



Educational-Stage Profiles of Learners' Trust in Artificial Intelligence Across Secondary and Higher Education Contexts

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Abstract

This study examined whether behavioral analytics derived from a Moodle-based learning management system could help identify early signs of learning disengagement in blended higher education. A quantitative predictive correlational design was used with 305 undergraduate students at Universitas Islam Negeri Raden Intan Lampung, Indonesia. Five behavioral indicators, login frequency, assignment submission timeliness, discussion participation, video completion rate, and LMS interaction breadth, were analyzed alongside scores from a 24-item Learning Disengagement Index (LDI). Multiple linear regression and four machine learning classifiers were evaluated using stratified 10-fold cross-validation. The composite behavioral model was significantly associated with LDI scores ($R^2 = .671$, $p < .001$), with login frequency ($\beta = -.42$) and assignment submission timeliness ($\beta = -.38$) showing the strongest standardized associations. At the Week 4 checkpoint, Random Forest showed the highest classification performance among the tested algorithms (Accuracy = .832; AUC = .912), followed by Gradient Boosting. These findings suggest that early LMS behavioral traces can provide useful decision-support signals for student support in blended courses. The results should be interpreted as context-specific predictive evidence rather than causal evidence, and local validation is recommended before institutional deployment.

Keywords: behavioral analytics; machine learning prediction; learning disengagement index; blended education engagement

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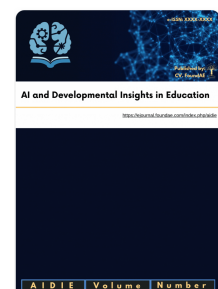
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Introduction

Research on blended higher education increasingly treats learning management system (LMS) traces as valuable but partial evidence of student engagement. Logins, submission timestamps, discussion activity, video-viewing records, and navigation breadth can reveal patterns that are difficult to observe in face-to-face meetings, particularly when students disengage quietly rather than formally withdraw. Recent reviews show that higher education learning analytics has moved beyond simple access counts toward multidimensional interpretations of engagement, yet they also warn that behavioral traces should not be treated as direct equivalents of cognitive, emotional, or motivational engagement (Bergdahl et al., 2024; Johar et al., 2023).

The current evidence base demonstrates that learning analytics can support early identification of students who may need academic support. Studies using reading behavior, clickstream data, assessment traces, and machine learning have shown that at-risk patterns can often be detected before final course outcomes are known (Dai et al., 2025; Flanagan et al., 2022; Waheed et al., 2023). More recent work has also emphasized that predictive systems are useful only when their outputs are timely, interpretable, and connected to feedback or intervention practices that instructors can reasonably implement (Alfredo et al., 2024; de Vreugd et al., 2024; Topali et al., 2025).

Recent studies have refined the technical side of educational prediction by comparing traditional classifiers, ensemble models, neural approaches, and explainable AI techniques. Ensemble models and interpretable machine learning approaches are especially relevant for educational settings because they can capture nonlinear behavioral patterns while still offering information that instructors can inspect and discuss (Adnan et al., 2022; Fazil et al., 2024; Lee et al., 2025; Yağcı, 2022). In parallel, research on dashboards and self-regulated learning indicates that analytics should be designed as a feedback mechanism rather than merely as a monitoring system (Alhazbi et al., 2024; Heikkinen et al., 2023; Ramaswami et al., 2023).

Despite these advances, three unresolved issues limit the direct translation of prior findings into blended higher education practice. First, many studies predict performance, dropout, or course completion, while fewer examine disengagement as a multidimensional learning condition that may precede failure. Second, many models report aggregate end-of-semester accuracy but provide limited evidence about the week when predictions become sufficiently reliable for instructor review. Third, models developed in one institutional or platform context may not transfer automatically, as LMS design, instructor expectations, course structure, and student access conditions shape the meaning of each behavioral indicator (Bergdahl & Bond, 2022; Cheng et al., 2025; Drugova et al., 2024).

These issues are particularly important in Indonesian blended higher education, where institutions may rapidly adopt LMS-mediated instruction while still developing local evidence for ethical, pedagogically useful early-warning systems. A practical model in this context should therefore be low-cost, based on behavioral indicators already available in the LMS, interpretable enough for instructor review, and explicitly framed as decision support rather than automated diagnosis. The present study addresses this need by testing whether five LMS behavioral indicators can identify early signs of learning disengagement among university students in blended courses.

