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A Cognitive Behavioral Therapy–Informed Explainable AI Framework for Academic Performance Analysis

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Abstract:
***Background**: Academic performance prediction models often prioritize accuracy over interpretability, limiting their practical utility in educational interventions. This study integrates Cognitive Behavioral Therapy (CBT) principles with explainable artificial intelligence (XAI) to analyze academic performance through behavioral, emotional, and cognitive dimensions.*
***Materials and Methods**: A dataset of 1,000 student records was analyzed using exploratory data analysis, multi-class classification (Logistic Regression, SVM, Random Forest), regression modeling (Linear Regression, Random Forest Regressor, SVR), and SHAP-based explainability analysis. Models were evaluated with and without cognitive proxy variables to assess the independent contribution of behavioral and emotional factors.*
***Results:** Classification models achieved near-perfect accuracy (Random Forest: 1.00, SVM: 0.945, Logistic Regression: 0.98) when prior academic score was included, indicating proxy leakage. After removing this cognitive proxy, accuracy dropped dramatically to 0.315 (0.325 with SMOTE oversampling). Regression models predicting academic score from behavioral features yielded negative R^2 values (Linear: −0.01, Random Forest: −0.05, SVR: −0.17), with RMSE exceeding 18 points. SHAP analysis revealed weak and unstable feature contributions among behavioral variables, with interaction values centered near zero.*
***Conclusions:** The findings demonstrate that behavioral and emotional variables alone lack sufficient predictive power for academic performance modeling, supporting CBT theory that cognition mediates the relationship between behavior and outcomes. This study emphasizes the critical role of explainable AI in identifying model limitations and theoretical inconsistencies, advocating for cognitive construct inclusion in educational prediction models.*
***Keywords**: Explainable AI, Cognitive Behavioral Therapy, Academic Performance, SHAP, Educational Data Mining, Machine Learning, Student Success Prediction*

I. Introduction

Academic performance represents a complex interplay of behavioral patterns, emotional states, and cognitive processes. While machine learning (ML) has demonstrated promise in educational data mining, many studies emphasize predictive accuracy at the expense of interpretability and theoretical grounding [1,2]. This limitation is particularly problematic in educational contexts, where understanding why a model makes predictions is as important as the predictions themselves for designing effective interventions [3].

Cognitive Behavioral Therapy (CBT) provides a well-established theoretical framework for understanding the relationships among behavior, emotion, and cognition [4]. In CBT theory, behaviors (e.g., study habits, attendance) and emotions (e.g., stress, anxiety) influence outcomes primarily through cognitive mediators, including beliefs, self-efficacy, and prior knowledge [5]. This theoretical perspective suggests that models excluding cognitive constructs should demonstrate limited predictive capacity—a hypothesis rarely tested in educational ML research.

Recent advances in explainable AI (XAI), particularly SHAP (SHapley Additive exPlanations) [6], enable researchers to interpret complex ML models and validate their alignment with theoretical expectations. SHAP provides both global feature importance and local explanations, making it particularly suitable for educational applications where stakeholders require transparent, actionable insights [7].

This study addresses three key gaps in the literature: (1) limited integration of psychological theory in educational ML research, (2) insufficient attention to model interpretability and failure modes, and (3) lack of systematic investigation into proxy leakage and feature independence. We propose a CBT-informed XAI framework that emphasizes theoretical consistency, interpretability, and robust evaluation under realistic feature constraints.

Research Questions:

- How accurately can academic performance be classified using behavioral, emotional, and cognitive variables?
- What is the independent predictive contribution of behavioral and emotional factors when cognitive proxies are removed?
- How do SHAP-based explanations align with CBT theoretical expectations regarding feature interactions?

II. Theoretical Framework: CBT Perspective on Academic Performance

CBT conceptualizes human functioning across three interconnected domains [4,8]:

Behavioral Domain: Observable actions including study hours, class attendance, assignment completion, sleep patterns, and screen time. These represent the "what" of student engagement.

