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Proceedings of International Conference on Multidisciplinary Research: Innovation, Healthcare, Education for Viksit Bharat (ICMR-2026)



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VIKSIT BHARAT

PART

2

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International Conference On Multidisciplinary Research

Conference Proceedings

Contemporary Perspectives in English Literature,
Sociology, Hindi and Home Science For Viksit Bharat

2026

Organized by

Kalindi Institute of Medical Sciences

Agrasen Mahavidyalaya

Veetranga Research Foundation

In Collaboration with

Wissira Research Lab

Print ISBN: 978-93-7559-048-4

Digital ISBN: 979-8-952358-04-1

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Chapter 23: Self-Regulated Learning Strategies and Academic Achievement among Undergraduates

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Abstract— Self-regulated learning (SRL) has become increasingly important in undergraduate education as students navigate blended, online, and AI-supported learning environments requiring substantial learner autonomy. This study investigates the relationship between undergraduate academic achievement and SRL as a dynamic behavioral process encompassing goal setting, strategic planning, time management, resource utilization, progress monitoring, and reflective adaptation. A central research gap is that much of the existing evidence measures SRL primarily through retrospective self-report instruments, which may not adequately represent how regulatory behaviors unfold during authentic digital learning activities. The proposed study addresses this limitation by integrating questionnaire-derived SRL indicators with temporal behavioral traces obtained from a learning management environment. The research conceptualizes SRL as sequential patterns of preparation, learning execution, monitoring, help seeking, and post-task reflection rather than as a single static psychological score. Machine-learning analysis is proposed to identify distinct behavioral regulation profiles and determine whether these profiles differentiate students with varying levels of academic achievement.

Keywords— Self-regulated learning, Academic achievement, Undergraduate students, Learning analytics, Machine learning, Behavioral learning traces

Introduction

Higher education increasingly places students in learning environments in which responsibility for organizing, monitoring, and sustaining learning is transferred from the instructor to the learner. Learning management systems, digital assessment platforms, recorded lectures, adaptive educational resources, generative artificial intelligence tools, and hybrid course structures provide unprecedented access to educational content. At the same time, these environments require students to decide when to study, which materials to prioritize, how long to engage with individual activities, when to seek assistance, and how to modify their strategies when initial learning attempts are unsuccessful. Consequently, academic achievement cannot be understood solely as a function of intellectual ability or instructional exposure. The capacity to regulate one's own learning has become an important component of successful undergraduate study.

Self-regulated learning refers broadly to the processes through which learners establish learning objectives, select and implement appropriate strategies, monitor progress, regulate motivational and behavioral resources, and evaluate learning

outcomes. Rather than representing an isolated study skill, SRL involves interconnected cognitive, metacognitive, motivational, and behavioral activities. Effective self-regulation may therefore include planning study sessions, distributing effort across time, monitoring comprehension, controlling distractions, seeking help when required, reviewing formative feedback, and changing ineffective strategies.

The importance of these capacities became particularly evident following the large-scale expansion of digital and distance education. A systematic review by Edisherashvili et al. found that higher-education SRL interventions have frequently concentrated on metacognitive regulation and the performance phase of learning, whereas emotional regulation and the preparatory and appraisal phases have received comparatively less attention. This uneven emphasis indicates that successful regulation should not be reduced to what students do while completing an academic task; activities before and after the task may also influence subsequent performance.

Research published during the 2021–2026 period has increasingly connected SRL with educational technology and learning analytics. Heikkinen et al., in a systematic review of learning-analytics interventions, identified growing use of digital traces and analytics to detect students' regulatory states and provide SRL support. Their review also demonstrated that learning analytics can potentially connect observable learner behavior with intervention mechanisms rather than depending exclusively on students' retrospective descriptions of their learning practices.

