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SUSTAINABLE
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VIKSIT BHARAT

PART

2

Editors

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Chapter 27: Student-Centred Pedagogy and Active Learning in Undergraduate Classrooms

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Abstract— Student-centred pedagogy has become increasingly important in undergraduate education because it shifts classroom activity from information transmission toward participation, inquiry, collaboration, reflection, and learner agency. Although active-learning approaches frequently improve academic achievement, conventional evaluations often represent engagement through final grades, questionnaires, attendance, or isolated digital interaction counts rather than examining how engagement develops during learning. This study addresses that limitation by conceptualising active learning as a multidimensional and temporally evolving process involving behavioural participation, cognitive investment, peer interaction, learner autonomy, and perceived academic well-being. A pedagogy-sensitive learning-analytics framework is proposed to integrate classroom activity records, learning-management-system traces, formative assessment patterns, collaborative interactions, and short learner-reported indicators. The framework is designed to distinguish genuinely productive engagement from high-frequency digital activity that may not reflect meaningful knowledge construction.

Keywords— Student-centred pedagogy, Active learning, Undergraduate education, Learning analytics, Explainable artificial intelligence, Student engagement

Introduction

Higher education has undergone a substantial pedagogical transition during the first half of the 2020s. The expansion of blended learning environments, learning-management systems, collaborative digital platforms, artificial intelligence applications, and digitally supported assessment has increased the number of ways in which students can participate in university learning. At the same time, these technological developments have intensified an older pedagogical question: whether students are genuinely constructing knowledge or are simply interacting more frequently with educational content. Student-centred pedagogy provides an important conceptual response because it places learner activity, autonomy, dialogue, inquiry, reflection, and responsibility at the centre of the instructional process.

Student-centred pedagogy differs fundamentally from instructional models in which the teacher serves primarily as the transmitter of predetermined information. In a student-centred classroom, instructors continue to provide disciplinary expertise and pedagogical structure, but learning activities are organised so that students interpret information, formulate questions, test

ideas, solve problems, discuss alternative viewpoints, produce artefacts, evaluate evidence, and reflect on their own understanding. Active learning can therefore be understood as one of the principal operational manifestations of student-centred pedagogy.

Evidence supporting active learning is substantial. Kozanitis and Nenciovici (2023), for example, conducted a meta-analysis of 104 studies involving 15,896 students in humanities and social-science courses. Their analysis showed that students exposed to active instruction achieved higher assessment performance than students receiving conventional lectures, with an overall standardised mean difference of approximately 0.49. Importantly, beneficial effects were observed across multiple disciplines, course levels, assessment forms, and class sizes, although effect magnitude varied between contexts. Such findings indicate that the relevant research question is no longer simply whether active learning can work. A more consequential issue is identifying **which forms of learner activity become educationally productive, under which pedagogical conditions, and for which students.**

This distinction is particularly important in contemporary digitally mediated classrooms. Clicking resources, submitting frequent responses, maintaining prolonged LMS sessions, or producing numerous discussion posts may create the appearance of participation without demonstrating conceptual engagement. Conversely, a learner who spends relatively little time generating digital traces may be deeply engaged in reflection, peer explanation, problem solving, or synthesis. Treating all observable activity as equivalent engagement consequently risks confusing technological visibility with learning quality.

Recent learning-analytics scholarship confirms this measurement problem. Bergdahl et al. (2024) systematically reviewed 159 higher-education studies investigating student engagement through learning analytics. Behavioural engagement dominated the literature: approximately 95% of reviewed studies measured observable behaviours, whereas cognitive, emotional, and social dimensions appeared considerably less frequently. More than half of the studies operationalised engagement exclusively as behavioural activity. The review therefore demonstrates a substantial theoretical and methodological imbalance between the multidimensional nature of engagement and the variables most commonly analysed computationally.

