded by the learning management system (LMS), yet the same underlying log can lead to different early-warning decisions depending on how events are

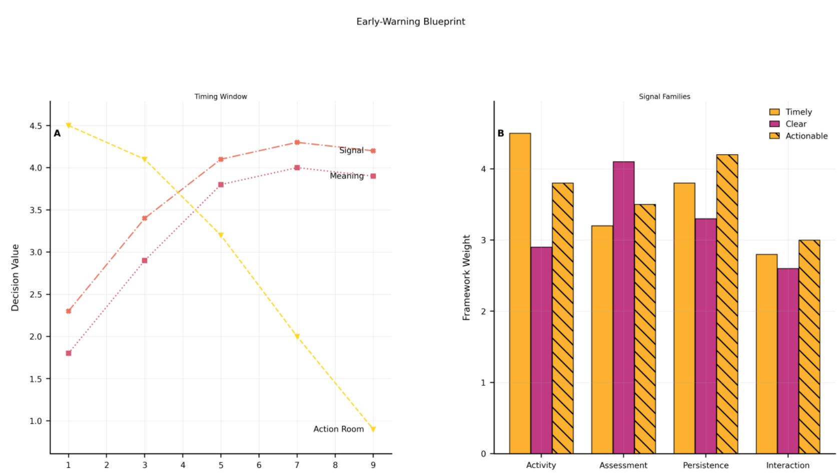

Fig. 2: Early-warning blueprint

Table 2: Timing and actionability gap checklist

Failure Mode	What Goes Wrong	Practical Effect	Design Check
Late Identification	Risk flag arrives after the key learning moment has passed	Prediction exists but cannot support timely help	Define what early means and align prediction timing to support windows
Timing Not Defined	No clear link between when risk is predicted and when harm is expected	Early warning claim becomes unclear and hard to evaluate	Specify decision points and the usable time remaining for action
Low Interpretability	Model output is hard to explain to educators or support staff	Flag is difficult to translate into an intervention	Add an interpretive layer that connects signals to understandable risk indicators
No Intervention Link	Risk scores are produced without a response pathway	Prediction-only framing, limited educational usefulness	Map each risk flag to a realistic support action and urgency

grouped and interpreted. Fig. (3) situates this choice by summarizing how common LMS data sources are converted into features and then organized into risk signal families. This family-based organization differentiates what is straightforward to measure from what is educationally meaningful, and it clarifies which signals can plausibly support early action, by contrast with post hoc explanation.

Taken together, activity, assessment, persistence, and interaction signals bring distinct strengths and blind spots that should be treated as design constraints for an early-warning system, particularly when considering failure cases and safe use. Tab. (3) elaborates that activity traces can flag disengagement early, however they can degrade into prediction-only scoring if no response pathway is defined. Assessment outcomes often align with risk labels, but they may arrive after support would matter most, which limits their value for timely intervention. Persistence patterns help reason about timing and escalation, but they still require an explicit link to specific support actions to be practically useful. Interaction signals can aid interpretation and fairness checks, while also constraining what claims remain appropriate for deployment.

Timing and the actionability gap

Timing often determines whether an accurate at-risk prediction can support learning rather than only document failure after the fact. In online courses, risk evidence accumulates across the term, so streaming or incremental prediction updates revise risk estimates as new information becomes available [6]. However, actionability depends on when risk is flagged: early,