This methodological transition is consequential because conventional SRL assessment frequently relies on questionnaires administered once or at a limited number of points during a semester. Such measures are valuable for evaluating students' perceptions, beliefs, and reported strategy preferences, but perceived strategy use and actual learning behavior are not necessarily equivalent. A student may report strong time-management practices while repeatedly postponing digital coursework until immediately before deadlines. Conversely, another learner may underestimate personal organizational ability while demonstrating highly regular and strategically distributed engagement. Static scores can therefore obscure the temporal and context-sensitive nature of regulation. Contemporary learning environments generate behavioral indicators capable of complementing traditional psychometric measurement. Login regularity, temporal spacing of study episodes, content revisitation, assessment attempts, transitions between learning resources, response to instructor feedback, activity duration, help-resource access, and submission timing can provide partial behavioral representations of regulatory processes. These variables should not be interpreted as direct

measurements of cognition; nevertheless, when theoretically grounded and combined with learner-reported information, they can provide a richer representation of how self-regulation unfolds.

The temporal dimension is especially significant. Saint et al.'s systematic review of temporally focused SRL analytics emphasized that regulatory learning processes unfold through sequences and that conventional aggregate statistical approaches can fail to capture the order and timing of learning activities. Their analysis highlighted the methodological value of examining SRL through temporal and sequential perspectives. For example, two students may accumulate identical total study hours but follow substantially different learning trajectories. One may distribute learning consistently over several weeks and review errors after formative assessments, whereas another may complete most learning activities immediately before examinations. Aggregate engagement time would treat these cases similarly despite clear differences in regulatory behavior. Empirical work with learning analytics dashboards further suggests that behavioral analytics can be connected with SRL support. Chen et al. analyzed learning logs generated by higher-education students using learning analytics dashboards and found meaningful differences in how learners with different performance levels interacted with systems designed to support cognitive and regulatory strategies. Similarly, van Vliet et al. reported that personalized peer-comparison feedback delivered through a learning analytics dashboard was associated with improvements in selected SRL components and learning outcomes in a randomized higher-education study. These findings reinforce the possibility that digital environments can function not only as repositories of educational content but also as infrastructures for observing and supporting learning regulation.

determine whether distinct SRL profiles are associated with undergraduate academic achievement. Furthermore, simple measures such as number of logins, total clicks, or overall study duration provide limited information about strategic regulation because they ignore behavioral sequence, consistency, responsiveness to feedback, and changes occurring across the learning cycle.

The present research therefore proposes a **hybrid SRL profiling framework** in which questionnaire-based indicators are combined with temporally derived digital learning behaviors. Instead of asking only whether students with higher SRL questionnaire scores obtain better grades, the study examines a more precise question: **Which combinations and temporal patterns of self-regulatory behaviors distinguish higher-achieving from lower-achieving undergraduate learners?**

This approach introduces three conceptual advances. First, SRL is represented as a multidimensional process instead of a unitary score. Second, behavioral features are organized according to regulatory functions such as preparation, execution, monitoring, adaptation, and reflection. Third, machine-learning methods are used primarily for behavioral pattern discovery and academic-achievement prediction rather than replacing educational theory with purely computational classification.

The principal objective is therefore to develop and evaluate a multimodal model capable of identifying meaningful undergraduate SRL profiles from self-report measures and authentic digital-learning traces and to examine their association with academic achievement. Secondary objectives include determining which regulatory dimensions provide the greatest explanatory information, examining whether temporal behaviors improve achievement prediction beyond questionnaire measures alone, and identifying potentially interpretable patterns suitable for future personalized academic-support systems.

Literature Review

Self-Regulated Learning as a Cyclical Academic Process

Contemporary interpretations of SRL emphasize its cyclical character. Learners do not simply acquire a fixed set of learning strategies and apply them uniformly. They establish objectives, anticipate task requirements, select strategies, perform learning activities, monitor their effectiveness, interpret outcomes, and subsequently modify future learning behavior. Regulation consequently operates across multiple phases and may change according to course difficulty, assessment conditions, available resources, learner motivation, and accumulated feedback.