The rapid incorporation of artificial intelligence into education further increases the importance of this issue. Machine-learning systems can discover complex relationships between student

activities and educational outcomes, but prediction accuracy alone does not establish pedagogical meaning. Susnjak (2024) argues that learning analytics must move beyond purely predictive models toward explainable and prescriptive approaches capable of showing why predictions occur and how their outputs can support educational decisions. Similarly, Tiukhova et al. (2024) demonstrate that explainable artificial intelligence can reveal whether predictors of student success remain stable as learning contexts change. This is particularly relevant to student-centred instruction because the significance of a given behaviour can vary according to the learning task. Frequent interaction may indicate productive collaboration during a peer-learning exercise but uncertainty or inefficient navigation during independent study.

Another increasingly relevant dimension concerns student well-being. Student-centred and active-learning environments can enhance belonging, autonomy, interpersonal connection, and confidence, but poorly designed active-learning tasks can also create cognitive overload, excessive performance pressure, unequal participation, or collaborative fatigue. Ribeiro-Silva et al. (2022), reviewing active learning and well-being in higher education, concluded that student-centred methodologies can potentially support academic, emotional, physical, and social aspects of well-being. However, the evidence base connecting instructional activity and well-being remained comparatively limited. This suggests that educational effectiveness should not be defined exclusively by grades or digital activity.

The emergence of generative AI makes learner agency particularly significant. UNESCO's guidance on generative AI in education emphasises a human-centred approach in which AI enhances rather than replaces human agency, critical thinking, inclusion, creativity, and meaningful pedagogical interaction. The increased availability of automated explanations, summaries, text generation, tutoring systems, and adaptive learning technologies creates a paradox for student-centred education: digital systems can expand opportunities for personalised learning while simultaneously reducing intellectual participation if students delegate essential cognitive processes to automated tools.

Research Gap

The literature therefore reveals a specific unresolved problem. Active-learning research has established broad evidence of educational benefit, while learning analytics has developed sophisticated methods for observing student behaviour. Yet these two research streams remain insufficiently integrated. Active-learning studies frequently evaluate pedagogy using achievement tests and retrospective questionnaires, whereas computational learning-analytics studies frequently infer engagement from behavioural traces without adequately representing the pedagogical structure generating those behaviours.

Consequently, there remains limited research that simultaneously examines:

1. the **intensity of student-centred pedagogical exposure**;

2. behavioural, cognitive, social, and affective dimensions of active engagement;
3. the temporal development of engagement during an undergraduate course;
4. learning achievement and perceived academic well-being; and
5. interpretable machine-learning explanations linking pedagogical activities with educational outcomes.

This study addresses that gap through a **Pedagogy–Engagement–Well-being Analytics framework**, in which engagement is treated as a dynamic educational process rather than a single score. The central objective is to determine whether multimodal, pedagogy-aware learning indicators can identify productive active-learning patterns more accurately and meaningfully than conventional behavioural measures alone.

