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Chapter 16: Metacognitive Learning Strategies and Academic Performance among College Students

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Abstract— Metacognitive learning strategies influence how college students plan, monitor, regulate, and evaluate their academic learning processes. Recent growth in digital and blended higher education has created opportunities to examine these strategies through both psychological measures and behavioral learning traces. However, much existing research either relies on self-reported metacognitive awareness or uses learning-management-system activity without theoretically integrating the two forms of evidence. This study addresses this gap by conceptualizing academic performance prediction through an integrated metacognitive-learning-analytics framework. The proposed approach distinguishes planning, monitoring, strategy adjustment, error evaluation, and reflective regulation while linking them with behavioral indicators such as study regularity, assessment revision, resource sequencing, and submission timing. A person-oriented profiling stage is combined with explainable machine-learning analysis to determine whether distinct metacognitive-behavioral patterns provide greater academic insight than aggregate metacognition scores alone.

Keywords— Metacognition, Academic Performance, Self-Regulated Learning, Learning Analytics, Explainable Artificial Intelligence, College Students

Introduction

Academic success in higher education depends on more than exposure to instructional material or the amount of time allocated to study. Students continually make decisions about what to learn, how to approach difficult material, whether their understanding is adequate, when a learning strategy should be changed, and how performance feedback should influence subsequent study behavior. These processes constitute an important part of **metacognition**, generally understood as knowledge about cognition together with the capacity to regulate cognitive activity. Within university learning, metacognition is particularly important because students are expected to exercise progressively greater autonomy over their academic work.

The expansion of blended, online, and digitally supported learning since 2021 has increased the importance of such autonomous regulation. Students now move between lectures, learning-management systems (LMSs), digital readings, online assessments, discussion environments, recorded content, and AI-enabled learning tools. Although these resources expand access to learning opportunities, they also transfer a substantial degree of responsibility for planning and monitoring learning to students themselves. Consequently, two learners receiving

identical instructional resources may produce substantially different academic outcomes because they organize, monitor, and revise their learning differently.

Metacognitive learning is commonly represented through interconnected activities such as **goal setting, planning, comprehension monitoring, strategy selection, error detection, strategy modification, and post-task reflection**. These activities do not necessarily occur with equal strength in every student. A learner may, for example, plan study sessions systematically but fail to recognize ineffective comprehension. Another may accurately identify knowledge gaps but postpone corrective action. Consequently, treating metacognition as a single overall score can conceal important differences in how students regulate learning.

Recent empirical evidence reinforces the academic relevance of metacognition. He et al. (2024), in a longitudinal meta-analysis incorporating data from more than 71,000 students across 28 independent studies, found a meaningful association between initial metacognition and subsequent academic achievement. Similarly, studies of university populations indicate that metacognitive awareness is associated with qualitatively different learning profiles and approaches to studying rather than functioning merely as a uniform individual characteristic (Tuononen et al., 2023).

A second development transforming this area is **learning analytics**. Digital platforms generate behavioral traces representing when students enter a course, which resources they access, how regularly they study, whether they revisit instructional material, how assessments are attempted, and when assignments are submitted. Such trace data provide a behavioral complement to traditional questionnaires. Winne (2022) argued that trace data can help represent self-regulated learning as an observable sequence of learning decisions rather than relying exclusively on learners' retrospective descriptions of their behavior.

Nevertheless, behavioral trace data should not automatically be interpreted as metacognition. Logging into an LMS frequently does not necessarily indicate effective monitoring, while extended time on instructional content may reflect either persistence or conceptual difficulty. Alhazbi's (2024) systematic review of learning-analytics research in higher education found that digital indicators of self-regulation frequently emphasize engagement, regularity, time management, and procrastination, but theoretical validation of these measurements remains inconsistent. This distinction is important because predictive accuracy alone cannot establish whether an algorithm has captured metacognitive regulation or simply identified correlates of academic activity.