Three research questions guided the study. First, to what extent do login frequency, assignment submission timeliness, discussion participation, video completion rate, and LMS interaction breadth predict Learning Disengagement Index (LDI) scores? Second, which of four algorithms--Random Forest, Gradient Boosting, Decision Tree, and Logistic Regression--

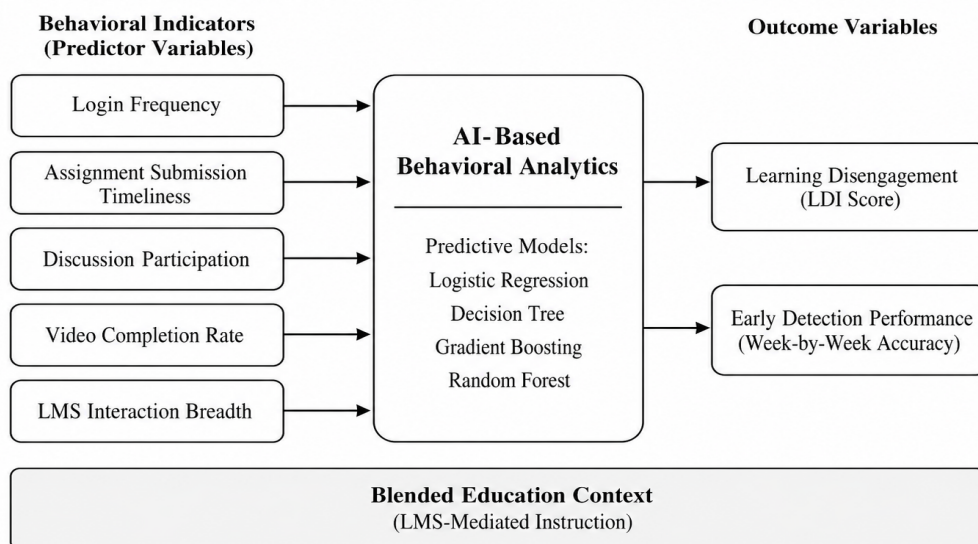
-shows the strongest classification performance? Third, at which instructional week does the strongest model reach an operational accuracy threshold of .80, defined as a practical point for initiating instructor review rather than as a diagnostic certainty? The corresponding hypotheses were that the composite behavioral indicator set would significantly predict LDI scores, that an ensemble model would perform better than linear or single-tree alternatives, and that sufficient behavioral evidence would accumulate by Week 4 for operationally useful review.

Conceptual Framework

Figure 1 summarizes the working conceptual model used in this study. The model treats LMS behavioral traces as observable indicators that can be aggregated and modeled to estimate disengagement risk, while retaining the blended course context as a boundary condition for interpretation.

Figure 1

Integrative behavioral analytics framework for predicting early signs of learning disengagement in blended education.



Note. The framework positions AI models as decision-support tools rather than autonomous diagnostic systems. RF = Random Forest; GB = Gradient Boosting; DT = Decision Tree; LR = Logistic Regression; LDI = Learning Disengagement Index.

The framework therefore narrows the study's claim: behavioral analytics may help instructors detect patterns that warrant follow-up, but the model should not be used to label students without contextual review or ethical safeguards.

Method

Research Design

This study employed a quantitative predictive correlational design. Naturally occurring behavioral data extracted from LMS logs were examined as predictors of measured learning disengagement outcomes. No experimental manipulation was introduced; the study observed the digital footprints generated by students during routine blended course participation across a single academic semester. This design was selected because the aim was to estimate predictive associations and compare model performance, not to establish causal effects of LMS behavior on disengagement.

Participants and Data Sources

Participants were undergraduate students enrolled in blended learning courses at a state Islamic university in Lampung Province, Indonesia, during the 2023–2024 academic year. The final analyzed sample comprised $N = 305$ students from eight blended courses spanning STEM and social science disciplines. Participants ranged in age from 18 to 24 years ($M = 20.3$, $SD = 1.4$). The gender distribution was 54.1% female ($n = 165$) and 45.9% male ($n = 140$). Academic semesters represented included the 3rd semester (44.9%, $n = 137$), 5th semester (35.4%, $n = 108$), and 7th semester (19.7%, $n = 60$).