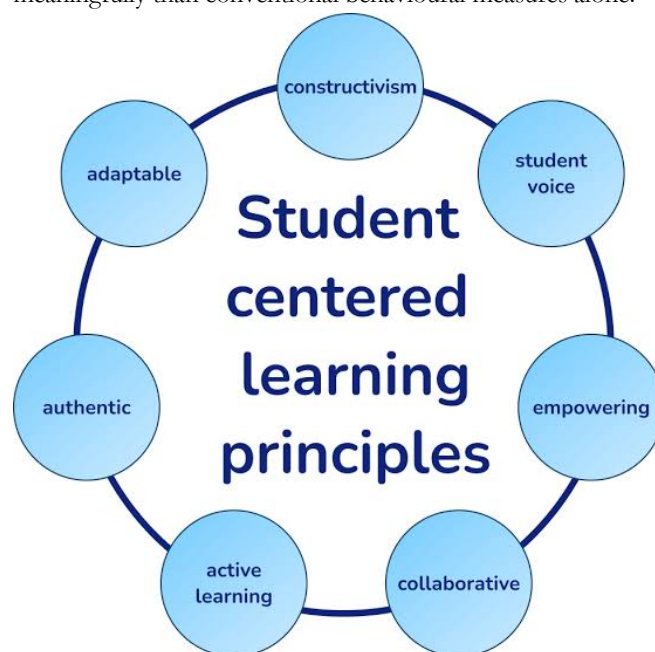


Fig. 1: Student-Centered Learning Principles

Source: <https://thirdspacelearning.com/us/blog/student-centered-learning/>

Literature Review

2.1 Student-Centred Pedagogy as a Learning Architecture

Student-centred learning should not be interpreted merely as allowing students greater freedom or reducing instructor involvement. Effective student-centred pedagogy requires deliberate instructional architecture. The instructor establishes learning outcomes, selects authentic problems, structures interaction, provides scaffolding, monitors misconceptions, creates feedback opportunities, and gradually transfers appropriate responsibility to learners. The student becomes more active, but instructional design remains critical.

Active learning operationalises this architecture through activities requiring students to act on knowledge. Kozanitis and Nenciovici (2023) describe active learning through behavioural, cognitive, and social dimensions. Behavioural activity includes producing responses or manipulating learning materials;

cognitive activity includes analysis, interpretation, synthesis, and reflection; and social activity involves interaction with peers or instructors as part of knowledge construction. Examples include problem-based learning, peer instruction, collaborative tasks, case analysis, formative questioning, experiential learning, simulations, debates, and structured discussion.

The distinction between student-centred learning and unstructured participation is important. Simply placing students into groups does not ensure collaboration, just as introducing classroom technologies does not ensure active cognition. Pedagogical effectiveness depends on alignment between the intended learning outcome, student task, feedback mechanism, assessment approach, and degree of learner responsibility.

2.2 Evidence for Active Learning in Undergraduate Education

Contemporary research largely supports active instruction compared with passive lecture-dominated teaching. The meta-analysis by Kozanitis and Nenciovici (2023) is particularly relevant because it extends the evidence beyond the STEM disciplines that historically dominated active-learning research. Their findings indicate meaningful performance improvements across sociology, psychology, political science, economics, management, education, and language courses.

However, substantial heterogeneity was also present across the analysed studies. This heterogeneity has important theoretical implications. If active learning were a uniform intervention, relatively consistent effects might be expected. Instead, differences in instructional design, student population, course level, assessment structure, group size, instructor facilitation, and type of activity appear to influence its effectiveness.

Accordingly, describing a classroom merely as “active” or “student-centred” provides limited analytical precision. Two courses may both employ discussion and group work while generating very different levels of autonomy, cognitive demand, equitable participation, and learning. The present study therefore conceptualises student-centred pedagogy as a measurable configuration of instructional practices rather than a binary treatment condition.

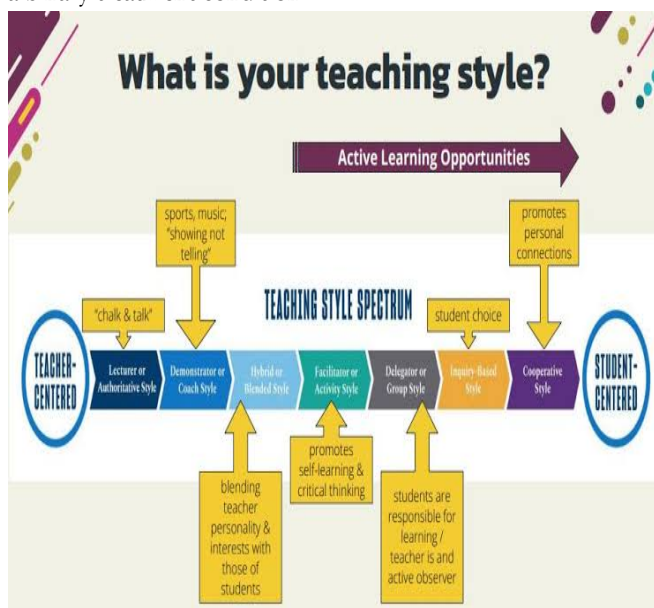


Fig. 2: Active Learning

Source: <https://concordia.ab.ca/instructional-supports/student-engagement-active-learning/active-learning-activities-for-student-engagement/>

2.3 Multidimensional Student Engagement

Student engagement represents one of the principal mechanisms through which student-centred pedagogy is expected to influence learning. Yet engagement itself is multidimensional. Behavioural engagement concerns participation and task involvement; cognitive engagement concerns strategic processing, reflection, persistence, and knowledge construction; social engagement concerns academically meaningful interaction; and affective or emotional engagement concerns interest, belonging, enthusiasm, frustration, or related experiential responses.