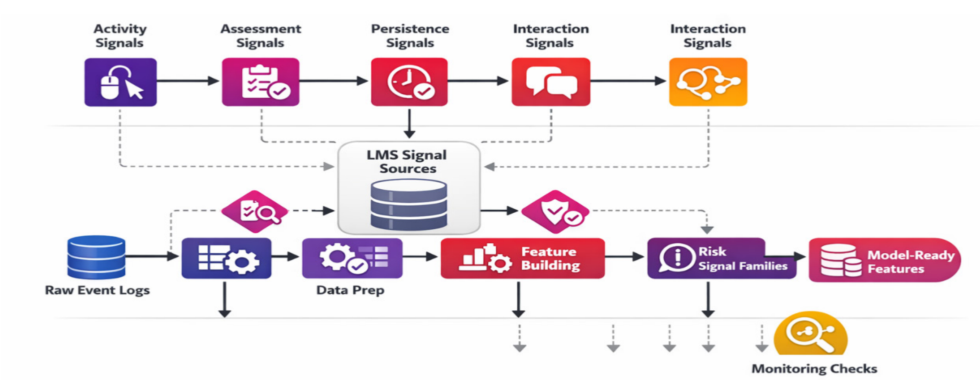

Fig. 3: LMS signal sources and feature flows

Table 3: Signal families strengths and blind spots

Signal Family	Strength For Early Warning	Blind Spot to Watch
Activity	Platform-based risk indicators for early identification in e-learning	Prediction-only framing without a clear response pathway (intervention linkage)
Assessment	Direct input to predictive modeling for at-risk identification	Timing risk: results can come too late to be actionable early warning
Persistence	Signals that support early-warning timing logic and interpretation	Risk of unclear practical usefulness if the link to support action is not specified
Interaction	Signals that can inform explainability and fairness discussions	Fairness and interpretation limits can constrain safe deployment and claims

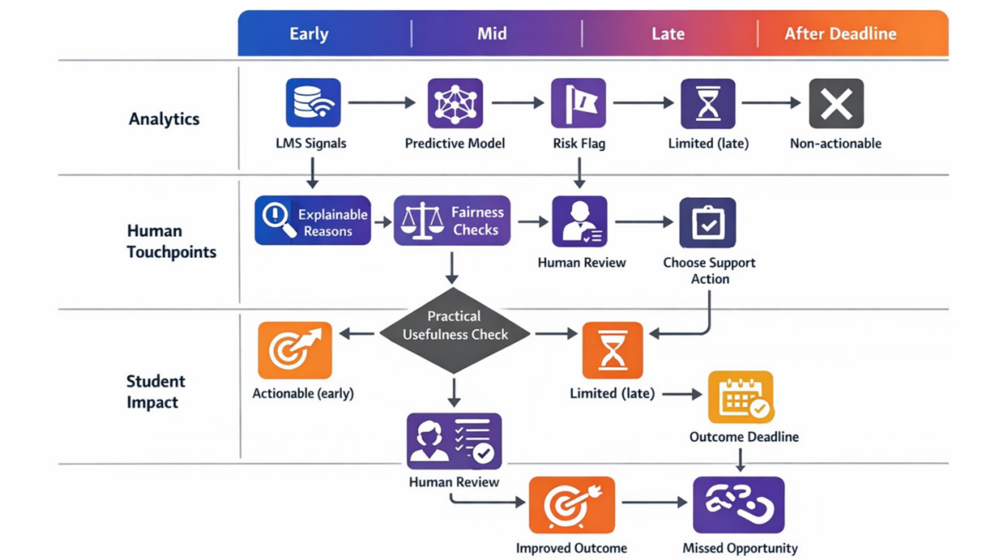

Fig. 4: Actionability across the course timeline

late, or only after the outcome is effectively decided, as illustrated in Fig. (4). A common failure regime is late identification, which can leave too little time for a meaningful response.

he **actionability gap** arises when prediction performance is reported without stating when the prediction is made and which decision it is intended to support. For this reason, timing-aware evaluation treats prediction as a sequence of updates, examining how early a stable risk signal becomes available and whether it remains consistent as evidence accumulates [6]. Measurement ideas from situation-awareness research clarify the design rationale for this emphasis: risk must be known in time for action, with sufficient lead time and clarity to support interpretation and the selection of support options within the evaluated setting.[7]

Key Concepts and Decision Boundaries

Actionable early warning in e-learning requires disciplined use of core terms that differentiates conceptual claims from measurable constructs. Core operational definitions and boundaries are summarized in Tab. (4). At-risk students are treated as a support-oriented target, not an objective label, and early identification is only useful when there is sufficient time for meaningful action. Practical usefulness is judged by timeliness, interpretability, and intervention relevance. Each construct should be operationalized with evidence of validity and reliability.[8]

Defining at-risk and early identification

In e-learning contexts, this study defines at-risk students as learners with an elevated likelihood of an

