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EXPLAINABLE LEARNING ANALYTICS AND ADAPTIVE FEEDBACK FOR SELF-DIRECTED LEARNING IN ENGINEERING HIGHER EDUCATION

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Abstract

This article addresses a persistent problem in technology-enhanced engineering education: learning management systems record abundant activity data, yet such data do not necessarily produce timely, interpretable pedagogical support for self-directed learning. Drawing on self-regulated learning theory and research on learning analytics, the paper proposes an explainable feedback cycle that combines validated learning indicators, student reflection, teacher oversight, and adaptive task selection. It presents a conceptual architecture, an intervention rubric, a mathematically explicit decision rule, and a prospective evaluation design. Rather than reporting invented learning gains, the article distinguishes theoretical justification from evidence that remains to be collected. Its contribution is a testable methodological framework for connecting system-generated indicators with educational action.

Keywords: learning analytics; adaptive feedback; engineering education; self-directed learning; explainability; formative assessment; information systems.

1. Introduction

Engineering students are expected to solve unfamiliar technical problems, manage complex assignments, and transfer knowledge between digital simulations and practical situations. Digital platforms can log attempts, time stamps, submissions, and interactions, but the pedagogical interpretation of such traces remains difficult. A student who spends many hours online may be struggling rather than learning effectively; conversely, a student with few clicks may have mastered the task quickly. The central problem is therefore not a lack of data but the weak transition from digital records to valid, actionable feedback.

UNESCO's 2023 Global Education Monitoring Report cautions that robust independent evidence of educational technology effectiveness remains limited [4]. Recent synthesis research likewise identifies unresolved issues concerning the theoretical validity of indicators used to measure self-regulated learning [3]. These findings justify a framework in which interpretations are explicit, interventions are documented, and improvement is tested rather than assumed.

2. Theoretical foundation and related work

Self-regulated learning includes the cyclical processes of forethought, performance monitoring, and self-reflection (Zimmerman, 2002) [1]. An information system may support these

phases by capturing planning statements, intermediate attempts, revision histories, and post-task reflections. However, behavioral traces alone are incomplete proxies for cognition, motivation, and strategic decision-making. The comprehensive review by Ifenthaler and Yau (2020) highlights the potential of learning analytics for supporting student success while also emphasizing the design of meaningful interventions [2].

Accordingly, this study uses two complementary evidence sources: system-produced events (what happened) and human-authored explanations (why it happened). The proposed framework makes the evidence-to-action relationship visible to learners and instructors, enabling them to challenge misleading automated signals.

3. Research problem, purpose, and questions

The study asks how explainable learning analytics can be embedded into independent engineering assignments so that digital evidence leads to timely pedagogical feedback without substituting algorithmic judgments for teacher expertise. Three research questions guide the proposed investigation: (1) Which digital and reflective indicators can validly represent learning regulation? (2) Which explanations make alerts actionable to teachers and learners? (3) Does the intervention improve self-directed learning outcomes compared with ordinary LMS feedback?

4. Proposed methodological architecture

The model starts with minimally necessary learning traces, including attempt timestamps, task revisions, formative test outcomes and documented milestones. A validation layer checks missing values, contextual factors, and construct alignment. A transparent rules layer identifies potential needs for assistance, then generates an explanation identifying the evidence involved. Teachers approve or revise suggested interventions. The student receives a concrete action (for example, a worked-example comparison, a planning prompt, or a targeted consultation), followed by a reflection checkpoint. The next cycle incorporates the newly observed evidence.



Figure 1. Explainable feedback and pedagogical intervention workflow

Table 1. Evidence-to-feedback mapping

Indicator	Possible interpretation	Feedback response	Safeguard
Repeated unsuccessful attempts	Conceptual or procedural gap	Offer scaffolded example	Review task difficulty
Missed self-set milestones	Planning difficulty	Prompt schedule revision	Check access constraints
Improved revision quality	Effective monitoring	Encourage strategy reflection	Verify rubric score

Indicator	Possible interpretation	Feedback response	Safeguard
Low platform activity	Ambiguous evidence	Ask for learner explanation	No automatic penalty

5. Analytical justification and decision rule

Let x_1, x_2, and x_3 denote normalized, pedagogically reviewed scores for planning, monitoring, and reflection, each within [0, 1]. A descriptive support-needs index can be defined as $R = \Sigma_i w_i(1 - x_i)$, subject to $w_i \geq 0$ and $\Sigma_i w_i = 1$. Therefore, $0 \leq R \leq 1$: the index is bounded because it is a convex combination of bounded shortfall measures. Larger values indicate a potentially greater need for support, not a diagnosis of inability or a probability of failure. Thresholds for teacher review must be calibrated using independent validation data rather than asserted in advance.