The learning-analytics literature has struggled to maintain this multidimensional interpretation when operationalising engagement computationally. Bergdahl et al. (2024) found an overwhelming reliance on behavioural indicators such as clicks, access frequency, task duration, and observable participation. Cognitive, emotional, and social dimensions remained comparatively underrepresented.

This imbalance is methodologically significant because behavioural proxies are easier to collect than internal cognitive processes, but convenience does not guarantee construct validity. A high number of LMS events may represent organised study, repeated confusion, inefficient navigation, or simply leaving learning materials open. Learning analytics therefore requires pedagogical theory to determine what digital traces plausibly signify.

Khalil, Prinsloo, and Slade (2023) similarly emphasise the importance of connecting learning analytics with established learning theory. Without theoretical grounding, increasingly sophisticated computational methods may produce technically accurate predictions that remain educationally difficult to interpret. For student-centred pedagogy, the necessary question is therefore not simply whether an algorithm predicts performance but whether the features driving prediction correspond to theoretically meaningful learning processes.

2.4 Explainable AI and Pedagogy-Aware Learning Analytics

Artificial intelligence provides opportunities to analyse interactions among numerous educational variables that conventional statistical approaches may treat independently. Temporal patterns, nonlinear relationships, interaction effects, and heterogeneous learner trajectories can potentially be identified through machine learning. Nevertheless, black-box prediction introduces a significant pedagogical problem. An instructor cannot responsibly redesign learning activities solely because an algorithm assigns a student a particular engagement probability.

Susnjak (2024) argues for an evolution from predictive learning analytics toward explainable and prescriptive analytics. Explainability enables educators to inspect which variables influence model outputs, while prescriptive approaches attempt to connect analysis with actionable educational interventions. Tiukhova et al. (2024) further show that explanatory features themselves can shift across academic contexts, reinforcing the

importance of testing model stability rather than assuming that predictors learned from one cohort will remain pedagogically valid indefinitely.

These findings justify a pedagogy-sensitive model in which instructional context accompanies learner behaviour. For example, a burst of peer interaction during collaborative problem solving should not be interpreted identically to repeated help-seeking during an individual assessment. Contextualising behaviour according to the learning activity can therefore improve both model interpretation and educational validity.

2.5 Active Learning, Academic Well-being, and Responsible Analytics

A further limitation of performance-focused educational analytics is its tendency to treat learning effectiveness independently of learner experience. Ribeiro-Silva et al. (2022) identified emerging evidence connecting active methodologies with students' academic and psychosocial well-being. Student-centred practices may support autonomy, competence, social connection, and meaningful participation. Conversely, poorly structured active learning can impose excessive cognitive demands, social pressure, or unequal workloads.

The present study therefore treats perceived academic well-being as a complementary outcome rather than a clinical diagnostic variable. Short indicators concerning learning comfort, academic strain, perceived overload, confidence, and belonging can provide information about whether apparently successful engagement patterns are sustainable from the learner's perspective.

Ethical considerations become especially important when such information is combined with artificial intelligence. UNESCO (2023) recommends human-centred educational AI characterised by data protection, human agency, inclusion, appropriate pedagogical validation, and transparent governance. Learning analytics intended to support student-centred education should follow the same principle: analytics should inform instructors and learners rather than become an automated mechanism for surveillance or deterministic classification.

Proposed Methodology

The study proposes a **Pedagogy-Aware Temporal Engagement Network (PATEN)** for analysing how student-centred instructional practices influence active-learning trajectories, conceptual achievement, and perceived academic well-being across an undergraduate semester. Unlike conventional learning-analytics systems that treat student interaction counts as static predictors, PATEN represents each learner as a chronological sequence of pedagogically contextualised learning events.