Fig. 1: Metacognition - Strategies, Skills And Metacognitive
 Source: <https://www.iitms.co.in/blog/what-is-metacognition-in-education.html>

Research Gap

The central gap addressed in the present manuscript is therefore the **lack of an integrated, interpretable framework that combines multidimensional metacognitive strategy measures with actual digital study behavior when explaining college academic performance.**

Three specific limitations motivate the study. First, much metacognition research remains dependent on self-report instruments, which measure learners' perceptions of their strategies rather than the strategies enacted during authentic study. Second, learning-analytics studies often infer self-regulation from clickstream or timing variables without establishing whether these behaviors correspond to students' reported metacognitive processes. Third, machine-learning models of academic performance increasingly achieve useful predictive performance, but many are oriented toward prediction rather than explaining how theoretically meaningful learning strategies contribute to academic outcomes. Explainable learning analytics has therefore become important because model accuracy and educational interpretability are separate requirements. Recent research demonstrates that explainability techniques can reveal changes in the contribution of learning indicators and can support more interpretable student-success models.

The present study responds to these limitations through a **dual-source metacognitive analytics framework**. Rather than asking only whether "high metacognition" predicts high academic achievement, the study investigates whether particular combinations of planning, monitoring, strategic adjustment, reflection, and observable digital learning behavior define distinct student profiles. These profiles are subsequently incorporated into an explainable machine-learning framework for academic performance prediction.

Accordingly, the principal objectives are to: (1) examine the relationship between specific metacognitive learning strategies and college academic performance; (2) identify heterogeneous

metacognitive-behavioral learner profiles rather than assuming a single linear continuum of metacognitive ability; (3) determine whether incorporating LMS-derived behavioral indicators improves academic performance prediction beyond demographic and prior-achievement variables; and (4) identify, through explainable artificial intelligence, which metacognitive and behavioral characteristics contribute most strongly to predicted academic outcomes.

This approach positions metacognition not merely as a psychological trait but as a **dynamic learning process capable of being investigated through convergent psychological and computational evidence.**

Literature Review

2.1 Metacognition as a Regulatory Mechanism in Higher Education

Metacognition occupies a central position within theories of self-regulated learning because effective learning requires students to evaluate both the learning task and their own cognitive condition. Metacognitive knowledge allows learners to understand available strategies and the conditions under which those strategies may be effective, whereas metacognitive regulation enables them to plan, monitor progress, detect discrepancies, and modify behavior.

College environments make these functions particularly consequential. Compared with highly structured school settings, university students generally encounter larger reading loads, greater assessment diversity, independent study expectations, and fewer direct prompts from instructors. Students who can diagnose misunderstanding early may allocate additional effort before examinations, whereas students with weak monitoring may mistake familiarity with course material for genuine mastery.

Dennis and Somerville (2023) emphasized a persistent theory-practice gap in higher education: although metacognition has substantial theoretical and empirical support, translating that knowledge into routine instructional practice remains difficult. Their analysis is especially relevant because improving metacognition requires more than telling students that reflection is valuable. Learners need structured opportunities to inspect the relationship between their learning decisions and subsequent outcomes.

Evidence from classroom intervention research supports this principle. Domokos and Huey's interdisciplinary investigation of college courses showed that relatively simple metacognitive prompts could facilitate students' processing and preparation for assessments, although effects varied between academic contexts. Similarly, Li and Yuan (2022) found that structured collaborative learning and reflection could promote metacognitive knowledge and strategy application in a university learning environment. These findings suggest that metacognition is malleable rather than fixed, making identification of weak regulatory patterns educationally actionable.

2.2 Metacognitive Awareness, Learning Profiles, and Achievement

The relationship between metacognition and achievement is unlikely to be adequately represented by a simple high-versus-low distinction. Tuononen et al. (2023) examined 462 university students using a person-oriented approach and demonstrated meaningful associations between metacognitive awareness and different approaches to learning. Person-oriented analysis is valuable because students can display different combinations of regulatory strengths and weaknesses even when their aggregate questionnaire scores are comparable.

