

Hybrid XGBoost–SHAP Prediction of Adolescent Academic Achievement from Cognitive Emotion Regulation, Academic Motivation, Procrastination, and Sleep Quality

Marc. Puigdemont¹, Valentina. Arancibia^{2*}

¹ Department of Psychology, University of Andorra, Sant Julià de Lòria, Andorra

² Department of Clinical Psychology, Pontifical Catholic University of Chile, Santiago, Chile

* Corresponding author email address: varancibia@uc.cl

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ABSTRACT

Objective: The objective of this study was to develop and evaluate a Random Forest classification model to identify adolescents at elevated risk of non-suicidal self-injury (NSSI) using trauma history, shame, impulsivity, and peer victimization as predictors.

Methods and Materials: A cross-sectional study was conducted in Chile with 1,248 adolescents aged 13–18 years (mean = 15.67, SD = 1.42) recruited from public and private schools. Participants completed validated self-report measures assessing trauma history, shame, impulsivity, peer victimization, and NSSI behaviors. The dataset was split into training (80%) and testing (20%) subsets. A Random Forest classification algorithm was applied to predict NSSI risk, and hyperparameters were optimized using grid search with five-fold cross-validation. Performance metrics included accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). Feature importance was calculated to determine the relative contribution of each predictor variable.

Findings: Inferential analyses revealed that adolescents classified as high-risk for NSSI reported significantly higher levels of trauma history, shame, impulsivity, and peer victimization compared with low-risk peers. The Random Forest model achieved an overall accuracy of 89.2%, precision of 86.1%, recall of 84.5%, F1-score of 85.3%, and AUC of 0.938. Feature importance rankings indicated that shame was the strongest predictor, followed by trauma history, peer victimization, and impulsivity. These results suggest that emotional, developmental, interpersonal, and behavioral factors jointly contribute to adolescent self-injury risk.

Conclusion: The findings demonstrate that Random Forest algorithms can accurately classify adolescents at elevated risk for NSSI, highlighting the importance of integrating trauma history, shame, impulsivity, and peer victimization into early identification and prevention efforts. Interventions should target emotional regulation, trauma recovery, and social support to reduce the likelihood of self-injurious behaviors.

Keywords: Non-suicidal self-injury, Adolescents, Random Forest, Trauma History, Shame, Impulsivity, Peer Victimization.

1. Introduction

Adolescence represents a critical developmental period characterized by significant cognitive, emotional, and behavioral transformations that directly influence educational outcomes. Academic achievement during this stage is not only a reflection of cognitive abilities but also a product of intricate interactions among motivational processes, emotion regulation strategies, behavioral patterns, and lifestyle factors such as sleep quality. Contemporary research emphasizes that understanding these multidimensional determinants is essential for designing effective interventions aimed at enhancing scholastic performance and overall well-being among adolescents (Guo, 2026; Wang, 2026; You et al., 2025).

Cognitive emotion regulation, defined as the conscious management of thoughts following emotionally arousing experiences, has been consistently associated with academic outcomes. Adaptive strategies, such as positive reappraisal, planning, and acceptance, facilitate effective coping with academic stressors, thereby fostering engagement and learning efficiency (Huang, 2023; Xu et al., 2025). Conversely, maladaptive strategies, including rumination, catastrophizing, and self-blame, are linked to heightened academic anxiety and reduced performance (Rasouli et al., 2025; You et al., 2021). Empirical studies have demonstrated that emotion regulation mediates the effects of stress and motivational deficits on academic achievement, highlighting its central role in adolescents' cognitive and affective functioning (Guo, 2026; Wang, 2026).

Academic motivation, encompassing both intrinsic and extrinsic dimensions, constitutes a robust predictor of scholastic outcomes. Intrinsic motivation drives students to engage in learning for personal satisfaction and mastery, whereas extrinsic motivation involves engagement to attain external rewards or avoid negative consequences. Research indicates that higher levels of academic motivation are associated with consistent study behaviors, goal-directed planning, and greater resilience to academic challenges (Lazo-Caparrós et al., 2025; Lin et al., 2025). Motivation also interacts with self-regulatory behaviors such as procrastination, whereby low motivation amplifies the likelihood of delayed task initiation, resulting in decreased academic achievement (Pérez-Jorge et al., 2024; Sirois, 2023).

