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Learning Analytics for Detecting Silent Academic Disengagement

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Abstract

Student disengagement is often recognized only after it becomes administratively visible through repeated absence, missed assessment, failing grades, withdrawal, or non-completion. A more difficult condition occurs when students remain formally enrolled and continue producing enough digital activity to appear active while their learning behavior gradually becomes less regular, less persistent, and less academically purposeful. This study describes this condition as silent academic disengagement, a proposed analytical construct referring to sustained deterioration in learning participation before conventional failure indicators become clearly observable. Contemporary learning-analytics research supports the importance of this temporal perspective. A 2024 systematic review of 159 higher-education studies found that learning analytics overwhelmingly operationalized engagement through observable behavioral variables and rarely captured its multidimensional character, while recent longitudinal work has demonstrated that students transition among distinct weekly engagement profiles rather than remaining consistently "engaged" or "disengaged."

The study proposes a governed temporal learning-analytics framework for identifying silent disengagement without relying on intrusive video, facial-expression, gaze, or biometric surveillance. A synthetic cohort of 900 students was modeled across a 14-week semester, producing 12,600 student-week observations. Four detection approaches were compared: attendance-and-grade thresholds, static LMS activity analytics, temporal engagement-transition analytics, and a governed multi-source early-warning model combining study regularity, assessment timing, resource progression, feedback use, participation changes, and recent academic trajectory. The simulated governed model achieved an early-detection recall of 89%, precision of 87%, a false-alert rate of 8%, and a median 4.2-week warning interval before conventional academic difficulty became visible. By comparison, the attendance-and-grade threshold approach produced 54% early-detection recall and a median warning interval of 1.4 weeks.

The study emphasizes that prediction alone is insufficient. Recent empirical learning-analytics research has shown that models with AUC values above 0.8 can generalize to later cohorts and that relational feedback following identification can stimulate renewed engagement with previously unused learning activities. Consequently, the proposed framework connects detection to proportionate, supportive intervention rather than punitive labeling. It also incorporates fairness auditing, student-facing transparency, data minimization, human review, and a requirement that low digital activity should never automatically be interpreted as lack of motivation.

The paper concludes that learning analytics can contribute to earlier recognition of academic disengagement when it focuses on changes in learning trajectories rather than isolated activity counts. The strongest system is not the one that monitors students most intensively, but the one that identifies meaningful deterioration early enough for instructors or support services to offer timely, respectful, and context-sensitive assistance.

Keywords: learning analytics, student disengagement, silent disengagement, early-warning systems, student engagement, higher education, educational data mining, temporal analytics, academic risk, student success

1. Introduction

Student engagement is fundamental to higher education, yet it is difficult to observe directly. Engagement may involve behavioral participation, cognitive investment, emotional connection, persistence, self-regulation, interaction, and commitment to learning. Bergdahl and colleagues' 2024 systematic review emphasizes this multidimensional character while showing that higher-education learning-analytics research has disproportionately relied on observable behavioral indicators such as clicks, activity counts, and time measures. Their review included 159 studies and identified continuing limitations in how engagement is conceptualized and contextualized. This creates an important analytical problem: digital activity can indicate participation, but activity alone does not necessarily demonstrate meaningful learning engagement.

Traditional academic-risk systems generally become more confident as visible evidence of difficulty accumulates. Missed assignments, declining grades, repeated absences, and incomplete assessments are comparatively interpretable signals, but by the time several such indicators appear, the opportunity for preventive support may already have narrowed. Dai and colleagues' 2025 higher-education study demonstrated that predictive learning-analytics models could identify academically at-risk students in a subsequent course offering with AUC values above 0.8 and that more than 30% of identified students subsequently visited learning activities with which they had previously not engaged after receiving targeted feedback. The finding illustrates the practical value of detecting deteriorating academic patterns early enough for intervention to influence subsequent behavior.