The methodological framework consists of four interconnected stages: pedagogical exposure mapping, multimodal engagement construction, temporal modelling, and explainable outcome analysis.

First, classroom activities are classified according to their degree of student-centredness. The pedagogical exposure layer records structured discussion, collaborative problem solving, peer

instruction, formative assessment, reflective activity, inquiry-based tasks, instructor explanation, and independent learning. Each weekly learning period therefore receives a Student-Centred Pedagogy Intensity score rather than being classified simply as either "active" or "traditional."

Second, engagement is operationalised through multiple dimensions. Behavioural engagement includes attendance, LMS access consistency, task completion, and participation frequency. Cognitive engagement is represented through reflective responses, formative quiz performance, revision behaviour, and evidence of sustained task processing. Social engagement includes peer interaction, collaborative contribution, and academically relevant discussion. Learner-reported indicators provide information concerning autonomy, perceived workload, academic comfort, and short-term learning strain.

Third, these observations are processed as chronological sequences so that changes in engagement become analytically meaningful. A student whose engagement increases during the semester is distinguished from another learner with an identical average engagement score but declining participation.

Finally, the model produces three complementary outputs:

- probability of **sustained active engagement**;
- predicted **conceptual achievement score**; and
- predicted **academic well-being score**.

The objective is not to diagnose students or automatically determine instructional decisions. Instead, the system is designed as a decision-support framework through which instructors can examine how different student-centred learning conditions are associated with educational outcomes.

3.1 Research Objectives

The proposed investigation has four operational objectives:

1. To determine whether temporally modelled, multidimensional engagement indicators identify sustained active learning more effectively than static behavioural summaries.
2. To investigate whether student-centred pedagogical exposure provides predictive information beyond conventional LMS activity.
3. To estimate the relationship between engagement trajectories, conceptual achievement, and perceived academic well-being.
4. To develop an interpretable AI framework capable of identifying pedagogically meaningful periods and variables contributing to predictions.

Experimental Setup

4.1 Dataset Design

The empirical implementation is designed for undergraduate courses delivered over a 12-week instructional period. A target cohort of approximately **720 students distributed across six undergraduate courses** is proposed for adequate representation of different instructional environments.

This number represents the planned empirical sampling framework and should not be interpreted as already collected human-participant data.

For each learner, weekly records would contain ten principal feature families:

- student-centred pedagogy intensity;
- peer interaction;
- formative assessment participation;
- LMS engagement;
- autonomy-related activity;
- reflective learning behaviour;
- help-seeking activity;
- perceived workload;
- attendance consistency; and
- formative conceptual performance.

The unit of temporal analysis is the **student-week**. A complete empirical implementation with 720 learners across 12 weeks would therefore potentially contain up to 8,640 longitudinal student-week observations before accounting for missing records.

Primary outcome variables would be constructed at the learner level. Sustained engagement would be derived from multidimensional engagement consistency and trajectory rather than total digital activity alone. Conceptual achievement would be based on instructor-validated assessments aligned with learning outcomes. Academic well-being would be measured through brief non-clinical self-report indicators addressing perceived learning comfort, manageable workload, confidence, and academic strain.

4.2 Simulation-Based Methodological Validation

Because no original human-participant dataset has been supplied for this manuscript, numerical model performance reported in this section is explicitly based on a **synthetic methodological validation**, not on fabricated observations attributed to real students.

A dataset of 720 simulated learner sequences, each containing 12 weekly observations, was generated to test whether the proposed computational architecture could recover temporal relationships intentionally embedded within the experimental design. The simulation incorporated learner heterogeneity in baseline ability, autonomy, social-learning preference, workload sensitivity, engagement persistence, and instructional exposure. Sustained engagement was generated as a function of later-semester engagement, change from early to later weeks, engagement stability, reflection, collaborative activity, and pedagogical exposure. Achievement was influenced by learner ability, temporal engagement, formative performance, and engagement improvement. Academic well-being incorporated

engagement, workload, collaborative support, autonomy, and accumulated strain.