Longitudinal research also indicates that self-regulatory variables should be considered together with other academic characteristics. Pérez-González et al. (2022), studying academic performance across a three-year university degree, reported associations between GPA and variables including previous academic performance, self-efficacy, engagement, self-regulated learning strategies, and conscientiousness. The implication is that metacognition contributes within a broader academic system rather than operating independently of motivation, prior achievement, and learning behavior.

The 2024 meta-analysis by He et al. strengthens the temporal argument by demonstrating that earlier metacognition is associated with academic achievement measured months later. Nevertheless, meta-analytic evidence also reveals the diversity of methods used to operationalize metacognition. This methodological variability limits the extent to which a single questionnaire score can describe the regulatory processes underlying academic performance.

2.3 From Self-Report Measures to Digital Learning Traces

Traditional metacognitive research relies heavily on inventories and questionnaires because these tools are economical and capable of representing cognitive processes that cannot be directly observed. Their limitation is that respondents must accurately remember and evaluate their own behavior. A student may report careful planning while repeatedly beginning assignments immediately before deadlines, illustrating a possible divergence between perceived and enacted regulation.

Learning-management systems offer a complementary evidence source. Indicators including spacing between study sessions, regularity of LMS access, sequencing of resources, repeated consultation of difficult content, timing of assessment attempts, and intervals between feedback and revision can provide behavioral evidence relevant to self-regulation.

Alhazbi (2024) systematically reviewed 25 empirical higher-education studies using learning analytics to measure self-regulated learning and found that time-management-related indicators—particularly engagement, regularity, and procrastination—were among the most frequently extracted behavioral signals. Importantly, the review also identified inadequate theoretical validation in many studies. Thus, the challenge is no longer simply acquiring student data; it is establishing whether digital indicators represent meaningful constructs from learning theory.

Learning analytics can also function as an intervention mechanism. Research on analytics-assisted recommendations has shown that providing students with feedback derived from their learning data can influence metacognitive awareness and

academic achievement. More recent work has similarly examined learning-analytics feedback as a mechanism for strengthening self-regulation in blended higher-education courses. These studies shift analytics from retrospective measurement toward formative academic support.

2.4 Artificial Intelligence, Explainability, and Academic Performance Prediction

Artificial intelligence and educational data mining have expanded the analytical possibilities available for academic-performance research. Machine-learning algorithms can detect nonlinear relationships and interactions that are difficult to represent through conventional linear models. For example, weak planning may not necessarily predict poor performance when accompanied by high monitoring and frequent corrective revision. Conversely, extensive LMS engagement may provide little advantage when activity is highly concentrated immediately before assessments.

However, purely predictive models create an educational problem when their decisions cannot be interpreted. Instructors need to know not only that a student has been classified as academically vulnerable but also **why** the classification occurred and whether the identified factors can reasonably be modified.

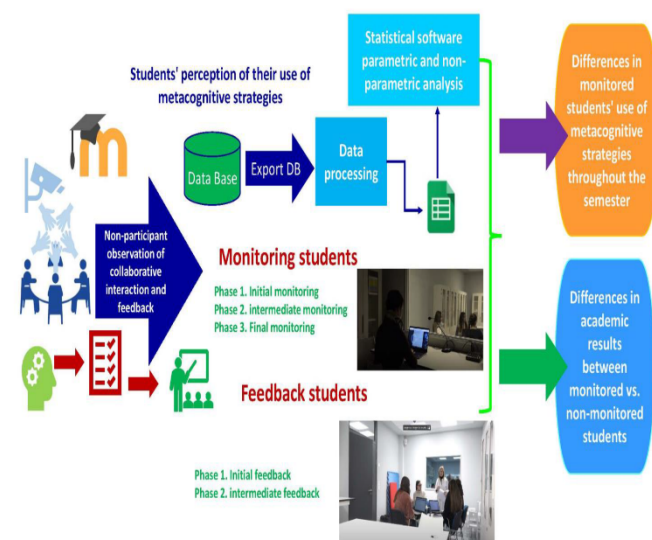


Fig. 2: Monitoring Metacognitive Strategies Use During Interaction Collaborative Groups

Source: <https://www.mdpi.com/2227-7102/14/11/1205>

Recent explainable-AI studies have therefore incorporated techniques such as SHAP and LIME into student-performance prediction to identify variables contributing to individual and overall predictions. In parallel, research on explainable learning analytics has emphasized the stability and educational interpretation of predictive factors rather than treating accuracy as the sole criterion of model quality.