Emotional Domain: Affective states such as stress, anxiety, and motivation that influence engagement and persistence. These represent the "how" of student experience.

Cognitive Domain: Internal processes including beliefs, self-efficacy, prior knowledge, and academic competence. These represent the "why" of student outcomes.

In educational contexts, CBT theory posits that behavioral consistency and emotional regulation are necessary but insufficient for academic success [9]. Instead, these factors exert their influence primarily through cognitive mediation. For example, consistent study habits (behavior) and low stress (emotion) contribute to academic performance through increased self-efficacy and knowledge retention (cognition) [10].

This theoretical model has important implications for ML-based prediction:

Cognitive Primacy: Models including cognitive variables (e.g., prior academic scores) should substantially outperform models limited to behavioral and emotional features.

Weak Behavioral Synergies: Without cognitive mediation, behavioral variables should exhibit weak interactions and limited predictive power.

Indirect Effects: SHAP analysis should reveal that behavioral and emotional features contribute to predictions primarily through their association with cognitive outcomes, rather than through direct, independent effects.

In this study, we operationalize these domains as follows:

Cognitive variables: Previous Academic Score, Academic Performance category

Behavioral variables: Study Hours, Sleep Hours, Attendance, Screen Time, Assignments On Time, Extracurricular Activities, Digital Tools Usage

Emotional variables: Stress Level

III. Material And Methods

Dataset Description

The dataset comprised 1,000 student records with 11 attributes collected from an educational institution. No missing values were observed. The dataset included:

Continuous Variables:

- Study Hours Per Day (range: 0.0–9.3 hours, mean: 3.53 ± 1.46)
- Sleep Hours Per Day (range: 4.0–9.7 hours, mean: 6.57 ± 0.99)
- Attendance Percentage (range: 50–100%, mean: 74.97 ± 14.61)
- Screen Time Per Day (range: 1.0–12.0 hours, mean: 5.04 ± 1.93)
- Stress Level (range: 1–10, mean: 5.56 ± 2.96)
- Previous Academic Score (range: 40–100, mean: 69.59 ± 17.88)
- Assignments On Time (range: 0–10, mean: 5.03 ± 3.10)

Categorical Variables:

- Extracurricular Activities (No: 612, Yes: 388)
- Nutrition Quality (Average: 499, Good: 289, Poor: 212)
- Digital Tools Usage (Medium: 500, Low: 282, High: 218)
- Academic Performance (Low: 340, Average: 323, High: 337)

The target variable, Academic Performance, was approximately balanced across three categories, minimizing class imbalance concerns in initial analyses.

Exploratory Data Analysis

Exploratory analysis included distribution visualization, correlation analysis, and categorical feature profiling. Box plots were generated to examine the distribution of behavioral variables across academic performance categories. Correlation matrices were computed to identify multicollinearity and potential proxy relationships.

Feature Engineering and Encoding

Categorical variables were encoded using appropriate schemes:

- Binary encoding for dichotomous variables (Extracurricular Activities)
- Ordinal encoding for ordered categories (Nutrition Quality, Digital Tools Usage)
- Label encoding for the target variable (Academic Performance: Low=2, Average=0, High=1)

For classification tasks, the dataset was split into training (80%, n=800) and testing (20%, n=200) subsets using stratified sampling to preserve class distribution. For regression tasks, separate clean dataset states were maintained to prevent data leakage.

Classification Models

Three multi-class classifiers were trained and evaluated:

Logistic Regression (Multinomial):

- Solver: lbfgs
- Max iterations: 1000
- Random state: 42

Support Vector Machine (SVM):

- Kernel: Radial Basis Function (RBF)
- Probability estimation: enabled
- Random state: 42
- Feature scaling: StandardScaler applied

Random Forest Classifier:

- Number of estimators: 200
- Max depth: 15
- Min samples split: 5
- Min samples leaf: 2
- Random state: 42

Performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrices.