Sampling and Recruitment

A stratified purposive sampling approach was employed to ensure representation across disciplines and semesters. Initial recruitment targeted all students ($N = 347$) enrolled in designated blended courses during the study period, yielding a participation rate of 89.9% ($n = 312$) following voluntary opt-in consent. After accounting for course withdrawal, incomplete LMS records, and survey non-completion, the final analytical sample was $N = 305$. Recruitment was conducted through course instructors, who distributed study information sheets during the second week of instruction. The institutional ethics committee of Universitas Islam Negeri Raden Intan Lampung approved all procedures (Protocol No. UIN-RIL-ETH-2023-047), and written informed consent was obtained from all participants prior to data collection.

Sample Size, Power, and Precision

A priori power analysis was conducted using G*Power 3.1 for multiple linear regression with five predictors. Assuming a medium-to-large anticipated effect size ($f^2 = 0.20$), $\alpha = .05$, and power $(1 - \beta) = .90$, the required minimum sample size was $N = 189$. The obtained sample ($N = 305$) exceeded this threshold. For classification analyses, the high-disengagement group contained 106 students, meeting the minimum event-per-predictor criterion for the four models used. Missing data (2.3%) were evaluated using Little's MCAR test, $\chi^2(28) = 29.14$, $p = .407$, and handled using listwise deletion.

Measures, Instruments, and Data Sources

Three measurement sources were used. First, the Learning Disengagement Index (LDI) was a 24-item researcher-developed self-report instrument assessing cognitive, behavioral, and affective dimensions of disengagement on a 5-point Likert scale, with higher scores indicating greater disengagement. Second, behavioral trace data were extracted automatically from the institutional Moodle-based LMS. Third, instructor ratings were used as an auxiliary validity criterion for convergence checks. Because the LDI was developed for this study, its interpretation should remain provisional until independently validated in future research.

Table 1 provides a compact overview of the main behavioral variables, LDI subscales, and the instructor-rated auxiliary measure. Presenting the descriptive statistics before model testing is important because the scale ranges and reliability coefficients define the measurement context for the later regression and classification results.

Table 1

Descriptive statistics and psychometric properties of study variables.

Variable	n	M	SD	Range	α
Login frequency (times/week)	305	4.20	1.80	0.50–9.80	—

Variable	n	M	SD	Range	α
Assignment timeliness (days)	305	2.10	1.90	−3.20–7.40	—
Discussion participation (posts/week)	305	3.70	2.10	0–10.30	—
Video completion rate (%)	305	62.4	18.3	8.70–100	—
LMS interaction breadth (activities/week)	305	9.30	3.40	2–21	—
LDI – Cognitive subscale	305	16.1	4.20	8–38	.87
LDI – Behavioral subscale	305	15.8	3.90	8–36	.83
LDI – Affective subscale	305	16.4	4.10	8–37	.85
LDI – Total scale	305	48.3	11.7	24–88	.91
Instructor-rated engagement risk measure	305	34.7	6.80	18–58	.84

Note. LDI = Learning Disengagement Index. LMS = learning management system. Dashes indicate that internal consistency is not applicable for behavioral trace variables.

The descriptive profile indicates adequate variability across the behavioral indicators and acceptable internal consistency for the LDI subscales. These properties supported the decision to proceed with regression and classification analyses, while still treating the LDI as a study-specific instrument requiring further validation.

Data Collection Procedures

LMS behavioral data were extracted continuously throughout Weeks 1–10 of the 14-week semester. Student self-report data were collected at Week 7, concurrent with instructor ratings. LMS data extraction was performed by a designated research assistant with read-only database access using scripts that aggregated raw logs into weekly behavioral metrics per student. Instructors completed ratings through a secure online form. For a random subsample of 50 ratings, interrater reliability was acceptable ($ICC = .82$, 95% CI [.74, .88]).

Data Analysis

Data analysis proceeded in three stages. For RQ1, multiple linear regression with simultaneous entry was conducted using the five behavioral indicators as predictors and total LDI score as the criterion. Assumption checks included residual normality, homoscedasticity, and multicollinearity diagnostics. For RQ2, four classification models—Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting—were trained and evaluated using stratified 10-fold cross-validation. Students scoring at or above the 75th percentile on the LDI (score ≥ 60) were classified as high-disengagement for classification purposes. For RQ3,

detection accuracy was tracked week-by-week using incrementally accumulated behavioral log data. Analyses were conducted using Python and SPSS.