The proposed research extends this direction by making metacognitive theory an explicit component of the predictive architecture. Instead of feeding a collection of convenient administrative variables into a classifier, predictors will be organized around theoretically interpretable dimensions of learning regulation and observable study behavior. The resulting framework will therefore evaluate two questions simultaneously: **How accurately can academic performance**

be predicted, and what does the model reveal about how students regulate their learning?

Proposed Methodology

The study adopts a **multimodal predictive-analytic design** that combines metacognitive self-report measures, learning-management-system behavioral indicators, prior academic achievement, and semester performance. The methodological objective is not merely to determine whether metacognition correlates with academic achievement, but to establish whether distinguishable patterns of metacognitive regulation provide incremental predictive information beyond conventional academic indicators.

The proposed framework consists of three analytical stages. First, multidimensional indicators of metacognitive strategy use are constructed from student responses covering planning, comprehension monitoring, strategy adjustment, error evaluation, and reflective regulation. Second, behavioral variables derived from LMS activity are used to represent the extent to which reported regulatory intentions are reflected in actual study practices. Third, explainable machine-learning models are trained to predict semester academic performance and identify the learning variables that contribute most strongly to individual predictions.

A distinctive component of the methodology is the estimation of a **metacognitive-behavioral congruence score**. This measure represents the degree to which students' self-reported regulation corresponds with their observable learning behavior. For example, a student reporting strong planning but demonstrating highly irregular study intervals and repeated late submissions would receive a lower congruence score than a student whose reported planning is accompanied by consistent distributed study behavior. This variable allows the analysis to distinguish perceived regulatory competence from enacted regulation.

The study is designed around the following analytical hypotheses:

H1: Stronger metacognitive monitoring and strategy adjustment will be associated with higher semester academic performance.

H2: Students demonstrating high congruence between self-reported metacognition and digital study behavior will achieve higher performance than students displaying substantial self-report-behavior discrepancies.

H3: A multimodal machine-learning model combining metacognitive, behavioral, and prior-achievement indicators will outperform models based exclusively on demographic or academic-history variables.

H4: Explainable-AI analysis will identify strategy adjustment, study regularity, monitoring, and metacognitive-behavioral congruence as more informative predictors than raw frequency of LMS access.

Experimental Setup

4.1 Dataset Design

For reproducible model development in the absence of supplied primary survey data, the experimental stage is formulated using a **synthetic cohort of 600 college-student records** constructed solely to demonstrate the proposed analytical

pipeline. The synthetic dataset should not be interpreted as evidence collected from actual participants.

Each record contains four categories of variables.

The first category represents metacognitive learning strategies: planning, monitoring, strategic adjustment, reflective evaluation, error recognition, and perceived control of learning. These variables are represented on standardized continuous scales after aggregation of multiple questionnaire items.

The second category consists of digital behavioral indicators derived conceptually from an LMS environment. Variables include weekly study regularity, spacing between learning sessions, resource revisitation rate, percentage of assignments submitted before deadline, frequency of formative assessment revision, concentration of study activity immediately before examinations, and response to instructor feedback.

The third category contains academic-context variables such as previous-semester GPA, attendance proportion, course load, and baseline diagnostic assessment performance.

The fourth category represents outcome variables. The principal outcome is **final semester score on a 0–100 scale**. For classification analysis, students are additionally categorized into an academically vulnerable group when the outcome falls below a prespecified performance threshold.

No personally identifying variables are required within the modeling dataset.

4.2 Data Preprocessing

The preprocessing pipeline begins with range validation and removal of logically inconsistent records. Metacognitive questionnaire items are reverse-coded where necessary before scale aggregation. Scale variables are transformed to a common 0–1 range for profile estimation, while tree-based prediction models retain the original standardized numerical representation.