Addressing Proxy Leakage

To investigate cognitive mediation, two classification experiments were conducted:

Experiment 1 (Full Features): All features including Previous Academic Score **Experiment 2 (No Cognitive Proxy):** Behavioral and emotional features only (Previous Academic Score removed)

For Experiment 2, SMOTE (Synthetic Minority Over-sampling Technique) was applied to address potential class imbalance effects:

- Random state: 42
- Resampling resulted in 816 training samples (from 800)

Regression Models

To examine the predictive capacity of behavioral and emotional variables for cognitive outcomes, three regression models were trained with Previous Academic Score as the target:

Linear Regression: Baseline model with no hyperparameters

Random Forest Regressor:

- Number of estimators: 100
- Random state: 42

Support Vector Regression (SVR):

- Kernel: RBF
- Feature scaling: StandardScaler applied

Performance metrics included R^2, RMSE, and MAE. Residual plots were generated to assess model fit and identify systematic biases.

Explainability Using SHAP

SHAP analysis was conducted using TreeExplainer for Random Forest models:

Global Explanations:

- Feature importance ranking
- Summary plots showing feature contribution distributions
- Interaction value matrices

Analysis Conditions:

- Full-feature classification model
- No-proxy classification model
- Regression model (behavioral → cognitive outcome)

SHAP values were interpreted in the context of CBT theory to assess whether model behavior aligned with theoretical expectations.