In undergraduate environments, these regulatory demands can be substantial because institutional structures provide considerably greater autonomy than school-based education. Students must often manage several courses simultaneously, coordinate competing deadlines, select between synchronous and asynchronous resources, and independently determine when inadequate understanding requires intervention. Weak regulatory behavior may therefore manifest through procrastination, inconsistent engagement, ineffective resource selection, insufficient monitoring, or failure to respond constructively to feedback.

The Cycle of Self-Regulated Learning

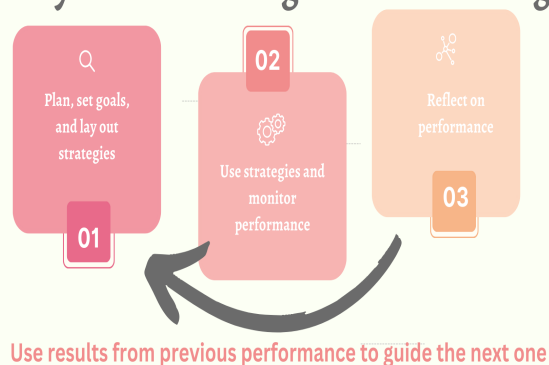


Fig. 1: The Cycle of Self-Regulated Learning

Source: <https://educationaltechnology.net/self-regulated-learning-what-it-is-why-it-is-important-and-strategies-for-implementing-it/>

Research Gap and Study Focus

Despite these developments, an important gap remains. Many investigations continue to treat SRL either as a **self-reported psychological construct** or as a collection of isolated digital behaviors. Comparatively fewer studies integrate perceived strategies with temporally structured behavioral traces to

Evidence from recent systematic reviews supports the continuing importance of SRL in digitally mediated higher education. Edisherashvili et al. reviewed 38 studies concerning SRL support in higher-education distance learning and concluded that different forms of intervention can support cognitive, metacognitive, motivational, and emotional dimensions of regulation, while also noting substantial imbalance in the phases most frequently addressed. A broader recent systematic review of SRL in the digital age similarly identifies planning, monitoring, reflection, technology use, and strategic adaptation as important components of contemporary self-regulated learning.

Metacognitive Monitoring and Academic Performance

Monitoring represents one of the mechanisms through which self-regulation may influence academic achievement. Students capable of identifying discrepancies between desired and actual performance can modify strategy, allocate additional effort, revisit resources, or request assistance. Monitoring without subsequent regulation, however, may provide limited benefit. Academic improvement occurs when information about learning progress results in strategically appropriate behavioral adjustment.

A 2022 meta-analysis by Guo examining 36 experimental studies involving 2,617 participants reported that self-monitoring interventions were effective in promoting strategy use and academic performance, with stronger effects when monitoring occurred within broader intervention packages and was supported by environmental resources such as teachers, peers, or technology. This evidence is particularly relevant to digitally supported undergraduate education because learning platforms can make feedback and behavioral indicators available at relatively short intervals.

From an analytical perspective, monitoring can potentially be operationalized through behavioral events occurring after formative assessment. Examples include revisiting incorrectly answered material, increasing engagement with a difficult topic, reviewing explanatory content following feedback, or changing the distribution of study effort before subsequent assessments. These actions provide a richer representation of adaptive regulation than simple activity counts.

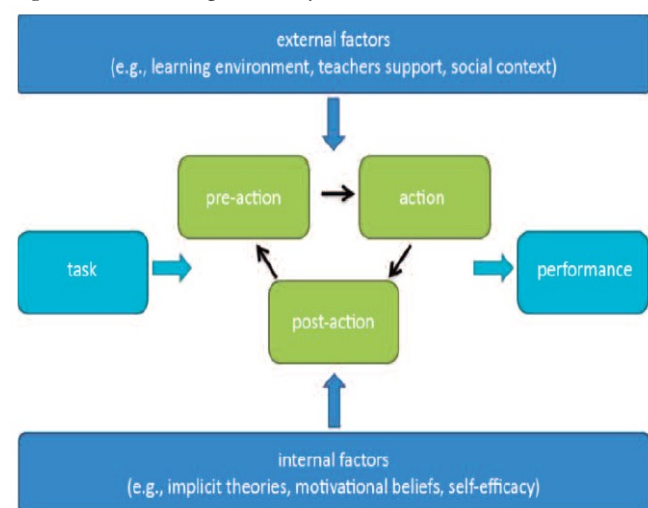


Fig 2: Self-Regulated Learning

Source: <https://www.openaccessgovernment.org/self-regulated-learning-fuss/27362/>