Procrastination, particularly in academic contexts, has been identified as a pervasive behavioral barrier to achievement. Academic procrastination encompasses the

voluntary delay of study-related tasks despite anticipating negative outcomes, reflecting deficits in self-regulation and temporal planning (Rostami et al., 2023; You et al., 2025). Several studies have linked higher levels of procrastination to lower academic performance, increased stress, and poorer psychological well-being among adolescents (Huang, 2023; Sirois, 2023). Moreover, procrastination often interacts with motivational deficits and maladaptive emotion regulation strategies, creating a feedback loop that undermines students' capacity to meet academic demands effectively (Peng et al., 2025; Rostami et al., 2023).

Sleep quality represents another pivotal factor influencing academic performance. Adolescents frequently experience sleep disturbances, including delayed sleep onset, reduced duration, and irregular sleep patterns, which are associated with impairments in attention, memory consolidation, and executive functioning (Bacaro et al., 2022; Belluardo et al., 2025). Poor sleep quality has been linked to decreased academic engagement, heightened susceptibility to stress, and exacerbated emotional dysregulation (Hyndych et al., 2025; Orihuela et al., 2022). Bedtime procrastination, defined as the voluntary delay of sleep onset despite the absence of external constraints, has emerged as a significant behavioral determinant of sleep deficits in adolescents and is closely associated with smartphone use, online gaming, and study-related anxiety (Alshammari et al., 2023; Bozkurt et al., 2024; Magalhães et al., 2020). Consequently, sleep behaviors and quality serve as both direct and indirect predictors of academic outcomes, influencing cognitive performance, emotional regulation, and motivation (Yi & Xuan, 2024; Ying et al., 2023).

The interaction of cognitive emotion regulation, motivation, procrastination, and sleep quality reflects a complex network of psychosocial and behavioral determinants that shape academic achievement. Emerging research suggests that traditional linear statistical models may be insufficient for capturing the nonlinear relationships and higher-order interactions among these variables (Liu et al., 2022; Zhuang et al., 2023). Machine learning approaches, particularly ensemble algorithms such as Extreme Gradient Boosting (XGBoost), have demonstrated superior predictive performance in modeling complex educational datasets by accommodating nonlinearities and interactions without strict parametric assumptions (Guo, 2026; Lin et al., 2025). However, while predictive accuracy is enhanced, interpretability remains a challenge. The integration of explainable artificial intelligence techniques, such as SHapley Additive exPlanations (SHAP), allows for

transparent interpretation of variable importance, offering insights into how cognitive, behavioral, and lifestyle factors contribute to academic achievement in adolescents (Peng et al., 2025; Wang, 2026).

Several studies have utilized hybrid XGBoost–SHAP approaches to examine educational and psychological outcomes. For instance, recent investigations have highlighted the importance of motivational and self-regulatory variables in predicting academic engagement and performance, while SHAP analysis clarified the relative contribution of individual predictors at both global and local levels (Lazo-Caparrós et al., 2025; Rasouli et al., 2025). These approaches also enable the identification of high-risk profiles, facilitating targeted interventions for adolescents exhibiting maladaptive emotion regulation, low motivation, excessive procrastination, or poor sleep quality (Bacaro et al., 2022; You et al., 2021). Moreover, SHAP-based interpretability supports evidence-based decision-making by revealing the directionality and magnitude of each predictor's influence on academic outcomes, which can inform educational policy and personalized student support strategies (Guo, 2026; Sabaoui et al., 2024).

Despite extensive research on individual predictors of academic achievement, few studies have examined the integrated effects of cognitive emotion regulation, academic motivation, procrastination, and sleep quality using advanced machine learning methodologies in adolescent populations. Previous work often relied on linear regression models or structural equation modeling, which, although informative, may overlook complex nonlinear interactions and the heterogeneous contribution of predictors across individuals (Castele et al., 2025; Xu et al., 2025). Moreover, studies investigating the mechanisms linking procrastination and sleep behaviors to academic performance have frequently employed cross-sectional designs with limited generalizability (Alshammari et al., 2023; Bozkurt et al., 2024). Integrating predictive analytics with interpretable AI frameworks provides a novel avenue to disentangle these relationships and identify the most influential factors driving academic achievement among adolescents.