Validity, Reliability, and Methodological Integrity

Content validity of the LDI was evaluated through expert panel review by seven faculty members with expertise in educational psychology and learning analytics. Construct validity was examined through confirmatory factor analysis, which produced acceptable model fit indices (CFI = .943, RMSEA = .062, SRMR = .058). Convergent validity was supported by a significant correlation between LDI total scores and instructor ratings ($r = .61$, $p < .001$). The behavioral analytics pipeline was checked by comparing system-extracted data with instructor attendance records for a random 10% subsample, producing 97.8% agreement. These procedures strengthen confidence in the measurement pipeline but do not remove the need for independent validation in other institutions.

Ethical Considerations

The study received approval from the Research Ethics Committee of Universitas Islam Negeri Raden Intan Lampung (Protocol No. UIN-RIL-ETH-2023-047). All participants provided written informed consent and were informed that LMS data would be used only for research purposes. Student identifiers were replaced with alphanumeric codes prior to analysis. Instructors were not given individual behavioral risk scores during the study to reduce the possibility of grading bias. Because predictive analytics may create risks of stigmatization or surveillance, the interpretation of results in this article is limited to decision support and does not recommend automated academic action without human review.

Results

Participant Flow and Preliminary Analysis

Of the 347 students initially recruited, 312 provided consent and participated in data collection. Seven participants withdrew mid-semester and were excluded. Missing LMS log data affected seven additional students, who were excluded via listwise deletion after the missingness pattern was judged compatible with MCAR. The final analytical sample was $N = 305$.

Assumption testing for multiple regression indicated acceptable residual normality (Shapiro–Wilk $W = .981$, $p = .062$) and homoscedasticity (Breusch–Pagan $\chi^2(5) = 7.21$, $p = .205$). Multicollinearity was not a concern, with VIF values ranging from 1.12 to 3.18. LDI total scores ranged from 24 to 88 ($M = 48.3$, $SD = 11.7$), and 34.8% of participants ($n = 106$) were classified as high-disengagement using the pre-specified 75th percentile threshold.

Behavioral Predictors of Learning Disengagement

Table 2 reports the multiple regression results for the five LMS behavioral indicators. This table is placed immediately after the preliminary assumptions because the coefficients should be interpreted only in light of the acceptable diagnostic results described above.

Table 2

Multiple regression results for behavioral predictors of learning disengagement ($N = 305$).

Predictor	B	SE B	β	t	p
Login frequency	-2.73	0.33	-.42	-8.23	< .001

Predictor	B	SE B	β	t	p
Assignment timeliness	-2.34	0.33	-.38	-7.14	< .001
Discussion participation	-1.62	0.29	-.29	-5.67	< .001
Video completion rate	-0.13	0.03	-.21	-4.02	< .001
LMS interaction breadth	-0.62	0.18	-.18	-3.47	.001

Note. All predictors entered simultaneously. $R^2 = .671$, adjusted $R^2 = .666$, $F(5, 299) = 122.38$, $p < .001$. B = unstandardized coefficient; SE B = standard error; β = standardized coefficient.

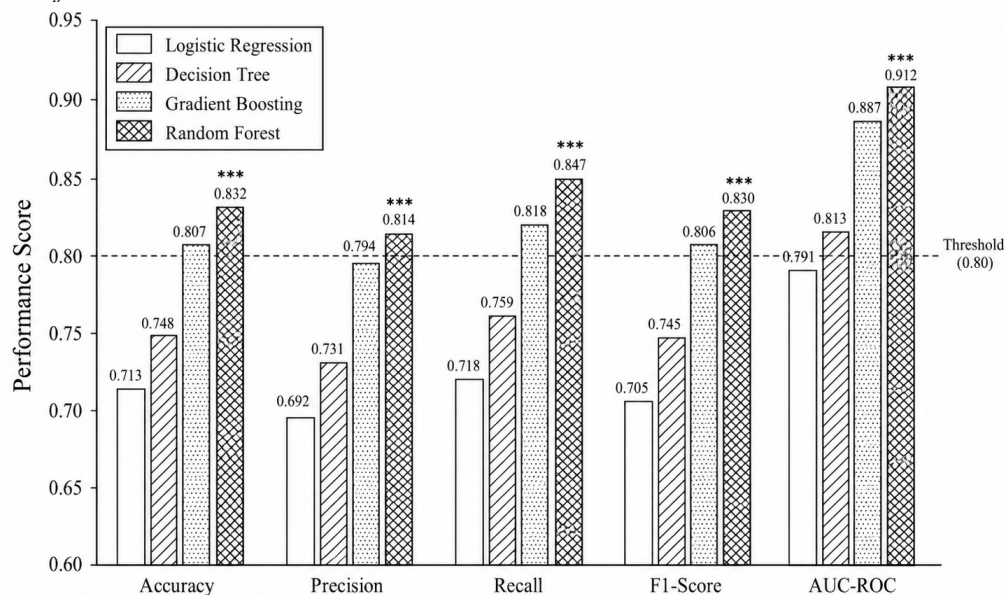
The model was statistically significant and explained 67.1% of the variance in LDI scores. The negative standardized coefficients show that higher behavioral engagement was associated with lower disengagement. Login frequency and assignment timeliness had the largest standardized coefficients, whereas video completion and interaction breadth made smaller but statistically significant contributions.