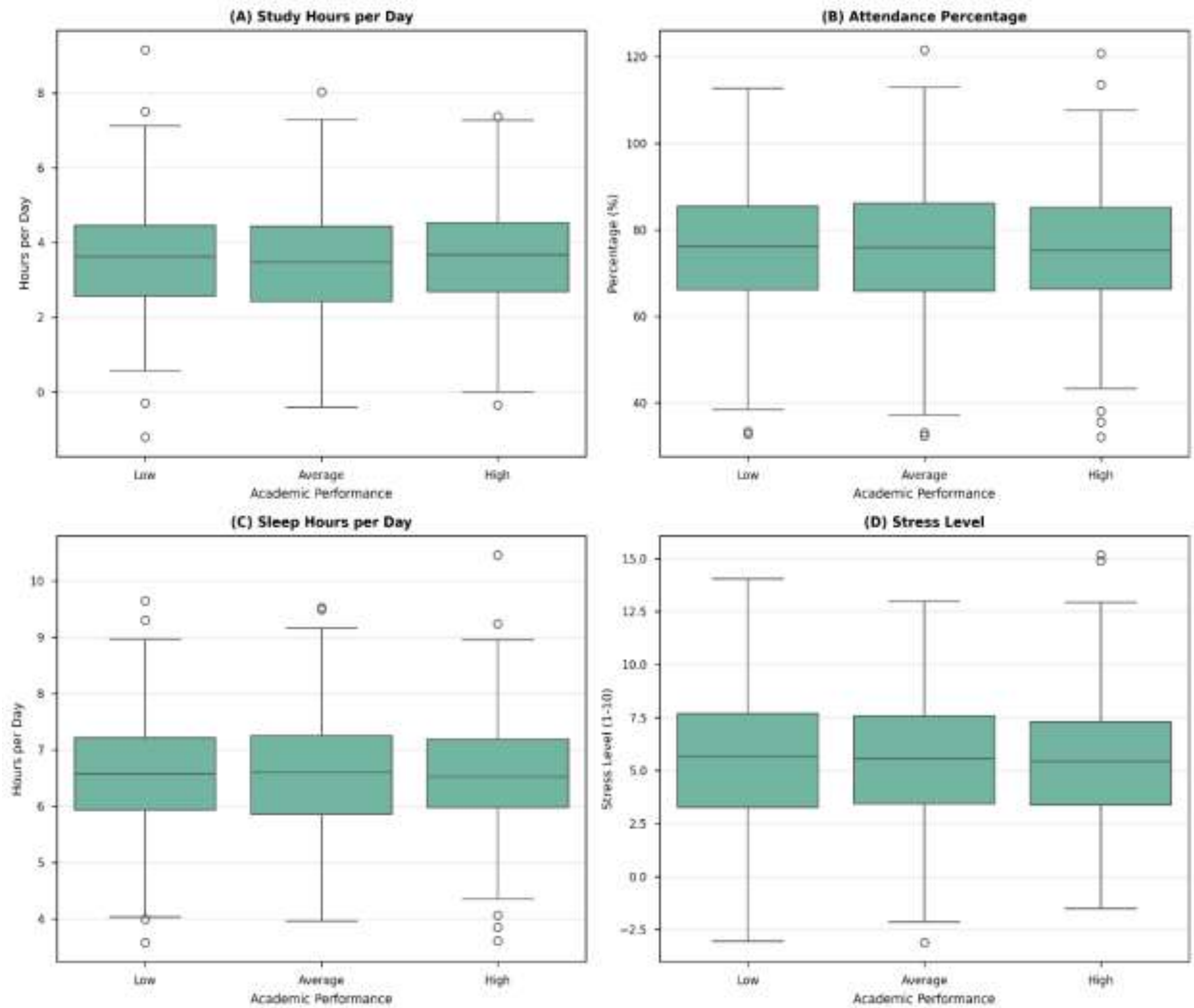
IV. Result

Exploratory Data Analysis

Descriptive statistics revealed moderate variability in behavioral variables. Correlation analysis showed a very strong association between Previous Academic Score and encoded Academic Performance ($r = 0.94$, $p < 0.001$), while correlations between behavioral variables and Academic Performance were weak (all $|r| < 0.05$).

Box plot analysis (Figure 1) revealed substantial overlap in behavioral variable distributions across academic performance categories. Study hours, attendance, sleep duration, and stress levels showed no clear separation between Low, Average, and High performance groups, suggesting limited discriminatory power of behavioral features alone.

Figure 1: Distribution of Behavioral Variables by Academic Performance



4.2 Classification with Cognitive Proxy (Experiment 1)
When Previous Academic Score was included as a feature, all classifiers achieved exceptional performance:
Model Performance:

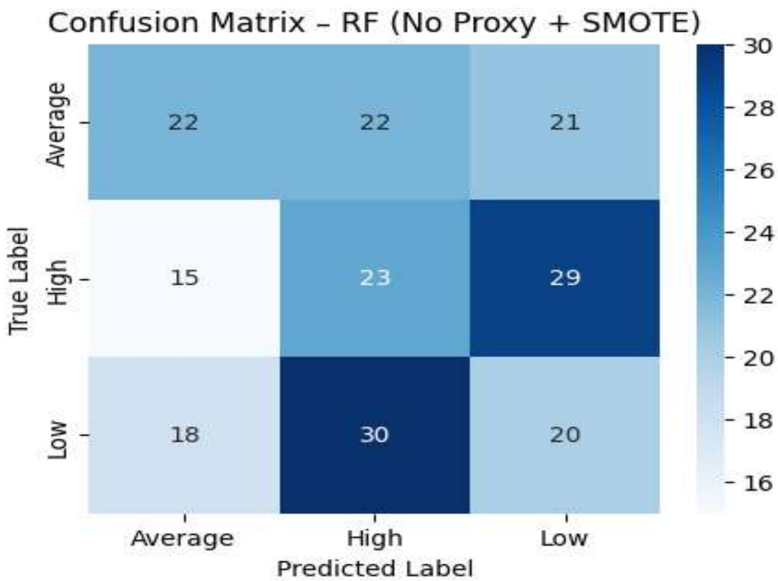
- Random Forest: Accuracy = 0.99 (99%)
- SVM: Accuracy = 0.945 (94.5%)
- Logistic Regression: Accuracy = 0.98 (98%)