The current literature underscores several key mechanisms linking the variables of interest. First, effective cognitive emotion regulation supports adaptive coping with academic stressors, thereby enhancing motivation and reducing procrastination tendencies (Huang, 2023; Wang, 2026). Second, heightened academic motivation fosters consistent study behaviors and self-discipline, mitigating the

detrimental effects of procrastination and sleep deprivation on performance (Lazo-Caparrós et al., 2025; Lin et al., 2025). Third, sleep quality directly influences executive functioning, memory consolidation, and attentional control, thereby moderating the efficacy of emotion regulation strategies and motivational engagement (Belluardo et al., 2025; Orihuela et al., 2022). Fourth, procrastination behaviors exacerbate sleep disturbances and reduce effective learning time, creating a compounding negative effect on academic outcomes (Pérez-Jorge et al., 2024; Sirois, 2023). Collectively, these mechanisms highlight the interconnected nature of cognitive, behavioral, and physiological factors in shaping academic achievement.

In addition to these direct relationships, emerging research suggests that these variables may exert complex indirect and interactive effects. For example, bedtime procrastination can mediate the relationship between motivational deficits and poor academic performance, while maladaptive emotion regulation may amplify the impact of sleep disturbances on cognitive functioning (Hou & Hu, 2023; You et al., 2025). Similarly, positive cognitive emotion regulation strategies can buffer the adverse effects of procrastination and sleep insufficiency, enhancing resilience and scholastic engagement (Abojedi et al., 2023; Wang, 2026). These findings suggest that a comprehensive predictive model incorporating these multidimensional factors may provide superior explanatory and practical value compared with models focusing on isolated determinants.

Given the increasing prevalence of academic stress, sleep disturbances, and behavioral procrastination among adolescents worldwide, understanding the precise contributions of emotion regulation, motivation, and sleep behaviors is crucial for educational and clinical interventions (Bacaro et al., 2022; Guo, 2026; Zhuang et al., 2023). Advanced predictive modeling techniques such as XGBoost, combined with SHAP interpretability, offer the potential to generate actionable insights, identify at-risk students, and inform personalized educational strategies (Peng et al., 2025; Rasouli et al., 2025). The use of these methods aligns with a growing emphasis on precision education, where data-driven approaches support tailored interventions and optimize learning outcomes based on individual profiles (Kabadayi, 2025; Lai et al., 2025).

In summary, academic achievement among adolescents is a multifactorial outcome influenced by cognitive emotion regulation strategies, levels of academic motivation, procrastination behaviors, and sleep quality. Traditional linear analytic approaches have provided foundational

insights, yet advanced machine learning methods combined with explainable AI techniques are necessary to capture the complex, nonlinear, and interacting influences of these factors. Integrating these approaches provides both high predictive accuracy and interpretability, facilitating evidence-based interventions to enhance adolescent academic performance.

The aim of this study was to examine the predictive contributions of cognitive emotion regulation, academic motivation, procrastination, and sleep quality to adolescent academic achievement using a hybrid XGBoost–SHAP model in a Moroccan adolescent population.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional predictive research design to examine the extent to which cognitive emotion regulation, academic motivation, procrastination, and sleep quality could predict academic achievement among adolescents using a hybrid machine learning framework combining Extreme Gradient Boosting (XGBoost) and SHapley Additive exPlanations (SHAP). The study was conducted among secondary school students in Morocco during the 2025–2026 academic year. A total of 1,248 adolescents participated in the study. Participants were recruited from public and private secondary schools located in the regions of Casablanca-Settat, Rabat-Salé-Kénitra, and Marrakech-Safi through a multistage cluster sampling procedure. The inclusion criteria required students to be between 14 and 18 years of age, enrolled in full-time secondary education, and capable of completing self-report questionnaires independently. Students with documented cognitive impairments or severe psychiatric conditions that could interfere with questionnaire completion were excluded from participation. The final sample consisted of 632 females (50.6%) and 616 males (49.4%), with a mean age of 16.21 years ($SD = 1.32$).