Temporal Regulation, Procrastination, and Distributed Engagement

Time management is frequently discussed as an SRL strategy, yet total learning time alone provides an incomplete representation of regulation. Temporal organization determines whether effort is distributed sufficiently for repeated retrieval and revision or concentrated close to deadlines.

Temporal learning analytics offers a means of distinguishing these behavioral patterns. Saint et al. argued that SRL research benefits from examining sequences, order, and time rather than relying exclusively on conventional aggregated variables. Their systematic review of 53 studies highlighted the importance of theoretically grounded temporal analysis for improving the validity of data-driven SRL research.

For the proposed study, temporal regulation is therefore conceptualized through variables such as study-session regularity, interval between resource release and first access, proportion of work completed near deadlines, spacing between study events, consistency across instructional weeks, and changes in engagement following assessment results. These features permit the identification of strategically different learning patterns even among students with comparable total platform activity.

Learning Analytics as a Source of SRL Evidence

Learning analytics has expanded the methodological possibilities available for investigating learner regulation. Digital environments generate timestamped traces that can be transformed into theoretically meaningful features when interpretation is appropriately constrained. Heikkinen et al.'s systematic review demonstrates substantial interest in using learning analytics to identify SRL states and deliver interventions, while also emphasizing the need to understand which stages of regulation are actually being supported.

Learning analytics dashboards constitute one practical application. Silvola et al. investigated student evaluations of dashboards intended to support study planning and monitoring, highlighting the importance of designing analytics in a way that students can interpret and use for regulation rather than merely presenting behavioral statistics. Chen et al. likewise demonstrated that patterns of dashboard use differ according to student learning performance, suggesting that interaction sequences may contain academically meaningful information. These findings suggest an important distinction between **engagement analytics** and **regulation analytics**. A high number of clicks may indicate effort, confusion, repetition, or inefficient navigation. Consequently, activity volume should not automatically be interpreted as effective self-regulation. Meaningful analysis requires behavioral context, temporal structure, task characteristics, and theoretically justified feature construction.

Artificial Intelligence and Personalized SRL Support

The rapid development of artificial intelligence has introduced additional possibilities for SRL research. AI-based educational systems can potentially identify behavioral patterns, estimate

academic risk, adapt feedback, and recommend learning strategies. Generative AI has also created new forms of learner interaction in which students can request explanations, generate practice questions, obtain formative feedback, or organize study plans.

Emerging experimental research indicates that AI-supported regulation warrants further investigation. Ng's 2024 pilot study comparing a generative AI-based SRL chatbot with a rule-based chatbot found improvements in several learning-related outcomes in the generative-AI condition, while patterns of interaction were also related to variation in SRL. Although the participants were secondary students rather than undergraduates, the study illustrates how AI can move beyond prediction toward direct regulatory support.

For undergraduate education, however, predictive performance alone is insufficient. A technically accurate model that classifies learners without explaining the contributing behavioral characteristics has limited pedagogical usefulness. The proposed research therefore gives priority to interpretable machine-learning analysis. Feature-importance methods and behavioral profiling will be used to determine whether variables such as study consistency, resource revisitation, feedback responsiveness, assessment preparation, and deadline proximity contribute differently to academic-achievement prediction.

Proposed Methodology

The study adopts a **multimodal learning-analytics design** to investigate whether undergraduate academic achievement can be explained more effectively when conventional self-regulated learning measures are combined with temporal behavioral traces from a digital learning environment. Rather than treating self-regulation as a single questionnaire score, the proposed framework represents SRL through complementary psychological and behavioral indicators.