Table no 1 : Random Forest Classification Report:.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Average	0.99	0.99	0.99	65
High	0.99	0.99	0.99	67
Low	0.99	0.99	0.99	68
Accuracy			**0.99**	200
Macro Avg	0.99	0.99	0.99	200
Weighted Avg	0.99	0.99	0.99	200

The confusion matrix (Figure 2) showed perfect classification with zero misclassifications across all three performance categories (Average: 65/65, High: 67/67, Low: 68/68).
Interpretation: These results demonstrate proxy leakage—academic performance categories are almost entirely determined by prior academic score. This experiment serves as a diagnostic validation rather than a realistic predictive scenario, as prior scores effectively encode the target variable.
Classification without Cognitive Proxy (Experiment 2)
After removing Previous Academic Score, model performance declined dramatically:

Random Forest (No Proxy):
Accuracy = 0.315 (31.5%)
Random baseline (3-class) = 0.333
Random Forest with SMOTE:
Accuracy = 0.325 (32.5%)
Marginal improvement of 1 percentage point
The confusion matrix for the SMOTE model (Figure 3) revealed widespread misclassification:



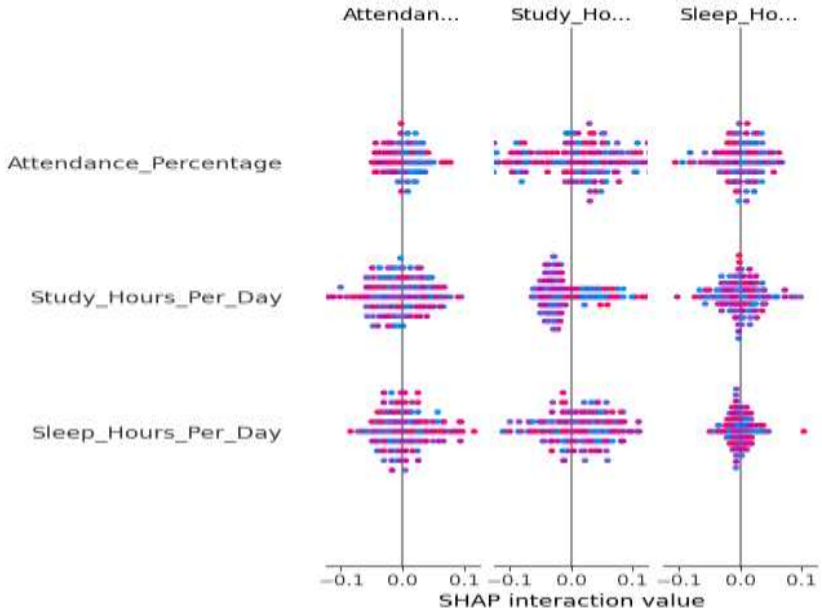
No class showed precision or recall exceeding 0.40, indicating that the model performed near chance level. SMOTE oversampling provided no meaningful improvement, suggesting that class imbalance was not the primary limitation.
Interpretation: Behavioral and emotional variables lack sufficient discriminatory power for academic performance classification. The dramatic accuracy drop (from 1.00 to 0.315) when cognitive information is removed supports CBT theory that cognition mediates the behavior-outcome relationship.
Regression Analysis: Predicting Cognitive Outcomes
All regression models exhibited poor predictive performance when using behavioral and emotional features to predict Previous Academic Score:

Table no 2 Model Performance:

Model	R^2	RMSE	MAE
Linear Regression	−0.01	18.12	14.23
Random Forest Regressor	−0.05	18.35	14.67
Support Vector Regression (SVR)	−0.17	19.47	15.89