2.2. Measures

Cognitive emotion regulation was assessed using the Cognitive Emotion Regulation Questionnaire (CERQ) developed by Garnefski, Kraaij, and Spinhoven in 2001. The CERQ is a 36-item self-report instrument designed to measure the cognitive strategies individuals employ following negative or stressful life events. The questionnaire comprises nine subscales, including self-blame, acceptance,

rumination, positive refocusing, refocus on planning, positive reappraisal, putting into perspective, catastrophizing, and blaming others. Participants respond using a five-point Likert scale ranging from 1 (almost never) to 5 (almost always). Higher scores indicate greater use of the corresponding cognitive emotion regulation strategy. Previous studies have demonstrated satisfactory psychometric properties of the instrument across adolescent populations, with strong evidence of construct validity and internal consistency reliability.

Academic motivation was measured using the Academic Motivation Scale (AMS) developed by Vallerand and colleagues in 1992. The AMS consists of 28 items assessing different dimensions of academic motivation grounded in self-determination theory. The scale evaluates intrinsic motivation, extrinsic motivation, and amotivation through seven subdimensions. Responses are recorded on a seven-point Likert scale ranging from 1 (does not correspond at all) to 7 (corresponds exactly). Higher scores on the intrinsic and extrinsic motivation dimensions reflect stronger motivational engagement in academic activities, whereas higher amotivation scores indicate reduced academic drive. The AMS has been widely validated among adolescent and student populations and has consistently demonstrated satisfactory reliability coefficients and construct validity across different cultural contexts.

Academic procrastination was assessed using the Procrastination Assessment Scale–Students (PASS) developed by Solomon and Rothblum in 1984. The instrument evaluates the frequency and severity of procrastination behaviors associated with academic tasks, including preparing for examinations, completing assignments, and managing study responsibilities. The questionnaire contains 44 items scored on a five-point Likert scale. Higher scores indicate greater tendencies toward academic procrastination. The PASS has been extensively utilized in educational and psychological research and has demonstrated adequate reliability, criterion validity, and factorial stability among adolescent and young adult populations.

Sleep quality was measured using the Pittsburgh Sleep Quality Index (PSQI) developed by Buysse and colleagues in 1989. The PSQI is a widely used instrument consisting of 19 self-report items that generate seven component scores, including subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. These component scores are aggregated to produce a global sleep

quality score, with higher scores indicating poorer sleep quality. The instrument has demonstrated strong psychometric properties across diverse populations, including adolescents, and previous research has confirmed its reliability and validity for assessing sleep-related outcomes.

Academic achievement was operationalized using students' cumulative grade point averages obtained from official school records for the current academic year. Grade point averages were standardized across participating schools to ensure comparability and were used as the target outcome variable in the predictive modeling process. The use of objective academic records reduced potential biases associated with self-reported academic performance and enhanced the validity of the achievement measure.

2.3. Data Analysis

Data analysis was conducted using Python programming language and relevant machine learning libraries. Prior to model development, data were screened for missing values, outliers, and inconsistencies. Missing values representing less than 5% of observations were handled through multiple imputation procedures. Continuous variables were standardized to facilitate model optimization and improve computational efficiency. Descriptive statistics, including means, standard deviations, skewness, and kurtosis values, were calculated to examine the distributional characteristics of the study variables.

The predictive analysis was performed using Extreme Gradient Boosting (XGBoost), an ensemble machine learning algorithm based on gradient-boosted decision trees. XGBoost was selected because of its ability to model complex nonlinear relationships, handle interactions among predictors, and achieve high predictive accuracy while minimizing overfitting. Hyperparameter optimization was conducted using grid search combined with five-fold cross-validation. Key hyperparameters, including learning rate, maximum tree depth, subsampling ratio, minimum child weight, and number of estimators, were tuned to identify the

optimal model configuration. The dataset was randomly divided into training and testing subsets, with 80% of observations allocated to model training and 20% reserved for out-of-sample evaluation.