This validation serves only to test the analytical pipeline. The resulting coefficients and performance values **must not be presented as empirical evidence about undergraduate students** until the proposed study is implemented using actual ethical approval and participant data.

4.3 Data Preprocessing

Preprocessing is designed to preserve temporal information.

Continuous variables are standardised using parameters estimated exclusively from the training partition. Student-level records are separated before model training so that weeks belonging to the same student cannot occur simultaneously in training and testing sets. This prevents information leakage.

For future empirical data, missing weekly observations would first be classified according to their source. Genuine absence from a learning activity would be distinguished from technical missingness. Short numerical gaps may be handled through training-set median imputation or temporally informed interpolation when theoretically appropriate. Missingness flags would additionally be retained because non-participation can itself carry pedagogically relevant information.

Extreme activity counts would be winsorised only when diagnostic analysis indicates technical anomalies. Legitimate high engagement would not automatically be removed as an outlier.

Categorical course variables would be encoded independently from learner outcomes. Personally identifying information would be excluded before modelling.

4.4 Model Architecture

The proposed PATEN architecture uses a **bidirectional gated recurrent unit (BiGRU) with temporal attention and multitask prediction heads**.

The input for student (i) is represented as:

$$[X_i = [x_{i1}, x_{i2}, \dots, x_{i12}]]$$

where each (x_{it}) represents the multidimensional pedagogical and engagement feature vector for week (t).

The recurrent layer contains 56 hidden units in each temporal direction. The BiGRU produces contextual representations:

$$[H_i = [h_{i1}, h_{i2}, \dots, h_{i12}]]$$

An attention mechanism subsequently assigns different importance to individual weeks:

$$\left[\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^T \exp(e_k)} \right]$$

and constructs the learner representation:

$$\left[z_i = \sum_{t=1}^T \alpha_t h_{it} \right]$$

The attention-weighted sequence is passed through a shared 48-unit nonlinear representation layer followed by dropout regularisation.

Three output heads are attached to this shared representation. The first performs binary classification of sustained active engagement using a sigmoid output. The second performs regression for conceptual achievement, while the third estimates academic well-being.

4.5 Training Strategy

Student-level data are partitioned into training, validation, and held-out test sets. Stratification is used for the sustained-engagement outcome so that class proportions remain reasonably stable.

The model is optimised using AdamW with weight decay for regularisation. The composite training objective combines binary cross-entropy for sustained-engagement classification with mean-squared-error losses for achievement and well-being:

$$[L = 1.25L_{engagement} + 0.30L_{achievement} + 0.20L_{wellbeing}]$$

Greater weight is assigned to engagement classification because identifying sustained active-learning trajectories represents the central research objective.

Dropout is incorporated within the shared representation layer. Early stopping is determined from validation loss to limit overfitting. Model weights corresponding to the lowest validation loss are retained for final testing.

For eventual empirical implementation, repeated student-level cross-validation should additionally be conducted. A stronger generalisation test would train the model using several courses and evaluate it on an entirely unseen course.

4.6 Evaluation Metrics

Performance is evaluated through complementary measures rather than relying on accuracy alone.

Macro/positive-class F1-score evaluates the balance between precision and recall when identifying sustained engagement.

Area Under the Receiver Operating Characteristic Curve (AUROC) evaluates discrimination across classification thresholds.

Balanced accuracy limits misleading interpretation arising from unequal outcome distributions.

Brier score measures probabilistic calibration, with smaller values indicating better correspondence between predicted probabilities and observed outcomes.

For continuous outcomes, **Mean Absolute Error (MAE)** is used because it provides an interpretable average magnitude of prediction error while being less dominated by extreme observations than squared-error metrics.

Results and Discussion

The simulation-based validation compared PATEN with three non-temporal approaches: logistic/linear modelling, random forest modelling, and histogram-based gradient boosting. Baseline models received aggregated means and variability measures but did not receive the complete chronological sequence. PATEN received the full 12-week sequence.