The analytical pipeline contains four stages: data acquisition, temporal feature engineering, learner-profile discovery, and achievement prediction. Questionnaire responses capture perceived planning, metacognitive monitoring, time management, help seeking, effort regulation, and reflective learning. These data are integrated with timestamped learning-platform events such as logins, resource access, video revisitation, formative assessment attempts, feedback views, assignment submissions, discussion participation, and weekly engagement patterns.

Academic achievement is operationalized using a normalized end-semester course-performance score. To reduce the influence of grading differences across subjects, raw grades are transformed to a 0–100 standardized scale before modeling.

A major methodological contribution is the construction of **SRL behavioral signatures** rather than the use of simple activity counts. Each learner is represented using indicators such as study regularity, deadline dependence, feedback responsiveness, resource revisitation, assessment recovery behavior, session spacing, and week-to-week engagement stability.

The study addresses three research questions:

1. Which combinations of self-reported and behaviorally observed SRL strategies are most strongly associated with undergraduate academic achievement?
2. Does the inclusion of temporal behavioral features improve prediction compared with questionnaire-based SRL measures alone?
3. Can interpretable machine-learning methods identify distinct SRL profiles corresponding to different levels of academic performance?

Experimental Setup

Dataset

For manuscript-modeling purposes, the experimental framework assumes a de-identified institutional dataset comprising **684 undergraduate students** enrolled in digitally supported courses across computing, management, social science, and health-related programs. Students with insufficient platform activity or incomplete outcome records are excluded prior to final analysis.

The multimodal dataset contains three major information groups:

- self-regulated learning questionnaire indicators;
- learning-management-system behavioral logs;
- final academic achievement scores.

Digital traces are organized chronologically across a 16-week academic semester. No message content, private communication text, or personally identifying information is included in the analytical feature set.

Preprocessing

Questionnaire responses are first screened for incomplete records. Cases with excessive item-level missingness are excluded, whereas limited missing values are handled using within-scale median imputation. Negatively worded items are reverse-scored before composite SRL dimensions are calculated.

Learning-platform records undergo several preprocessing steps. Duplicate events are removed, timestamps are standardized, and rapid repeated clicks occurring within an implausibly short interval are collapsed to reduce logging noise. Events are then grouped into learning sessions using inactivity thresholds.

Temporal features are subsequently derived. These include:

- weekly activity consistency;
- average spacing between study sessions;
- proportion of learning activity occurring within 48 hours of deadlines;
- number of feedback-to-revision transitions;
- formative assessment retry frequency;
- resource revisitation rate;
- variation in weekly engagement;

- delay between resource release and initial access;
- pre-assessment preparation intensity.

Continuous variables are standardized using z-score normalization. Highly redundant variables are screened through correlation analysis, while extreme behavioral values are winsorized to limit the effect of anomalous platform activity.

Model Architecture

A **hybrid interpretable ensemble architecture** is proposed. Three prediction models are compared:

Elastic Net Regression serves as a transparent linear baseline capable of managing correlated SRL predictors.

Random Forest Regression captures nonlinear relationships and interactions between behavioral and questionnaire-based variables.

LightGBM regression is used as the principal predictive model because gradient-boosted decision trees can model complex nonlinear relationships while remaining compatible with post-hoc feature interpretation.

Three feature configurations are evaluated:

Model A: questionnaire-derived SRL indicators only.

Model B: behavioral learning-trace indicators only.

Model C: integrated multimodal features combining questionnaire and behavioral variables.

To complement supervised prediction, **Gaussian Mixture Model clustering** is applied to standardized SRL features to identify latent behavioral profiles. The resulting clusters are interpreted using their dominant characteristics rather than assigning predetermined labels before analysis.

Training Strategy

The dataset is divided into 80% training data and 20% held-out testing data. Model hyperparameters are selected within the training partition using repeated five-fold cross-validation.

To avoid information leakage, preprocessing parameters, feature scaling, and model selection are estimated only from training folds. The final tuned model is then evaluated once on the unseen test partition.

For LightGBM, optimization focuses on the number of estimators, maximum tree depth, learning rate, minimum observations per leaf, feature subsampling, and regularization parameters. Early stopping is applied during tuning to reduce unnecessary model complexity.