Machine Learning Model Performance at Week 4

Figure 2 visualizes the Week 4 classification performance for the four tested algorithms across five metrics. The figure is used to show the relative pattern of model performance before the numerical table is presented.

Figure 2

Comparison of machine learning model performance at Week 4 across five evaluation metrics under stratified 10-fold cross-validation.



Note. Values represent mean scores from stratified 10-fold cross-validation. RF = Random Forest; GB = Gradient Boosting; DT = Decision Tree; LR = Logistic Regression.

The visual comparison indicates that ensemble models outperformed the single Decision Tree and Logistic Regression across most metrics. The distinction was especially

clear for AUC, where Random Forest showed the strongest discrimination among the tested models.

Table 3 provides the exact Week 4 cross-validated performance values. The table is presented after the figure so that readers can inspect both the overall visual pattern and the precise metric values.

Table 3

Week 4 machine learning model performance metrics from stratified 10-fold cross-validation (N = 305).

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
Random Forest	.832	.814	.847	.830	.912
Gradient Boosting	.807	.794	.818	.806	.887
Decision Tree	.748	.731	.759	.745	.813
Logistic Regression	.713	.692	.718	.705	.791

Note. AUC = area under the receiver operating characteristic curve. Values represent means across 10 cross-validation folds at the Week 4 checkpoint. Best performance per metric is shown in bold.

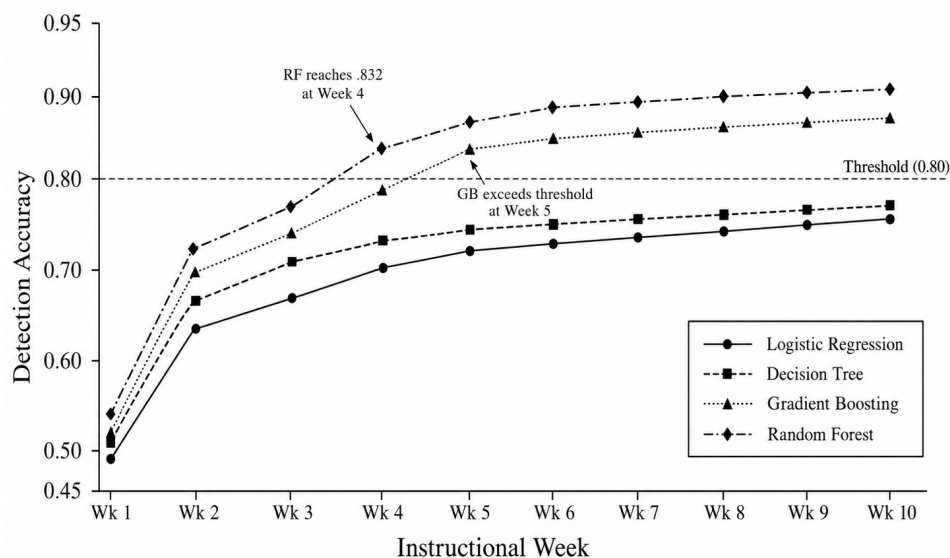
At Week 4, Random Forest produced the highest observed accuracy, recall, F1-score, and AUC-ROC. These results support H2 within this dataset, but they do not establish that Random Forest will necessarily outperform other algorithms in all blended learning contexts.