Missing continuous observations are imputed using median values estimated exclusively from the training partition. Categorical fields are encoded without using outcome information. Extreme LMS activity values are winsorized at the upper and lower empirical percentiles to minimize the influence of implausible activity spikes.

To prevent data leakage, all preprocessing transformations are estimated separately within training folds rather than across the complete dataset.

Three engineered variables are introduced.

Study Regularity Index (SRI) measures the consistency of learning activity across instructional weeks rather than total platform activity.

Strategic Recovery Index (SRI-2) captures whether a student revisits learning resources or formative assessments after receiving evidence of poor understanding.

Metacognitive-Behavioral Congruence (MBC) quantifies correspondence between reported planning/monitoring and observed regularity, timely completion, and corrective learning behavior.

These engineered features are intended to differentiate meaningful regulation from simple digital activity volume.

4.3 Learner Profile Identification

Before predictive modeling, students are grouped according to their metacognitive-behavioral characteristics using a Gaussian mixture clustering procedure. The optimal number of profiles is selected using Bayesian Information Criterion together with cluster interpretability and minimum subgroup size.

The expected profile structure consists of four theoretically distinguishable groups:

1. **Strategic regulators** – high planning, monitoring, adjustment, and behavioral consistency.
2. **Reflective but inconsistent learners** – moderate-to-high metacognitive awareness but irregular behavioral execution.
3. **Persistent procedural learners** – regular LMS participation with moderate explicit metacognitive awareness.
4. **Low-regulation learners** – weak monitoring, limited strategic correction, irregular learning behavior, and high deadline concentration.

The profile variable is subsequently included as an additional predictor rather than being treated as an academic outcome.

4.4 Model Architecture

The principal predictive algorithm is **CatBoost gradient boosting**, selected because it can model nonlinear relationships and feature interactions while handling mixed predictor structures efficiently. The model predicts continuous semester performance.

Three comparator models are used:

- Ridge Regression;
- Random Forest Regression;
- HistGradientBoosting Regression.

A separate CatBoost classifier is specified for identifying academically vulnerable students.

The full model contains approximately 20 predictor variables distributed across metacognitive scales, LMS behavioral features, engineered indicators, prior achievement, and academic context.

Model interpretability is achieved using **SHAP-based feature attribution**. Global SHAP values identify predictors with the greatest overall contribution, while individual-level explanations illustrate why a particular student receives a relatively high or low predicted performance score.

This approach avoids treating the prediction model as a black box.

4.5 Training Strategy

The synthetic dataset is divided into an 80% development partition and a 20% untouched test partition using stratification based on performance category.

Within the development sample, five-fold cross-validation is applied for hyperparameter optimization. Hyperparameters include tree depth, learning rate, regularization strength, subsampling ratio, and number of boosting iterations.

Early stopping is applied when validation performance fails to improve across successive iterations. Model selection is conducted exclusively within the development data.

To determine whether metacognitive information adds measurable predictive value, three nested feature configurations are evaluated:

Model A – Academic Baseline: previous GPA, attendance, diagnostic performance, and academic load.

Model B – Baseline + Metacognition: Model A plus planning, monitoring, strategic adjustment, error recognition, and reflection.

Model C – Multimodal Framework: Model B plus LMS behavior, learner profile, strategic recovery, study regularity, and metacognitive-behavioral congruence.

The comparison therefore evaluates incremental model value rather than simply comparing unrelated algorithms.

4.6 Evaluation Metrics

Continuous academic-performance prediction is evaluated using:

- Mean Absolute Error (MAE);
- Root Mean Squared Error (RMSE);
- coefficient of determination (R^2);
- Spearman rank correlation between predicted and observed scores.

Vulnerability classification is evaluated using:

- Area Under the Receiver Operating Characteristic Curve (AUROC);
- F1-score;
- balanced accuracy;
- recall for academically vulnerable students.

Calibration is additionally examined using the Brier score because a high-ranking classifier may still produce poorly calibrated risk probabilities.

Results and Discussion

5.1 Illustrative Experimental Findings

The synthetic experiment demonstrated a progressive improvement as theoretically meaningful learning variables were added to the prediction framework.