Table 4: Key terms and operational boundaries

Term	Operational Meaning in This Paper	Decision Boundary (What Counts)
At-Risk Students	Learners in e-learning who may need timely support	Use as an early-warning target, not as a fixed label or objective score
Early Identification	Flagging risk with enough time left to act	If timing is too late for meaningful support, it is prediction-only, not early warning
Practical Usefulness	Educational value of an early-warning output for real action	Judged by timeliness, interpretability, and intervention relevance, not prediction metrics alone
Intervention Linkage	Connecting a risk flag to a support response	A risk flag without a realistic response pathway is outside actionable early warning
Explainability And Fairness	Model understanding and responsible use across learners	Treat as design constraints for credible deployment, not optional add-ons or standalone ethics discussion

undesired academic outcome in the current course or program, such as failing required assessments, withdrawing, or not completing. Risk is treated as a decision-relevant status rather than a fixed trait, and is situated in the course design, the available learning management system signals (for example, activity, assessment progress, and participation patterns), and the support that can realistically be offered.

Early identification is defined as producing a risk indication with enough lead time to support meaningful action, not merely to describe what is already inevitable. An indication is early enough only when time remains to interpret the likely cause of risk, choose an appropriate response, and deliver support before the negative outcome becomes hard to change (for example, near the end of term or after key graded milestones have passed).

Usefulness lens: interpretability and fairness

Practical usefulness in early warning requires that risk information arrives early enough to enable a response and is presented in a form that support staff can readily interpret. In line with this design rationale, interpretability is treated as decision support: the model should indicate which signals drive a flag, rather than relying on post hoc visualizations [9].

Usefulness is also bounded by fairness and responsible use. Flags should not systematically disadvantage underserved groups and should not be deployed where no appropriate support exists. Education artificial intelligence syntheses clarify the need to examine who is flagged and how errors are distributed across learner groups [10]. This study therefore treats usefulness as timely, interpretable, and human-centred, with equity checks serving as a boundary for credible claims.[9, 10]

Actionable Early-warning Framework

This study proposes an actionable early-warning framework in which prediction is one stage of an educational response system rather than the end product.[11] It links platform signals to modeling and timing choices and to an interpretation layer that guides support actions, consistent with intelligent tutoring lessons on aligning feedback with learning needs.[12] The end-to-end pathway is summarized in Fig. (5).

Framework components and information flow

This framework treats early warning in e-learning as an information flow that translates raw platform traces into timely, interpretable risk information to support intervention decisions. It begins by defining what at-risk means in the specific course context and which negative outcomes the warning is intended to avert, because these choices clarify which indicators are relevant and what kinds of errors are tolerable. In a learning management system (LMS), candidate

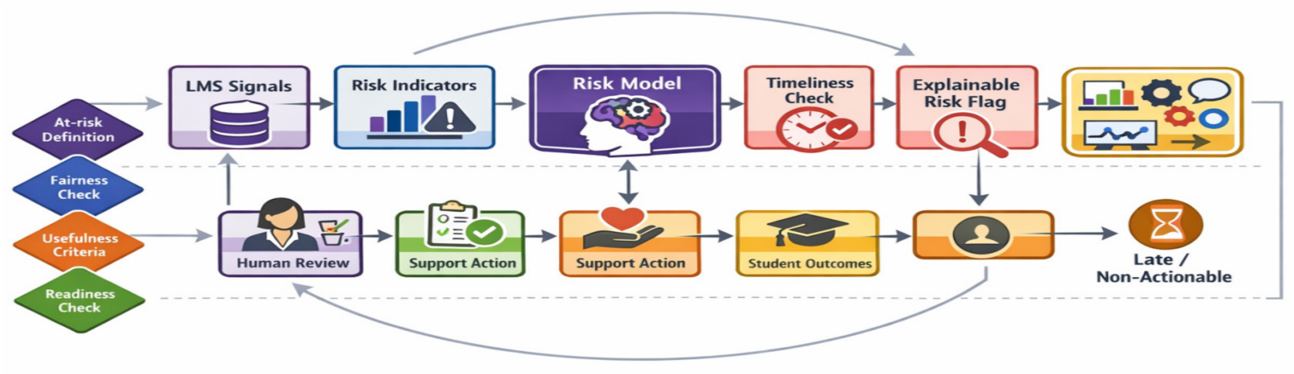

Fig. 5: Signals to intervention logic model

signals include activity, assessment progress, persistence, and interaction, but the final selection is differentiated by educational meaning and data reliability.