Detection Accuracy Across Instructional Weeks

Figure 3 extends the Week 4 comparison by showing how accuracy changed as additional weekly LMS data accumulated. This figure addresses the practical timing question: when does the model appear sufficiently stable to support instructor review?

Figure 3

Trajectories of learning disengagement detection accuracy across instructional weeks for four machine learning models.



Note. Accuracy values are based on incrementally accumulated LMS features. The dashed horizontal line at .80 represents the pre-specified operational threshold for initiating human review, not an automated intervention rule.

Random Forest exceeded the .80 threshold at Week 4 (Accuracy = .832), while Gradient Boosting crossed the same threshold at Week 5. Decision Tree and Logistic Regression remained below .80 through Week 10. These trajectories support H3 and suggest that Weeks 4–6 may be an appropriate window for instructor review in courses with comparable structure and LMS use.

Discussion

Summary of Findings

This study examined whether early LMS behavioral indicators could help predict learning disengagement in a blended higher education setting. Three findings are central. First, the five-indicator behavioral model was strongly associated with LDI scores, indicating that routine access, timeliness, participation, video engagement, and interaction breadth jointly provide meaningful decision-support information. Second, Random Forest showed the strongest classification performance among the tested models, although its advantage should be interpreted as comparative model performance within this dataset rather than as evidence that one algorithm is universally superior. Third, Random Forest reached the .80 operational accuracy threshold at Week 4, suggesting that behavioral evidence may become useful for instructor review before the middle of the semester. These findings are consistent with recent studies on early identification, predictive analytics, and feedback-oriented learning analytics, while also reinforcing the need for local validation before deployment (Dai et al., 2025; Flanagan et al., 2022; Lee et al., 2025; Talamás-Carvajal & Ceballos, 2023; Zerkouk et al., 2024).

Behavioral Indicators and Disengagement

Login frequency and assignment timeliness were the strongest behavioral predictors. This pattern is theoretically plausible because both indicators capture repeated access and task regulation, which are fundamental to participation in blended learning. However, these indicators should not be overinterpreted as direct measures of motivation, cognition, or learning quality. Frequent login may indicate routine access but not deep processing, while late submission may reflect workload, connectivity constraints, competing responsibilities, or unclear course design. The finding therefore supports the use of these variables as early prompts for supportive follow-up, not as definitive evidence of disengagement. This interpretation is consistent with recent reviews emphasizing that LMS traces are useful but incomplete proxies for student engagement (Bergdahl et al., 2024; Johar et al., 2023).

Video completion rate and LMS interaction breadth showed smaller unique contributions. Rather than weakening the behavioral analytics framework, this result clarifies that some LMS indicators are more context-dependent than others. Video completion is likely to be more informative in courses where video lectures are central to learning activities, whereas interaction breadth can reflect course architecture as much as student agency. Studies on self-regulated learning and learning design similarly suggest that analytics indicators gain meaning only when interpreted alongside task demands, instructional design, and the type of feedback available to students (Alhazbi et al., 2024; Drugova et al., 2024; Guo & Lee, 2023). Future analyses should therefore model course-level features rather than assuming that the same behavioral signal has equivalent meaning across courses.

Machine Learning Performance and Interpretability

Random Forest produced the strongest overall performance, which is consistent with evidence that ensemble approaches can capture nonlinear and interaction patterns in educational data (Fazil et al., 2024; Rodríguez et al., 2023; Yağcı, 2022). In this study, the advantage over Gradient Boosting was meaningful but not large enough to dismiss alternative ensemble models. From an implementation perspective, the key question is not only which algorithm has the highest AUC, but which model remains stable across semesters, transparent enough for instructors, and robust when deployed with new cohorts. Predictive performance should therefore be evaluated together with interpretability, calibration, fairness, and sustainability of institutional use.

Interpretability is especially important because predictive analytics can influence how educators perceive and support students. Explainable and human-centered learning analytics research indicates that model outputs are more useful when they help instructors understand why a student has been flagged and what type of support may be appropriate (Adnan et al., 2022; Alfredo et al., 2024; Lee et al., 2025; Topali et al., 2025). The present results therefore support an instructor-in-the-loop model: AI analytics may prioritize attention and reveal patterns, but decisions about outreach, advising, or intervention should remain contextual and humane. False positives may burden students and support teams, while false negatives may leave struggling students invisible; both risks require monitoring, transparency, and regular fairness audits (Bond et al., 2024; Cheng et al., 2025; Khalil et al., 2024).