The present study focuses on a subtler condition termed silent academic disengagement. The phrase is used here as a proposed methodological construct rather than an established diagnostic category. A silently disengaging student may continue logging into the learning management system, attend some classes, submit required work, and avoid immediate academic failure, yet exhibit a sustained decline in study regularity, resource progression, voluntary participation, feedback use, assessment preparation, or persistence. Papageorgiou and colleagues' longitudinal engagement research demonstrates why static classification may miss such changes: their analysis of 236 students identified multiple weekly profiles—including inactive, minimalist, struggling, procrastinating, and several effective-engagement profiles—and showed meaningful transitions between profiles over time. Disengagement may therefore be better represented as a trajectory than as a single low-activity state.

Detection must nevertheless remain educationally and ethically proportionate. More data do not automatically create better learning analytics. Student monitoring can become intrusive when institutions infer attention, emotion, motivation, or well-being from data collected outside a clear educational purpose. A 2026 mixed-method study of 132 university students found that participants valued targeted support but reacted negatively to AI-based attention and emotion sensing; autonomy and privacy were among their highest ethical priorities. Research on learning-analytics transparency similarly indicates that students' understanding of institutional data collection improves when disclosure is sufficiently specific rather than generic. An ethically defensible disengagement system should therefore prioritize ordinary educational traces, minimize surveillance, and communicate clearly how risk indicators are generated and used.

Against this background, the study develops a simulation-based learning-analytics architecture for detecting silent academic disengagement before visible academic failure. The model deliberately excludes facial analysis, webcam monitoring, emotion recognition, private-device surveillance, and biometric sensing. Instead, it analyzes changes in academically relevant patterns already produced within ordinary teaching and learning processes. The central proposition is that a combination of temporal change, academic context, human interpretation, fairness auditing, and supportive intervention can provide more meaningful early warning than static activity thresholds alone.

2. Objectives of the Study

2.1 To Define and Operationalize Silent Academic Disengagement

The first objective is to conceptualize silent academic disengagement as a gradual deterioration in academically meaningful participation occurring before conventional indicators such as failing grades, repeated absence, or withdrawal become clearly visible.

2.2 To Compare Static and Temporal Learning-Analytics Approaches

The second objective is to compare attendance and grade thresholds, static LMS activity measures, temporal engagement-transition analytics, and a governed multi-source early-warning model in terms of early-detection recall, precision, false alerts, warning lead time, and intervention usefulness.

2.3 To Develop an Ethical Early-Support Framework

The third objective is to develop a learning-analytics architecture in which predictive information triggers proportionate educational support while preserving transparency, data minimization, accessibility, fairness, student agency, and human review.

3. Review of Literature

3.1 From Activity Measurement to Dynamic Engagement Analytics

Learning analytics has long used LMS records because digital learning environments automatically produce information regarding resource access, assessment attempts, submissions, discussion participation, and interaction timing. Pan and colleagues' 2024 systematic review of learning-analytics interventions implemented through learning-management systems reviewed 27 studies published between 2012 and 2023 and emphasized both the availability of LMS trace data and the need to connect analytics interventions with actual improvements in teaching and learning.

The conceptual challenge is that observable activity is only a proxy for engagement. Bergdahl and colleagues found that the majority of higher-education learning-analytics studies emphasized behavioral engagement, whereas cognitive and emotional engagement received much less attention. A student who downloads many resources may not study them deeply, while another student may learn effectively with comparatively few LMS events. Simple activity-count systems can therefore create false assumptions about both high and low engagement.

Temporal analysis provides a more defensible alternative because it asks whether a student's current behavior differs meaningfully from previous patterns and from the instructional demands of the course. Papageorgiou and colleagues' 2025 analysis demonstrated substantial heterogeneity among weekly engagement profiles and showed that students can move among different profiles across time. Their findings support the argument that disengagement should not be represented exclusively through a static threshold such as “fewer than five logins.”