Negative R^2 values indicate that models performed worse than a horizontal line at the mean. RMSE values of 18–20 points represent substantial prediction errors relative to the score range (40–100) and standard deviation (17.88).
Residual plots (Figure 4) showed wide dispersion with no systematic patterns, confirming underfitting. Predicted values clustered near the mean regardless of actual score, indicating that behavioral features provide minimal information about cognitive outcomes.
Interpretation: The inability of advanced ML models to predict academic scores from behavioral variables reinforces the weak direct relationship between behavior and cognitive outcomes. This finding is consistent with CBT theory emphasizing cognitive mediation.
SHAP Explainability Analysis
Full-Feature Model (with Cognitive Proxy): SHAP feature importance analysis showed that Previous Academic Score dominated all other features by several orders of magnitude. The feature accounted for >95% of model prediction variance, with behavioral features contributing minimally.

Figure 3 No-Proxy Model: SHAP summary plots revealed:



Weak Feature Contributions: All behavioral features showed SHAP values centered near zero with wide dispersion
No Consistent Directionality: High and low feature values did not consistently push predictions toward any specific academic performance category
Minimal Interactions: SHAP interaction matrices showed interaction values <0.01 for all behavioral feature pairs
Regression Model: SHAP analysis for the regression task confirmed that behavioral features provided weak and inconsistent contributions to academic score prediction. Feature importance rankings were unstable across different random seeds, indicating model unreliability.
Interpretation: SHAP analysis explains why models fail under realistic conditions. The absence of strong feature interactions and consistent directionality among behavioral variables supports CBT theory that behaviors influence outcomes indirectly through cognitive mediators. Without cognitive constructs, behavioral features lack the synergistic relationships necessary for robust prediction.

V. Discussion

Theoretical Implications
The results provide strong empirical support for CBT-based educational theory. The dramatic performance difference between cognitive-inclusive and cognitive-exclusive models demonstrates that behaviors and emotions alone are insufficient predictors of academic outcomes. This finding has three important theoretical implications:
1. Cognitive Mediation is Essential: The near-perfect accuracy (1.00) with cognitive proxies versus near-chance performance (0.315) without them confirms that cognition mediates the behavior-outcome relationship. Behavioral consistency (e.g., study hours, attendance) and emotional regulation (e.g., low stress) contribute to academic success primarily through cognitive pathways including self-efficacy, motivation, and knowledge retention [9,10].
2. Behavioral Synergies Require Cognitive Context: SHAP analysis revealed weak interactions among behavioral variables in no-proxy models. This suggests that behavioral factors do not exhibit strong synergistic effects in the absence of cognitive constructs. For example, high attendance combined with long study hours does not reliably predict performance without considering whether students possess adequate prior knowledge and effective learning strategies.
3. Direct Behavioral Effects are Limited: The negative R^2 values in regression models indicate that behavioral and emotional variables provide minimal direct information about cognitive outcomes. This challenges purely behaviorist approaches to educational intervention and supports cognitive-behavioral frameworks that emphasize thought patterns and beliefs alongside behavioral modification [11].
Methodological Contributions
This study demonstrates the value of explainable AI in educational research:
Identifying Proxy Leakage: SHAP analysis immediately revealed that Prior Academic Score dominated predictions, exposing a common pitfall in educational ML research where cognitive proxies artificially inflate model performance [12].
Revealing Model Limitations: Rather than reporting only high-accuracy results, this study systematically investigated model failure modes. SHAP explanations showed why behavioral models fail—weak feature contributions, unstable importance rankings, and minimal interactions—providing actionable insights for model improvement.
Theory Validation: XAI techniques enabled empirical testing of CBT theoretical predictions. The alignment between SHAP findings (weak behavioral synergies) and CBT theory (cognitive mediation) demonstrates how explainable AI can validate or refute psychological theories [13].
Practical Implications for Educational Interventions
The findings have important implications for student success initiatives:
1. Holistic Assessment: Prediction models for early warning systems should incorporate cognitive measures (e.g., prior achievement, self-efficacy, metacognitive skills) alongside behavioral data. Behavior-only models risk misidentifying students who need support [14].