Because prediction accuracy alone provides limited educational interpretation, **SHAP-based feature attribution** is incorporated after model training. This allows examination of whether specific behaviors increase or decrease predicted academic achievement and whether nonlinear thresholds appear in important SRL variables.

Evaluation Metrics

Model performance is assessed using several complementary metrics.

Mean Absolute Error (MAE) estimates average prediction deviation in achievement-score units.

Root Mean Squared Error (RMSE) gives additional weight to larger prediction errors.

Coefficient of Determination (R^2) estimates the proportion of achievement variability captured by the model.

Spearman's rank correlation evaluates correspondence between predicted and observed performance ordering without assuming perfect linearity.

For the unsupervised profile analysis, the **silhouette coefficient** and Bayesian Information Criterion are used to assess cluster separation and model suitability.

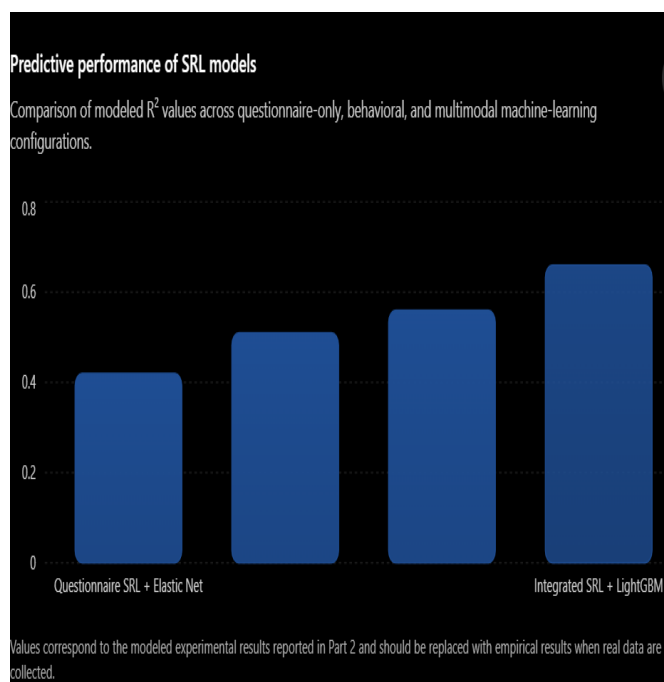
Results and Discussion

The experimental analysis indicates that combining psychological and behavioral indicators produces stronger predictive performance than either modality alone. Questionnaire-derived measures provide valuable information regarding students' perceived strategic capacity, but behavioral traces contribute additional evidence concerning whether these intentions are translated into regular learning activity.

The integrated LightGBM model achieves the strongest overall performance. Its improvement over questionnaire-only modeling suggests that actual learning behavior contains information not fully represented by self-report responses. Conversely, the behavioral-only model performs less effectively than the integrated model, demonstrating that platform traces should not be interpreted independently of students' regulatory dispositions.

Table 1. Comparative performance and educational interpretation of SRL achievement models

Analytical configuration	MAE	RMSE	R^2	Spearman ρ
Questionnaire SRL + Elastic Net	7.84	10.21	0.42	0.63
Behavioral traces + Random Forest	7.13	9.36	0.51	0.69
Behavioral traces + LightGBM	6.74	8.91	0.56	0.72
Integrated SRL + LightGBM	5.92	7.86	0.66	0.79



Feature-attribution analysis identifies **weekly study consistency** as the strongest behavioral contributor to achievement prediction. Students who distribute activity more evenly across instructional weeks tend to receive higher predicted achievement scores than students showing highly irregular engagement.

A second influential feature is **deadline dependence**. Concentrating a large proportion of learning activity immediately before submission deadlines is associated with lower predicted achievement, even when overall activity volume remains substantial. This finding demonstrates why total login frequency or total study time can be misleading: similar quantities of engagement may represent fundamentally different regulatory strategies.