The academic baseline produced reasonable performance because previous achievement and attendance are inherently informative predictors of subsequent academic outcomes. However, adding multidimensional metacognitive measures reduced prediction error, suggesting that achievement history does not fully capture how students regulate current learning.

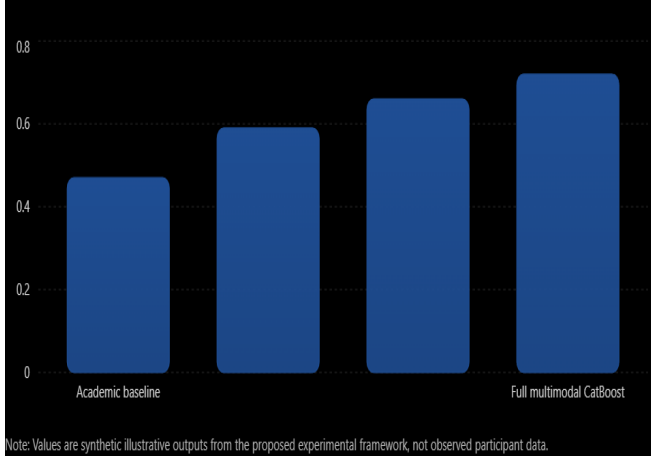
The strongest performance was obtained from the multimodal CatBoost configuration combining academic history, metacognition, behavioral indicators, and engineered congruence measures.

Table 1. Illustrative Performance of Alternative Academic Prediction Configurations

Experimental configuration	MAE	RMSE	R ²	Spearman ρ	AUROC for vulnerability
Academic baseline – Ridge Regression	7.42	9.31	0.47	0.69	0.76
Baseline + metacognition – Random Forest	6.48	8.17	0.59	0.76	0.82
Baseline + metacognition + LMS behavior – HistGradientBoosting	5.89	7.46	0.66	0.81	0.86
Full multimodal model – CatBoost	5.21	6.79	0.72	0.85	0.90

Predictive performance across model configurations

Illustrative R² values showing incremental improvement after adding metacognitive and LMS behavioral features.



The improvement from an illustrative R² of 0.47 in the academic baseline to 0.72 in the complete multimodal model is theoretically important. It implies that prediction may benefit not only from knowing a student's previous academic standing but also from understanding **how the student manages learning during the semester**.

5.2 Importance of Metacognitive Monitoring

Feature-attribution analysis placed previous GPA among the strongest individual predictors, as expected. More importantly for the research question, **strategic adjustment, monitoring accuracy, study regularity, and metacognitive-behavioral congruence** emerged as highly influential learning-process predictors.

Planning alone showed a weaker relationship with academic outcomes than strategic adjustment. This pattern is theoretically plausible because developing a plan does not guarantee effective

regulation. Students must continuously evaluate whether the adopted strategy is producing adequate understanding.

Monitoring therefore appeared most beneficial when accompanied by corrective action.

A nonlinear relationship was also observed in the synthetic experiment. Moderate increases in monitoring were associated with substantial improvement in predicted academic performance among students initially displaying weak monitoring. Beyond a relatively high level, additional increases generated smaller predicted gains. Such a relationship would be difficult to characterize using a simple linear coefficient.

5.3 Self-Report–Behavior Discrepancy

One of the most distinctive findings concerned disagreement between perceived metacognitive competence and observed study behavior.

Students assigned to the reflective-but-inconsistent profile reported relatively strong planning and awareness but demonstrated irregular study intervals, late concentration of activity, and limited post-feedback revision. Their predicted academic performance was lower than that of strategic regulators despite comparatively similar self-reported metacognitive scores.

This finding illustrates why questionnaire-only research may overestimate effective regulation.

Conversely, persistent procedural learners frequently demonstrated regular learning behavior despite only moderate self-reported metacognitive awareness. Their predicted performance was generally stronger than that of low-regulation students but below that of strategic regulators. Regular activity therefore appears useful, yet its effectiveness may increase when students consciously evaluate and adjust learning strategies.