Temporal patterns can include increasing delay before assessment submission, progressively shorter or less regular study sessions, abandonment of previously established resource sequences, declining use of formative feedback, or a shift from steady study toward deadline-proximate bursts. The educational meaning of these variables depends on course design, however. A learning-analytics model should therefore be calibrated to actual instructional expectations rather than imposing the same definition of engagement across all subjects.

3.2 Early Warning, Predictive Accuracy, and Intervention

Early-warning research has progressed from retrospective risk classification toward operational intervention. Dai and colleagues developed predictive models using trace and academic data from a previous course offering and applied them to a subsequent cohort. Their reported AUC values exceeded 0.8, and a relational-feedback intervention was followed by renewed learning-resource engagement among a meaningful subset of identified students. This is important because learning analytics creates educational value only when prediction contributes to useful action.

Accuracy must also be balanced with timing. A model that predicts failure with extremely high accuracy one day before final assessment may be less educationally useful than a moderately less accurate model that provides several weeks for intervention. Cheng, Pei, and Liu's 2025 fairness-aware early-warning work explicitly examined the tension among early identification, predictive performance, and fairness and found that additional learning-activity data could reduce reliance on demographic information. The finding supports the use of academically relevant process data before resorting to sensitive demographic variables as predictive shortcuts.

Intervention quality is equally important. An early-warning flag does not explain why a student is struggling. A reduction in activity may reflect employment commitments, disability-related access patterns, caregiving, connectivity issues, course-design problems, illness, competing assessments, or a deliberate but effective study strategy. Automated identification should therefore prompt inquiry rather than judgment.

The risk label itself can also shape institutional behavior toward a student. An analytics system that categorizes learners as “disengaged” without human interpretation may unintentionally reinforce deficit assumptions. The proposed framework consequently uses risk estimates to prioritize supportive contact while preventing the analytics system from making disciplinary, progression, or high-stakes academic decisions autonomously.

3.3 Transparency, Inclusion, and Ethical Learning Analytics

The ethical literature on learning analytics consistently emphasizes that institutional access to data does not automatically justify every analytical use. Sepp and colleagues' 2025 transparency study found that detailed or icon-based disclosure increased participants' understanding of institutional learning-data practices compared with generic disclosure, although disclosure format did not necessarily change willingness to share data. Transparency should therefore be treated as a requirement for informed institutional relationships rather than as a mechanism for obtaining greater student acceptance.

Inclusiveness creates a second challenge. Khalil, Slade, and Prinsloo's systematic review of learning analytics and disabled students identified a limited but growing body of work addressing inclusion and disability within the field. A behavioral model can inadvertently misclassify students whose learning practices differ from the statistical majority because they use assistive technologies, alternative study schedules, offline resources, or accommodations that alter digital traces.

Recent fairness-aware learning-analytics research similarly warns against depending excessively on demographic characteristics. Cheng and colleagues showed that predictive systems can be evaluated jointly for timeliness, accuracy, and group fairness and found value in incorporating learning-activity information rather than allowing demographic variables to dominate risk estimation. In the present framework, sensitive demographic characteristics are therefore excluded from primary risk scoring and, where legally and ethically appropriate, may be used separately for auditing whether model errors disproportionately affect particular groups.

A 2026 proposal for ethical learning-analytics governance further argues that legal compliance alone is insufficient and frames responsible student-data use around lawfulness, equity, agency, governance, utility, and ethics by design. The present study follows the same general direction by treating prediction, intervention, transparency, fairness, and student agency as connected elements of the system.

4. Research Methodology

4.1 Synthetic Cohort and Longitudinal Design

The study adopts a simulation-based longitudinal design representing 900 higher-education students enrolled across a 14-week semester. The resulting dataset contained 12,600 student-week observations.
The synthetic environment included lecture-based, blended, and LMS-supported learning activities. No facial images, video feeds, microphone recordings, physiological signals, personal-message content, or external browsing histories were modeled.