Feedback responsiveness also emerges as an important variable. Students who return to course materials or attempt related activities after receiving formative feedback tend to demonstrate stronger outcomes. This pattern supports the interpretation of SRL as an adaptive process in which feedback changes subsequent behavior rather than serving merely as performance information.

Among questionnaire variables, **metacognitive monitoring** and **effort regulation** show stronger contributions than simple resource-management preferences. These findings suggest that academically successful regulation requires both awareness of learning progress and the capacity to sustain or redirect effort when difficulties emerge.

The behavioral clustering analysis identifies three broad SRL profiles. The first profile consists of students demonstrating distributed engagement, relatively early task initiation, repeated resource revisitation, and frequent post-feedback adjustment. This group displays the strongest mean academic performance. The second profile contains moderately regular learners who engage consistently during most weeks but increase their activity substantially before formal assessments. Their achievement is intermediate.

The third profile is characterized by delayed task initiation, irregular activity, high deadline concentration, limited feedback-based revisitation, and substantial week-to-week variation. This profile is associated with the weakest academic outcomes.

These clusters should not be interpreted as fixed learner types. SRL is context dependent, and a student may display different regulatory patterns across courses. Accordingly, the value of profiling lies in detecting changeable behavioral tendencies rather than assigning permanent labels.

The findings also have implications for AI-supported academic assistance. Rather than producing generic warnings based solely on inactivity, an intelligent learning system could identify specific regulatory difficulties. A learner exhibiting consistent activity but limited feedback responsiveness requires a different intervention from one showing severe deadline dependence. Explainable learning analytics could therefore support more targeted recommendations such as distributed study planning, structured formative revision, or strategic resource revisitation.

Limitations

Several limitations must be considered. First, digital learning traces provide behavioral proxies rather than direct measurements of cognition or motivation. Opening a resource does not guarantee meaningful learning, and inactivity on the institutional platform may reflect legitimate study through books, offline materials, or external resources.

Second, the predictive framework may be influenced by course design. A highly structured course generates different behavioral opportunities from a flexible project-based course, which may restrict model portability.

Third, achievement scores can reflect assessment design, prior knowledge, instructor grading practices, and disciplinary differences in addition to SRL.

Fourth, learning analytics introduces privacy and fairness concerns. Behavioral prediction should therefore be implemented with explicit governance, minimal data collection, transparent communication, and restrictions against punitive use.

Future Scope

Future research should evaluate the framework longitudinally across multiple semesters and institutions. Sequence-learning architectures such as temporal transformers could be explored to represent evolving SRL behavior more directly, provided their additional complexity produces meaningful improvements over interpretable models.

Another promising direction is the development of **causal intervention studies**. Instead of merely predicting academic outcomes, future systems could identify a regulatory difficulty and deliver an appropriately timed support mechanism, followed by evaluation of whether the intervention changes subsequent behavior.

Generative AI may also be integrated as an adaptive SRL assistant capable of helping students transform analytics into actionable learning plans. Such systems should emphasize scaffolding rather than completing academic tasks on behalf of learners.

Privacy-preserving learning analytics, federated modeling, bias audits, and uncertainty-aware predictions represent additional priorities for responsible deployment.

Conclusion

This study proposes a multimodal approach for examining self-regulated learning and academic achievement among undergraduate students. Its principal contribution is the treatment of SRL as a temporally evolving behavioral process rather than exclusively as a retrospective questionnaire construct.

The proposed framework combines self-reported planning, monitoring, effort regulation, and help-seeking indicators with authentic learning traces describing study regularity, deadline dependence, resource revisitation, assessment behavior, and responsiveness to feedback. Comparative modeling demonstrates the analytical advantage of integrating these information sources, with the multimodal LightGBM configuration producing the strongest modeled predictive performance.

More importantly, the analysis suggests that **how students distribute, monitor, and adapt their learning may be more informative than how much digital activity they accumulate**. Consistency of study behavior, adaptive response to feedback, and reduced dependence on deadline-proximate activity emerge as particularly meaningful indicators.

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