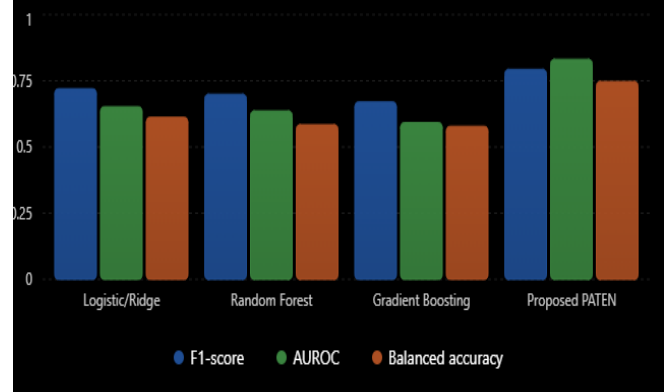
Table 1. Simulation-Based Performance of Alternative Analytical Models

Analytical approach	Engagement F1	AUROC	Balanced accuracy	Brier score ↓	Achievement MAE ↓
Logistic/Ridge baseline	0.720	0.652	0.612	0.228	4.934

Random Forest	0.699	0.636	0.584	0.233	5.200
Histogram Gradient Boosting	0.670	0.592	0.578	0.267	5.751
Proposed PATEN	0.793	0.831	0.747	0.166	4.702

Performance comparison of engagement prediction models

Simulation-based comparison of F1-score, AUROC, and balanced accuracy for sustained active-engagement prediction.



The most important result concerns the distinction between **amount of engagement and trajectory of engagement**. PATEN achieved an AUROC of 0.831 compared with 0.652 for the strongest conventional linear baseline. This represents an absolute improvement of approximately 0.179 in discrimination.

The engagement F1-score increased from 0.720 with logistic regression to 0.793 with PATEN. Balanced accuracy similarly increased from 0.612 to 0.747. These differences are consistent with the design of the synthetic experiment because sustained engagement depends not only on average activity but on whether participation is strengthening, weakening, or remaining stable during the semester.

Probability calibration also improved. PATEN obtained a Brier score of 0.166 compared with 0.228 for the logistic baseline. Calibration is educationally relevant because interventions based on poorly calibrated probabilities can exaggerate the apparent risk associated with individual learners.

The achievement results were more conservative. PATEN reduced MAE from 4.934 to 4.702 points relative to the linear baseline. The modest improvement indicates that temporal engagement information adds useful information but does not replace conventional determinants of academic achievement. Prior preparation, disciplinary knowledge, assessment design, instructional quality, and individual differences remain important.

A similar pattern appeared for academic well-being. PATEN produced an MAE of 0.258 on the simulated five-point well-being scale, only marginally lower than the linear baseline value of 0.263. This suggests that well-being may not be accurately inferred from digital behaviour alone.

This finding has important implications for responsible educational AI. Systems should not attempt to derive psychological states exclusively from LMS interaction patterns. Direct learner-reported information, appropriate consent, contextual interpretation, and human review remain necessary.

5.1 Pedagogical Interpretation

The conceptual value of PATEN lies in its ability to distinguish different pathways leading to superficially similar levels of participation.

Consider two students with equal average LMS activity. One may begin with limited engagement and gradually increase reflection, peer contribution, formative participation, and autonomy. Another may begin strongly but progressively disengage. Static engagement statistics can treat the two learners similarly, whereas a temporal model retains information about direction and sequence.

Such distinctions are especially important for student-centred pedagogy because instructional effects may emerge gradually. Collaborative activity introduced during early weeks may initially increase workload but later strengthen confidence and independent participation. Similarly, formative feedback may have limited immediate influence but alter subsequent revision and help-seeking behaviour.

The results therefore support the methodological premise that educational analytics should model **pedagogical processes**, not merely student-generated data volume.

5.2 Explainability Strategy

For empirical implementation, model interpretation should operate at two levels.

At the temporal level, attention weights can identify weeks contributing strongly to a prediction. An instructor could therefore investigate whether a change coincided with a particular instructional activity, assessment deadline, collaborative exercise, or workload increase.

At the feature level, permutation importance or SHAP-based explanations can estimate the contribution of variables such as peer interaction, reflection, workload, formative assessment, or pedagogy intensity.