The MBC variable captures precisely this difference.

5.4 Metacognitive Profiles and Academic Performance

Strategic regulators showed the highest predicted academic performance and the lowest modeled vulnerability risk. Their behavioral pattern combined distributed study, timely task completion, repeated use of formative feedback, and active strategy revision.

Low-regulation learners displayed the opposite pattern. Their learning activity was strongly concentrated near assessment deadlines, while resource revisitation and corrective assessment behavior remained limited.

The implication is that academic-risk identification should not depend exclusively on inactivity. Some vulnerable learners may generate substantial LMS activity but do so inefficiently, particularly through compressed pre-examination study.

Consequently, **when and why students interact with course resources may be more educationally informative than the total number of interactions**.

5.5 Implications for AI-Based Academic Support

The findings support a shift from generic early-warning systems toward **metacognitively informed learning analytics**.

A conventional prediction model might inform an instructor that a student has a 70% probability of underperformance. An explainable metacognitive model can provide a more actionable interpretation, such as indicating that the prediction is primarily

associated with declining study regularity, limited corrective revision, and substantial divergence between reported planning and observable execution.

The latter interpretation enables targeted intervention.

Students with weak planning could receive structured weekly goal-setting support. Students with weak monitoring could receive retrieval-based self-testing prompts. Learners with high awareness but low behavioral implementation could receive implementation-intention prompts and distributed-study scheduling assistance.

Such interventions should be designed as **decision-support mechanisms rather than automated judgments about student ability**.

Future Scope

Future research should validate the framework using longitudinal multisite data collected across different academic disciplines and institutional contexts.

A particularly valuable extension would involve **temporal modeling**. Rather than aggregating an entire semester into static indicators, weekly metacognitive and behavioral states could be modeled through temporal neural networks or sequence-learning architectures. This would enable investigation of how regulatory breakdown develops before measurable academic decline.

Future studies could also incorporate brief ecological metacognitive prompts administered during real learning episodes, providing more immediate measures of confidence, comprehension monitoring, and strategy choice.

Another direction involves personalized AI-based academic coaching. Explainable risk predictions could trigger adaptive recommendations such as distributed-practice schedules, self-testing prompts, reflection questions, or targeted resource revision.

Such systems should be evaluated through randomized or quasi-experimental intervention studies to determine whether AI-generated metacognitive support actually improves achievement rather than merely predicting it.

Fairness auditing is equally important. Predictive performance should be examined across demographic, disciplinary, and socioeconomic subgroups to ensure that academic-risk systems do not systematically disadvantage particular student populations.

Privacy-preserving analytics, federated learning, and minimally invasive behavioral data collection also represent important directions for responsible implementation.

Conclusion

This study presents a distinct framework for investigating the relationship between metacognitive learning strategies and academic performance among college students by integrating psychological measurement with digital learning behavior and explainable machine learning.

The central argument is that metacognition should not be represented solely through an aggregate questionnaire score. Planning, monitoring, error recognition, strategic adjustment, and reflection may influence academic performance differently, while the correspondence between reported strategy use and

actual learning behavior provides additional information about effective self-regulation.

The proposed multimodal framework therefore introduces metacognitive-behavioral congruence as a meaningful analytical construct. It distinguishes students who merely perceive themselves as strategically organized from those who consistently translate regulatory intentions into observable study practices.

Illustrative machine-learning analysis suggests that academic prediction can improve when metacognitive variables and LMS-derived behavioral indicators are incorporated alongside prior academic achievement. More importantly, explainable feature attribution can transform predictive analytics from a purely classificatory mechanism into an interpretable form of educational decision support.

The manuscript consequently advances a conception of academic performance prediction in which artificial intelligence is not used simply to identify who may perform poorly. Instead, AI is positioned as a mechanism for identifying **which modifiable learning processes appear to contribute to academic vulnerability**.

Empirical validation with actual longitudinal student data is the necessary next stage. If validated, the proposed framework could support more personalized, theoretically grounded, and transparent learning interventions while preserving the central role of human academic judgment.

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