The selected signals are then organized into comparable time windows, with explicit handling of missing, late, or irregular events so that the model reflects learning behaviour rather than logging noise. Feature construction preserves temporal direction by separating cumulative progress from recent change, and it records which inputs are sufficiently stable for use early in a term. The modeling stage maps the evolving feature set to a calibrated risk estimate and, when feasible, a brief explanation of the strongest contributing factors.

Timing logic then tests whether each estimate is actionable by comparing the prediction point with the remaining time in which support could still change the outcome, and alerts that arrive after the practical decision point are treated as too late. For use, outputs are converted into a small set of risk states with uncertainty cues and links to the underlying evidence, enabling human review before contact. The final handoff ties each state to an available support option and records follow-up, so the early-warning system can be monitored and refined.

Decision points: thresholds, interpretation, response

Early-warning outputs are educationally useful only when risk flags function as prompts for human judgment rather than as final labels. Thresholds should therefore be treated as triage points that trigger review, not as cutoffs that declare failure, and reviewers should build situation awareness by interpreting the flag alongside recent learning activity, assessment trajectory, and data quality signals.[13] Explanations should remain brief, comparative, and consistent so they fit limited attention and dual-channel processing, for example by pairing a small set of key drivers with a simple visual summary.[14]

Response selection should be guided by the interpreted need and the available support capacity, spanning low-cost nudges through advisor outreach, while recording the rationale to reduce automation bias and support later refinement. Interface and message design should minimize cognitive load by foregrounding the recommended next step, the main uncertainty, and the time sensitivity of the case, rather than presenting a score alone.[14, 15] A structured path from risk flag to support action is illustrated in Fig. (6).

Applying the Framework to Predictive Modeling Practice

Existing predictive analytics can be assessed through an actionability lens, asking whether timing, interpretation, and response are treated as design constraints rather than afterthoughts. Prediction-only, metric-led benchmarks often decouple risk scoring from support decisions, whereas the proposed framework and intervention-linked practice situate prediction points and explanations within feasible help pathways, summarized in Tab. (5).

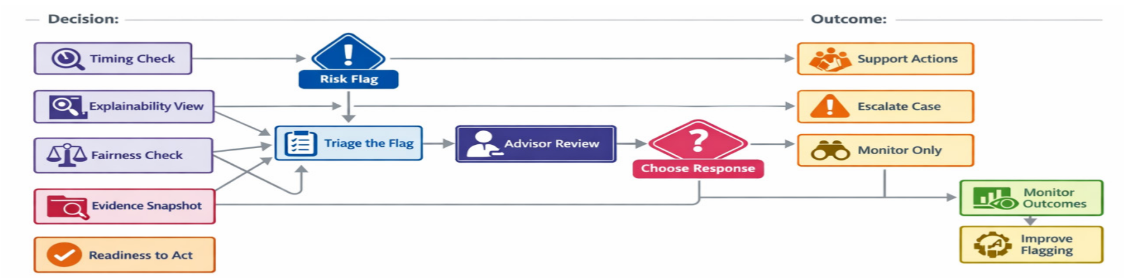

Fig. 6: Risk flag interpretation and response path

Table 5: Approaches mapped to usefulness dimensions

Approach Focus	Timing Fit	Interpretability Fit	Usefulness For Action
Prediction-Only Framing	Timing not central; may miss early identification needs	Interpretation often secondary to metrics	Weak link from risk score to intervention decisions
Metric-Led Model Benchmarking	Often evaluates performance without asking when support is still possible	Explainability not required to report strong metrics	Can look strong on paper but still be non-actionable for student support
Actionable Early-Warning Framework	Built around early-warning timing logic and usable lead time	Includes an interpretive layer before acting	Connects signals, prediction, interpretation, and a response pathway
Intervention-Linked Predictive Practice	Chooses prediction points that align with realistic support windows	Needs explanations that practitioners can use	Supports a decision path from risk flag to human interpretation to support action

Where published models fit in the framework

Published predictive modeling papers in educational data mining (EDM) often align well with the modeling and evaluation components of the early-warning framework, yet they do not consistently translate into actionable support decisions. One representative comparative study[16] clarifies **score-first comparisons,** where model families are contrasted primarily on predictive performance, while practical considerations such as whether a risk flag arrives early enough, how it should be interpreted, and what response it should prompt remain implicit.