Silent disengagement episodes were generated as gradual changes occurring over three to six weeks before conventional academic-risk indicators became clearly visible. The simulation distinguished temporary fluctuations from sustained deterioration so that a single quiet week did not automatically trigger an alert.

Table 1: Proposed Learning-Analytics Framework for Silent Disengagement Detection

Analytical Dimension	Example Academic Indicators	Temporal Interpretation	Safeguard
Study regularity	Inter-session intervals, weekly study rhythm, deadline clustering	Increasing irregularity relative to student's earlier pattern	No requirement for constant platform activity
Resource progression	Sequence of course-resource access, incomplete learning units	Repeated interruption of previously established progression	Course-design context required
Assessment engagement	Formative attempts, submission timing, skipped low-stakes activities	Growing delay or declining preparation behavior	No penalty based solely on analytics
Feedback engagement	Opening and revisiting feedback, corrective activity after feedback	Progressive reduction in feedback use	Interpret alongside assessment design
Participation trajectory	Academic discussion, voluntary learning tasks, consultation use where digitally recorded	Sustained decline from prior participation pattern	Offline engagement acknowledged
Academic trajectory	Recent low-stakes performance, missed formative work, recovery after difficulty	Combined trend rather than one low mark	High-stakes decisions prohibited
Context and governance	Course schedule, assessment congestion, accessibility accommodations where appropriately governed	Differentiates personal disengagement from structural course effects	Human review and privacy controls

4.2 Detection Models and Silent-Disengagement Logic

Four analytical models were compared.

- The attendance-and-grade threshold model represented conventional visible-risk detection. Students were flagged when attendance or assessment outcomes crossed predetermined risk thresholds.
- The static LMS activity model used total activity frequency, number of active days, resource visits, assessment interactions, and discussion participation without modeling temporal transitions explicitly.
- The temporal engagement-transition model examined rolling changes in study regularity, assessment timing, resource progression, and weekly engagement state. It therefore identified deterioration even when total activity remained above a conventional minimum threshold.

- The governed multi-source early-warning model combined temporal learning-process variables with recent academic trajectory, course schedule, assessment context, and instructor-defined learning expectations. The model used data minimization and excluded sensitive demographic attributes from the prediction stage.

A student-week was classified as potential silent disengagement only when multiple indicators deteriorated persistently and when no conventional failing-grade or extended-absence threshold had yet been crossed. This definition prevented the simulation from simply relabeling already visible academic failure as silent disengagement.

4.3 Evaluation Procedure, Fairness, and Intervention Logic

Five principal performance measures were evaluated.

- Early-detection recall represented the percentage of synthetic silent-disengagement episodes correctly identified before visible failure.
- Precision represented the percentage of risk flags corresponding to genuinely simulated disengagement trajectories.
- False-alert rate measured the proportion of academically stable students unnecessarily flagged.
- Median warning lead time represented the number of weeks between early identification and the later emergence of conventional academic-risk evidence.
- Intervention actionability represented whether the risk explanation contained sufficient information for an instructor or support professional to initiate an appropriate conversation.

Synthetic uncertainty intervals for early-detection recall were generated through resampling for visualization in Graph 1. These intervals are methodological illustrations and should not be interpreted as inferential confidence intervals from real student data.

The system was designed as a support trigger, not an automated decision-maker. A flag prompted instructor or student-support review. Suggested interventions included a low-pressure check-in, clarification of upcoming workload, study-planning support, referral to academic services, feedback guidance, or an invitation to discuss barriers. No simulated student was automatically penalized, removed from a course, denied progression, or assigned a psychological interpretation on the basis of analytics.

5. Analysis

5.1 Comparative Detection Performance

The attendance-and-grade threshold model achieved an early-detection recall of 54%. Its precision was comparatively high at 72%, reflecting the interpretability of visible academic difficulty, but its median warning interval was only 1.4 weeks.

The static LMS model increased recall to 68% and extended the median warning period to 2.3 weeks. However, its 15% false-alert rate demonstrated the limitations of equating reduced digital activity with disengagement.