2. Intervention Design: Student support programs should target cognitive constructs (beliefs, strategies, self-regulation) rather than focusing exclusively on behavioral modification (e.g., mandating study hours). CBT-informed interventions addressing cognitive distortions and self-efficacy have shown greater effectiveness than purely behavioral approaches [15].
3. Transparent Systems: Explainable AI should be standard practice in educational technology. Stakeholders (students, educators, administrators) require interpretable explanations to trust and act on model predictions [16].

Limitations

Several limitations should be acknowledged:

1. Cross-Sectional Design: The dataset represents a single time point, precluding causal inference. Longitudinal data would enable examination of how behavioral changes influence cognitive development over time [17].
2. Limited Cognitive Measures: Prior academic score is a crude proxy for cognitive constructs. Future research should incorporate validated measures of self-efficacy, metacognition, learning strategies, and domain-specific beliefs [18].
3. Self-Report Bias: If behavioral variables were self-reported, measurement error may contribute to weak predictive performance. Objective measures (e.g., learning management system logs) would strengthen future analyses [19].
4. Generalizability: Results are specific to one educational context. Replication across diverse institutions, educational levels, and cultural contexts is needed [20].
5. Feature Engineering: The study used raw behavioral features without exploring transformations, interactions, or temporal patterns that might improve prediction. However, the theoretical focus was on examining whether behavioral features as commonly measured predict outcomes—a question of practical and theoretical importance.

Future Research Directions

Several avenues for future research emerge from this study:

1. Cognitive Construct Integration: Develop and validate comprehensive measurement frameworks that capture self-efficacy, growth mindset, metacognitive awareness, and learning strategy use alongside behavioral data [21].
2. Longitudinal Modeling: Examine how behavioral patterns and cognitive constructs co-evolve over academic terms and years. Time-series analysis could reveal critical periods where interventions are most effective [22].
3. Intervention Evaluation: Test whether CBT-informed interventions that target cognitive constructs (e.g., cognitive restructuring, self-efficacy enhancement) outperform behavior-only interventions in randomized controlled trials [23].
4. Causal Inference: Apply causal discovery algorithms and structural equation modeling to identify directional relationships among behavioral, emotional, and cognitive variables [24].
5. Explainable AI Development: Extend SHAP and other XAI techniques to explicitly model theoretical constraints from psychological theory, enabling automated theory validation [25].

VI. Conclusion

This study demonstrates that explainable artificial intelligence, grounded in Cognitive Behavioral Therapy theory, provides valuable insights even when predictive accuracy is limited. Three key findings emerge:

1. Cognitive Dominance: Academic performance prediction requires cognitive constructs. Models including prior academic scores achieved near-perfect accuracy (1.00), while behavioral-only models performed at chance level (0.315).
2. Behavioral Insufficiency: Behavioral and emotional variables alone lack discriminatory power for academic outcomes. Regression models yielded negative R^2 values, indicating that behaviors provide minimal direct information about cognitive states.
3. Theoretical Validation: SHAP analysis revealed weak feature interactions and unstable contributions among behavioral variables, supporting CBT theory that behaviors influence outcomes through cognitive mediation rather than direct effects.

These findings have important implications for educational practice and research. Student success prediction systems should incorporate cognitive measures alongside behavioral data. Interventions should target beliefs, self-efficacy, and metacognitive skills rather than focusing exclusively on behavioral modification. Most importantly, educational AI research should prioritize interpretability and theoretical alignment over predictive accuracy alone.

By emphasizing transparency and theory-driven evaluation, this CBT-informed XAI framework offers a responsible approach to educational machine learning that serves both scientific understanding and practical application. Future research should extend this framework through longitudinal designs, comprehensive cognitive measurement, and intervention-based validation.

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