When mapped onto the framework, these comparisons typically emphasize (a) which learning management system (LMS) signals are engineered into features and (b) how alternative classifiers are trained and validated.[16] By contrast, they less consistently specify the timing logic that determines how much usable lead time remains before an adverse outcome, the interpretive layer required to justify a risk label to instructors or advisors, and the response pathway that connects a flag to a feasible intervention. Taken together, the reported scores are informative for prediction, but incomplete for early-warning use.[16]

Designing models for action, not scores

Actionable early warning modeling is best framed around the support action rather than the risk score itself. Accordingly, features should be selected because they are available early in a course, understandable to staff, and tied to responses that can be delivered. To keep risk flags actionable, model outputs should include brief reasons and recommended follow up so that alerts connect directly to feedback and support workflows.[17]

Training procedures can also be tuned for early separability, so the model differentiates students who later become at risk while usable time remains. Curriculum scheduling can emphasize earlier course examples and progressively add later signals.[18] Evaluation should weight timeliness and clarity for intervention readiness, not only end of term accuracy .[17, 18]

Discussion and Implications

Actionable early warning is defined by usefulness rather than accuracy, and it does not imply guaranteed prevention, Eq. (1).

$$U = \lambda_T T + \lambda_I I + \lambda_R R \tag{1}$$

Timeliness is measured as the normalized lead time between a flag and the outcome, Eq. (2).

$$T = max\left(0, \frac{t_{outcome} - t_{flag}}{\Delta t_{max}}\right) \tag{2}$$

Readiness clarifies how clear signals connect to non-ad hoc supports (Tab. (6)) [19], [20], Eq. (3).

$$R = \frac{C\,A}{1 + \sigma_H} \tag{3}$$

Because flagging uses a threshold, cases with weak explanations may not support immediate action and therefore need human interpretation before a support response is selected [21], Eq. (4).

$$\hat{y}_i = I(s_i \geq \tau) \tag{4}$$

Deployment also requires group checks via absolute TPR gaps, Eq. (5).

$$\Delta_{TPR} = \left|TPR_{g=0} - TPR_{g=1}\right| \tag{5}$$

Responsible deployment and claim boundaries

Predictive models in e-learning provide risk estimates that can prioritize support, but these estimates do not show that any action will change student outcomes. Early-warning outputs remain descriptive unless the intervention is evaluated, and a high score should prompt review rather than serve as proof of impending failure.

Credible deployment requires signals with usable lead time, interpretable reasons for flags, and a feasible response that is defined and resourced. Performance, drift, and equity should be monitored, and intervention effects should be established using separate experimental or quasi-experimental evidence.

Table 6: Interventions by timing and urgency

Decision Situation	Timing For Action	How To Interpret The Risk	Support Urgency	Readiness For Response
Clear early warning	Early identification, enough usable time remains	Explainable models and clear signals, low need for extra interpretation	Can be planned and targeted	Actionable early-warning, link directly to a support action
Early but hard to explain	Early identification, timing is good	Low explainability, needs human interpretation before action	Often moderate, depends on context	Use an interpretive layer, then choose an appropriate response pathway
Late warning	Prediction arrives late, little usable time remains	Interpretability still helps, but timing limits educational usefulness	Can be high because outcomes are near	Limited actionability, focus on what can still be supported without overclaiming
Urgent support needed	Any timing where risk is time-sensitive	Prefer clear, explainable indicators to avoid misdirected action	High urgency	Prioritize fast human review and rapid movement from risk flag to support action

Operational feasibility and equity considerations

In practice, early-warning is useful only if data arrive quickly, staff can review alerts, and the system can route cases into existing advising or tutoring workflows. For this reason, models should use simple, explainable indicators that enable triage and limit false alarms. Equity requires assessing uneven data coverage and systematic errors across student groups, and ensuring that flagged risk leads to supportive options rather than surveillance or exclusion.

Conclusion

This study differentiates predictive learning analytics in e-learning from score production by situating it as an actionable early-warning system. Actionability is clarified in decision terms: platform signals must flag risk with usable lead time, be interpretable in language staff can act on, and link to interventions that can be resourced. The framework elaborates a sequence of design choices spanning signal selection, time-aware modeling, human interpretation, and response pathways. Claims remain bounded: predictions guide attention rather than imply guaranteed prevention and require equity checks before deployment.

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