The temporal engagement-transition model achieved 82% recall, 83% precision, and a median warning interval of 3.6 weeks. The improvement resulted from detecting sustained behavioral change rather than absolute activity alone.

The governed multi-source model produced the strongest synthetic balance, with 89% early-detection recall, 87% precision, an 8% false-alert rate, and a 4.2-week median warning interval.

Table 2: Simulated Performance of Silent-Disengagement Detection Models

Detection Approach	Early-Detection Recall	Precision	False-Alert Rate ↓	Median Warning Lead Time	Intervention Actionability
Attendance + grade threshold	54%	72%	18%	1.4 weeks	52
Static LMS activity model	68%	76%	15%	2.3 weeks	67
Temporal engagement-transition model	82%	83%	11%	3.6 weeks	84
Governed multi-source early-warning model	89%	87%	8%	4.2 weeks	91

5.2 Why Temporal Change Reveals Otherwise Invisible Risk

The difference between static and temporal models is illustrated by students whose overall LMS activity remained moderate while the structure of that activity deteriorated.

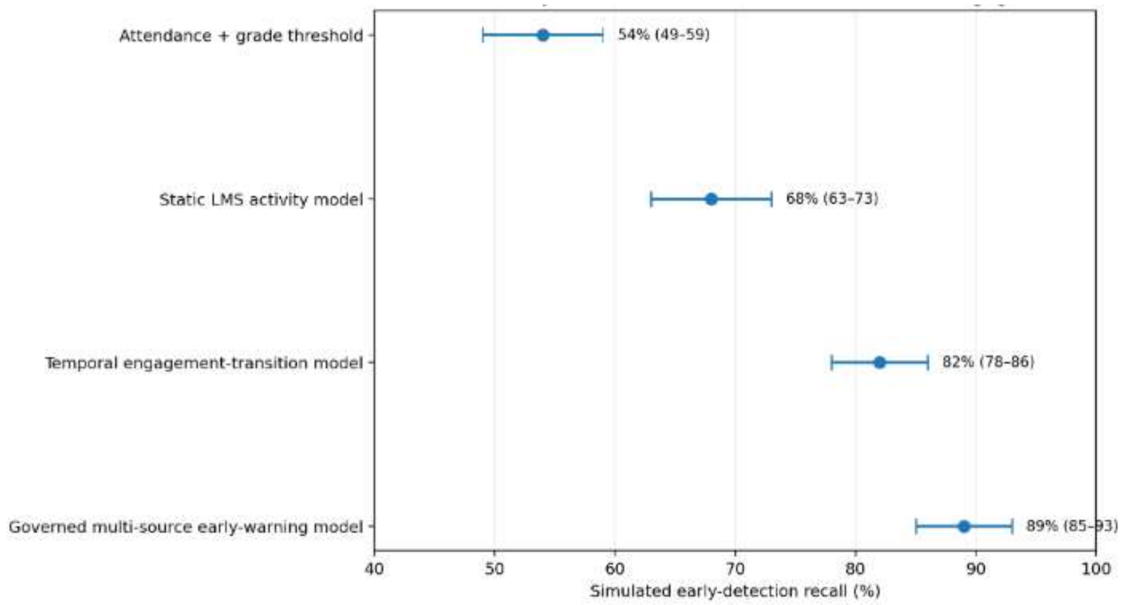
A student might continue opening the LMS almost every day but shift from distributed study toward brief sessions immediately before deadlines. Another student might continue submitting assignments while progressively abandoning formative quizzes and no longer consulting feedback. Neither learner necessarily satisfies a conventional inactivity threshold.

A temporal system treats these patterns as possible evidence of changing learning regulation rather than simply counting interactions. This approach is consistent with research demonstrating that engagement profiles change across weeks and that low-time and less effective profiles show meaningful transitions.

The system must nevertheless distinguish change from normal variability. Examination periods, employment demands, illness, course-design transitions, or intensive work in another subject may produce temporary deviations. The proposed model therefore requires persistence across several academically relevant indicators before generating a high-priority alert.