For example, with equal weights and component scores (0.25, 0.50, 0.75), R = [(0.75)+(0.50)+(0.25)]/3 = 0.50. This arithmetic illustration verifies the rule's operation; it is not an observed student case or evidence of predictive performance. Any alert should provide its component scores, missing-data warning, and an accessible explanation so that the instructor can inspect the basis of the recommendation.

Table 2. Hypotheses and empirical verification

Hypothesis	Outcome	Proposed test
H1: Feedback improves regulation	Change in validated SRL rubric	Pre/post group comparison
H2: Explanations improve usability	Teacher/student usefulness rating	Validated questionnaire and interviews
H3: Intervention reduces delays	Time to meaningful support	System logs and mixed-effects model
H4: Effects vary by prior attainment	Differential outcome changes	Interaction analysis

6. Research design and evidence requirements

A prospective quasi-experimental study may compare two groups enrolled in equivalent engineering information-technology modules. The comparison group uses standard LMS assignments and feedback; the intervention group uses the proposed explainable feedback cycle. Before implementation, task difficulty, assessment rubrics, baseline attainment, student access to devices, and instructor workload should be documented. Outcomes include independent-learning competence, on-time task improvement, intervention latency, and perceived feedback usability.

Analyses should report baseline differences, confidence intervals, effect sizes, and sensitivity checks. If random assignment is not feasible, covariate adjustment or a difference-in-differences approach may be considered only where its assumptions are defensible. The framework must be assessed for measurement validity, fairness, data minimization, and the rate of misleading alerts. A favorable experimental result would support the intervention in the tested context; it would not automatically establish universal effectiveness.

7. Discussion and limitations

A major contribution of the framework is its insistence on separating evidence, interpretation, and action. This separation permits an instructor to recognize why a particular prompt was generated and to overrule inappropriate recommendations. The approach is particularly relevant in engineering assignments, where low activity can indicate either expertise, disengagement, or offline practical work. The model also avoids using data-driven classifications as substitutes for direct assessment of competence.

Implementation challenges include inconsistent data quality, unequal connectivity, students' privacy expectations, varied course structures, and additional teacher review time. The proposed model should therefore be piloted with small cohorts, monitored for unexpected consequences, and revised through participatory design. No actual intervention or student outcome is claimed in the present conceptual study.

8. Extended conclusion

The paper identifies an important methodological gap between the collection of educational data and its translation into defensible instructional decisions. Digital records are abundant, but their meaning is context-sensitive. Effective information systems for self-directed learning should therefore make the interpretation of evidence transparent instead of treating raw activity frequency as educational achievement.

The proposed explainable feedback cycle provides a structured response to this gap. By linking validated indicators, human-readable reasoning, instructor oversight, adaptive support and student reflection, the framework extends conventional analytics dashboards toward a pedagogically accountable learning process. The purpose of such a system is not to automate the teacher but to improve the timing, relevance and traceability of educational assistance.

The mathematical support-needs index demonstrates how a bounded and auditable summary can be created from component-level information. Its value lies in consistency and interpretability rather than in any claimed predictive accuracy. Empirical work must establish whether the chosen components genuinely represent self-regulated learning, whether weights are justified, and whether alerts improve decisions rather than merely increasing intervention frequency.

For engineering higher education, pedagogical adaptation must remain connected to authentic technical tasks. Feedback may encourage a learner to revisit an incorrect circuit assumption, compare simulation outputs with theoretical expectations, or document a revised solution strategy. These actions allow independent learning competence to be evaluated through purposeful problem-solving, not exclusively through platform behavior.

Future studies should conduct controlled or carefully matched comparisons, examine differences across disciplines and prior achievement levels, and evaluate privacy, equity, and teacher workload alongside academic outcomes. The scientific contribution of the proposed framework should be judged through construct validation, reproducible analyses, transparent reporting, and comparison with established approaches. Until those studies are completed, this article offers a theoretically grounded and testable methodological proposal rather than a claim of demonstrated effectiveness.

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