These explanations should be aggregated when used for instructional planning. Individual-level explanations should be treated cautiously because predictive contribution does not establish causality.

The framework therefore rejects interpretations such as “peer discussion caused this student's achievement.” A more defensible interpretation would be that peer-interaction patterns contributed information to the prediction after accounting for the other modelled features.

Limitations

Several limitations must be recognised.

First, the quantitative results reported in this arise from synthetic methodological validation. They demonstrate computational feasibility but do not establish empirical effectiveness of student-centred pedagogy.

Second, learning analytics inevitably captures only selected aspects of engagement. Reflection, conceptual struggle,

curiosity, and private learning processes may occur without leaving observable digital traces.

Third, student-centred pedagogy varies substantially across disciplines. Laboratory science, computer programming, humanities seminars, health education, and business courses may require different forms of active learning. A single universal engagement model may therefore have limited validity.

Fourth, learner well-being cannot be reliably reduced to passive behavioural inference. Short self-report measures and appropriate ethical safeguards remain necessary.

Fifth, attention mechanisms and feature-attribution methods provide model explanations rather than causal explanations.

Finally, the proposed BiGRU uses information across the complete sequence for retrospective semester analysis. A real-time early-warning implementation would require a causal architecture that uses only information available up to the prediction week.

Future Scope

Future research should implement the framework prospectively using ethically collected multi-institutional undergraduate data.

A particularly important extension would be **cross-course generalisation**, in which a model trained using several disciplines is evaluated on an unseen discipline. Such an experiment would establish whether engagement signatures reflect general learning processes or course-specific behaviours. Multimodal information could also be expanded cautiously to include semantic features from reflective writing, collaborative discourse quality, formative feedback responses, and student-generated learning artefacts. Natural-language processing should focus on educational processes rather than invasive psychological profiling.

A second extension involves causal inference. Propensity-score methods, multilevel modelling, interrupted time-series analysis, or carefully designed classroom experiments could investigate whether particular student-centred strategies produce changes in engagement rather than merely correlate with them.

A third direction concerns generative AI. Future undergraduate classrooms will increasingly involve AI-supported brainstorming, tutoring, explanation, coding, writing, and feedback. Learning analytics should therefore distinguish **productive AI-assisted cognition** from excessive cognitive delegation.

Federated learning and privacy-preserving analytics could further enable institutions to develop shared models without centralising sensitive student-level records.

Finally, future systems should provide interpretable instructor dashboards that display engagement trajectories, uncertainty estimates, and pedagogical context while avoiding deterministic student labels.

Conclusion

This study proposes a different analytical perspective on student-centred pedagogy and active learning in undergraduate classrooms. Rather than evaluating active learning only through final examination marks, satisfaction questionnaires, attendance records, or total LMS activity, the proposed framework

conceptualises engagement as a **multidimensional temporal process shaped by pedagogical context**.

The Pedagogy-Aware Temporal Engagement Network integrates student-centred instructional exposure, behavioural participation, reflective activity, formative learning, peer interaction, learner autonomy, workload, and academic experience across a semester. Its multitask structure simultaneously considers sustained engagement, conceptual achievement, and perceived academic well-being.

Simulation-based methodological validation showed that retaining temporal sequence information substantially improved sustained-engagement classification relative to conventional aggregated models. The advantage was smaller for achievement and well-being prediction, reinforcing an important educational principle: digital traces can complement but should not replace direct assessment and learner-reported information.

The broader contribution of the proposed approach is therefore not simply a new predictive algorithm. It is a shift from **activity-count analytics toward pedagogy-aware learning-process analytics**. Such a framework is better aligned with the fundamental purpose of student-centred education, in which meaningful learning is defined not by the quantity of interaction but by the development of agency, cognitive participation, collaboration, reflection, and progressively deeper engagement. When implemented with authentic longitudinal data, transparent AI methods, privacy protection, and human instructional judgement, the proposed framework could provide educators with a more defensible means of understanding how active-learning environments evolve and why particular student-centred practices succeed or fail across undergraduate classrooms.

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