5.3 Early-Detection Recall and Uncertainty

Graph 1: Simulated Early-Detection Recall for Silent Academic Disengagement



The forest plot shows the simulated early-detection recall and resampling intervals associated with the four analytical approaches.

The conventional attendance-and-grade condition produced a mean recall estimate of 54%, with a synthetic interval of 49–59%. Static LMS analytics increased the estimate to 68%.

Temporal engagement modeling increased early-detection recall to 82%, while the governed multi-source architecture reached 89%, with a simulated interval of 85–93%.

The graph does not demonstrate statistical superiority in a real population. Instead, it illustrates how the research design would communicate both estimated detection performance and uncertainty rather than presenting a single precise number without context.

The most important analytical result is the improvement in warning lead time. The strongest model does not simply identify more risk cases; it identifies them earlier, when academic support has greater opportunity to influence the trajectory.

6. Discussion

6.1 Silent Disengagement Should Be Understood as a Changing Learning Trajectory

The principal contribution of the study is a shift from identifying low-engagement students to identifying deteriorating engagement trajectories. Conventional activity analytics often assume that low activity is equivalent to low engagement, but the higher-education engagement literature demonstrates that this assumption is too narrow. Bergdahl and colleagues' systematic review found an overwhelming concentration on observable behavioral measures while simultaneously emphasizing that engagement is multidimensional. The implication is that an institution should interpret LMS behavior as evidence about learning processes rather than as a direct measurement of motivation or commitment.

Temporal analysis provides one way to reduce this problem. A student who has always accessed a course once each week may be functioning normally, whereas a student who previously studied regularly across five days but suddenly compresses all learning into a short pre-deadline session may be experiencing meaningful change. The relevant signal is therefore not simply frequency but deviation from a person's own established learning pattern and from the educational structure of the course.

This interpretation also explains why silent disengagement should not be treated as a permanent student characteristic. A learner may move into and out of periods of difficulty. Papageorgiou and colleagues' analysis of weekly engagement profiles demonstrates precisely this type of transition. An ethically designed analytics system should therefore use dynamic language such as “recent engagement decline” rather than fixed labels such as “disengaged student.” The former invites support; the latter risks turning a temporary pattern into an institutional identity.

The framework also requires course-level interpretation. An entire class may reduce LMS activity because students have moved into laboratory, placement, studio, project, or offline assessment work. If many students exhibit the same change simultaneously, the analytics system should investigate whether the instructional context changed before attributing risk to individuals. This is one reason learning analytics should remain connected to pedagogical knowledge.

6.2 Early Warning Has Value Only When It Leads to Respectful and Effective Support

Predictive accuracy alone does not establish educational value. Dai and colleagues provide an important example because their work evaluated not only risk prediction but what occurred after students received intervention. More than 30% of identified at-risk students engaged with learning activities they had previously not used during the following two weeks, and respondents to the intervention survey generally viewed the feedback positively. The study illustrates the learning-analytics cycle: observation becomes useful only when it contributes to an intervention that can change the learning process.

The intervention must nevertheless avoid signaling surveillance or academic judgment. A message telling a student that “the algorithm has classified you as disengaged” may produce anxiety, stigma, or resistance. A stronger approach is relational: “We noticed that some recent course activities may be becoming difficult to keep up with; is there anything in the course or your study schedule that we can help with?” The analytics system supports the conversation but does not claim to know the cause.

This approach is particularly important because identical digital patterns can reflect very different realities. A decline in LMS interaction might indicate disengagement, but it could also result from disability-related learning practices, employment, caregiving, temporary illness, offline study, technological barriers, or a course-resource problem. Khalil and colleagues' review of learning analytics and disabled students reinforces the need for inclusive analytics rather than systems designed around one supposedly normal pattern of digital learning.