Timing of Early Detection

The Week 4 result is practically important because it appears early enough for instructors to respond before disengagement is reflected in final grades, withdrawal decisions, or accumulated task failure. It also aligns with evidence that feedback-oriented learning analytics can influence engagement when the information is timely and actionable (Brown et al., 2023; Dai et al., 2025; Garbers et al., 2023). The threshold should nevertheless be understood as operational rather than clinical or diagnostic. It identifies a point at which model output may justify careful review, not a point at which a student should be labeled disengaged.

The increasing accuracy after Week 4 highlights a central design trade-off in early-warning systems. Earlier alerts allow more time for support but involve greater uncertainty; later alerts may be more accurate but leave less time for meaningful intervention. Institutions should calibrate this trade-off based on course duration, available advising resources, the consequences of false alarms, and students' right to be treated fairly. A responsible deployment strategy would combine Week 4 screening with instructor judgment, confidential student outreach, and periodic recalibration of thresholds as new data become available.

Strengths and Limitations

The study has several strengths: it uses real LMS behavioral traces, a reasonably sized sample, stratified cross-validation, and a temporally indexed analysis of detection accuracy. It also contributes evidence from an Indonesian blended higher education context, which remains underrepresented in international learning analytics research. However, four limitations should guide interpretation. First, the study was conducted in one institution, so coefficients and thresholds may not generalize directly to other platforms or populations. Second, the LDI is researcher-developed and requires external validation, including measurement invariance testing across gender, discipline, and institutional settings. Third, the LDI was measured at one point in the semester, which limits causal and temporal inference. Fourth, course-level design differences were not modeled, even though they may substantially shape LMS behavior and the meaning of trace indicators.

Implications

For instructors, the findings suggest that a small set of LMS behavioral indicators can help prioritize supportive follow-up, especially when analytics are interpreted alongside course knowledge and direct communication with students. For institutions, the results support local validation before deployment and caution against importing thresholds from other contexts without recalibration. For AI developers, the study highlights the need to balance predictive performance with interpretability, fairness, privacy, and pedagogical usability. For researchers, the findings point toward designs that integrate behavioral traces with student perspectives, self-regulated learning measures, and intervention outcomes rather than relying on prediction accuracy alone (de Vreugd et al., 2024; Kleimola et al., 2025; Lee & Kim, 2025; Papageorgiou et al., 2025).

Recommendations for Future Research

Future research should first validate the LDI in broader samples and test whether its cognitive, behavioral, and affective structure is stable across disciplines, institutional types, gender groups, and different LMS platforms. Second, longitudinal studies should collect disengagement measures at multiple points in the semester so that temporal relationships between behavioral traces and disengagement can be modeled more precisely. Third, multilevel studies are needed to separate student-level behavioral patterns from course-level learning design effects, because the same LMS action may carry different meanings across courses.

Further work should also move beyond prediction toward intervention evaluation. Randomized or quasi-experimental studies could test whether AI-supported early alerts, combined with instructor feedback or academic advising, actually reduce disengagement without stigmatizing students. Future models should include explainability, calibration, fairness analysis, privacy safeguards, and student perceptions as core evaluation criteria. Mixed-methods designs that combine LMS traces, survey data, interviews, and carefully governed multimodal indicators would help explain why students disengage and which forms of support are most appropriate.

Conclusion

This study investigated whether AI-based behavioral analytics could support the early prediction of learning disengagement in blended higher education. In a sample of 305 undergraduate students, five LMS behavioral indicators collectively explained substantial variance in LDI scores, and Random Forest showed the strongest Week 4 classification performance among the four tested algorithms. The findings suggest that LMS behavioral traces can provide useful early decision-support signals, particularly around Week 4, when timely instructor review remains feasible. The study does not claim causal effects, universal generalizability, or diagnostic certainty. Instead, it offers context-specific predictive evidence that should be tested through multi-institutional replication, external validation of the LDI, and intervention studies that evaluate whether AI-supported early warning systems improve student outcomes without creating unfair or stigmatizing consequences.

Generative AI Statement

Generative AI tools were used only for language editing and manuscript polishing. The authors reviewed and approved all content and remain responsible for the integrity, accuracy, and originality of the work.

Conflicts of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request, subject to institutional ethics and privacy requirements.

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