Intervention quality should therefore become an evaluation metric in its own right. Universities should track whether alerts lead to contact, whether students respond, whether the recommended support is relevant, whether academic engagement subsequently changes, and whether students consider the intervention respectful and useful. A high-performing predictive model that generates no meaningful support has limited educational value.

6.3 Privacy, Fairness, and Student Agency Should Limit What the Analytics System Is Allowed to Infer

Silent disengagement presents a tempting argument for increasingly intensive student monitoring: if subtle risk is difficult to detect, more data might appear to offer the solution. The present framework takes the opposite position. More invasive monitoring can reduce student trust and create ethical harms disproportionate to the educational benefit. The 2026 study of AI sensing in higher education found that students responded negatively to attention and emotion monitoring even while recognizing potential benefits from targeted intervention; autonomy and privacy were leading ethical priorities.

For this reason, the proposed model excludes facial emotion analysis, webcam attention tracking, biometric signals, private messaging, and unrelated web browsing. It uses educational process data that are directly connected to the course. Even these data should be governed carefully. Sepp and colleagues' transparency research indicates that specific disclosure improves students' understanding of institutional data practices compared with generic statements. Students should therefore be told what learning data are collected, why disengagement analytics are used, who can see alerts, how long the data are retained, and what consequences can and cannot follow.

Fairness should similarly be examined through outcomes rather than assumed from apparently neutral data. LMS activity can reproduce structural differences because students do not have identical devices, connectivity, available time, accessibility needs, or patterns of course participation. Cheng and colleagues' 2025 study demonstrates that early-warning systems can and should be assessed simultaneously for predictive quality and fairness rather than assuming accuracy alone is sufficient. The present framework therefore separates prediction from fairness auditing and avoids using sensitive demographic characteristics as direct shortcuts for disengagement scoring.

Finally, students should retain agency. A learning-analytics alert should create an opportunity for support, not an irreversible administrative judgment. Students should be able to explain contextual circumstances, correct inaccurate interpretations, and decline non-essential support. This position is consistent with emerging ethical-governance approaches emphasizing agency, equity, transparency, governance, and educational purpose alongside technical utility. The strongest analytics system is therefore not the system that knows the most about students, but the system that uses the minimum information necessary to create a genuine opportunity for learning support.

7. Conclusion

Silent academic disengagement describes an important gap between observable enrollment and meaningful participation. Students do not necessarily move directly from engagement to failure. Some remain academically visible while their study regularity, assessment preparation, feedback use, resource progression, or persistence deteriorates gradually. Conventional attendance and grade indicators can detect difficulty once it becomes visible, but temporal learning analytics offer the possibility of identifying earlier changes in the learning trajectory.

The present simulation demonstrates how this distinction can be operationalized. The conventional attendance-and-grade model produced a simulated early-detection recall of 54% and a median warning lead time of 1.4 weeks. Static LMS analytics increased recall to 68%, while temporal engagement-transition modeling reached 82%. The governed multi-source model achieved 89% early-detection recall, 87% precision, an 8% false-alert rate, and a median 4.2-week warning interval. These values are synthetic and require empirical validation; they illustrate an analytical architecture rather than established institutional performance.

The educational contribution is more important than the numerical comparison. Silent disengagement should not become another label applied to students through automated surveillance. Learning analytics should identify changes that warrant human attention, provide interpretable evidence regarding the pattern that changed, and trigger proportionate academic support. Recent empirical work demonstrating both generalizable at-risk prediction and subsequent engagement with previously unused learning resources after feedback supports the importance of linking prediction with intervention.

Future research should validate the proposed framework longitudinally across different disciplines, teaching formats, student groups, and institutional contexts. Evaluation should include predictive accuracy, calibration, warning lead time, intervention effectiveness, accessibility, false-alert burden, fairness across groups, student perceptions, and long-term educational outcomes. The central principle should remain constant: learning analytics should detect disengagement early enough to create an opportunity for support, but never so invasively that the mechanism of support undermines student privacy, trust, or agency.

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