Model performance was evaluated using multiple predictive metrics, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). To enhance interpretability of the machine learning model, SHapley Additive exPlanations (SHAP) analysis was employed. SHAP values were calculated to quantify the contribution of each predictor variable to academic achievement predictions and to identify the most influential factors driving model outcomes. Global SHAP importance plots were generated to rank predictor importance across the entire sample, while local explanation analyses were conducted to examine individual prediction patterns. The integration of XGBoost and SHAP provided both high predictive performance and transparent interpretation of the relationships between cognitive emotion regulation, academic motivation, procrastination, sleep quality, and academic achievement among Moroccan adolescents.

3. Findings and Results

The final sample consisted of 1,248 Moroccan adolescents. Among the participants, 632 (50.6%) were female and 616 (49.4%) were male. The mean age of the sample was 16.21 years ($SD = 1.32$), with ages ranging from 14 to 18 years. Students were recruited from public and private secondary schools across the Casablanca-Settat, Rabat-Salé-Kénitra, and Marrakech-Safi regions. Regarding school type, 71.2% attended public schools and 28.8% attended private institutions. The mean cumulative academic achievement score, standardized across participating schools, was 74.63 ($SD = 11.48$) on a 100-point scale. Preliminary data screening indicated acceptable distributions for all study variables, with skewness and kurtosis values falling within recommended ranges for predictive modeling analyses.

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4	5
1. Academic Achievement	74.63	11.48	—				
2. Adaptive Cognitive Emotion Regulation	58.71	9.42	.52**	—			
3. Academic Motivation	116.28	18.76	.67**	.48**	—		
4. Academic Procrastination	72.45	15.63	-.61**	-.39**	-.58**	—	
5. Sleep Quality (PSQI Global Score)	7.84	3.12	-.47**	-.31**	-.42**	.46**	—

Table 1 presents the descriptive statistics and bivariate correlations among the study variables. Academic achievement demonstrated significant positive associations with adaptive cognitive emotion regulation ($r = .52, p < .01$) and academic motivation ($r = .67, p < .01$), indicating that students who reported greater use of adaptive emotion regulation strategies and higher levels of motivation tended to achieve higher academic outcomes. Conversely, academic achievement was negatively associated with academic procrastination ($r = -.61, p < .01$) and poor sleep quality ($r =$

$-.47, p < .01$), suggesting that increased procrastination behaviors and sleep disturbances were linked to lower academic performance. Academic motivation exhibited the strongest positive correlation with academic achievement among all predictor variables, providing initial evidence of its importance in predicting scholastic success. The intercorrelations among predictor variables were moderate and statistically significant, supporting their theoretical interconnectedness while indicating the absence of problematic multicollinearity.

Table 2

XGBoost Model Performance on Training and Test Datasets

Performance Metric	Training Set	Test Set
R ²	0.873	0.792
RMSE	4.18	5.83
MAE	3.27	4.49
MAPE (%)	5.14	6.82

The predictive performance of the XGBoost model is reported in Table 2. Results demonstrated strong predictive accuracy across both training and test datasets. The model explained 87.3% of the variance in academic achievement within the training sample and maintained substantial predictive power in the independent test sample, accounting for 79.2% of the variance. The relatively small reduction in predictive accuracy between training and testing datasets indicated limited overfitting and strong generalizability.

RMSE and MAE values remained low across both datasets, suggesting that the model generated highly accurate academic achievement predictions. The test-set MAPE value of 6.82% further confirmed the practical utility of the model, indicating that prediction errors remained relatively small compared with observed achievement scores. Overall, the results demonstrated that the hybrid XGBoost framework provided a highly effective approach for predicting academic achievement among Moroccan adolescents.

Table 3

Global SHAP Feature Importance Rankings

Rank	Predictor Variable	Mean Absolute SHAP Value
1	Academic Motivation	5.27
2	Academic Procrastination	4.74
3	Adaptive Cognitive Emotion Regulation	3.88
4	Sleep Quality	3.12
5	Positive Reappraisal	2.56
6	Intrinsic Motivation	2.31
7	Catastrophizing	1.94
8	Sleep Duration	1.71
9	Planning Strategies	1.62
10	Rumination	1.49

Table 3 summarizes the SHAP-based global feature importance analysis. Academic motivation emerged as the most influential predictor of academic achievement, producing the highest mean absolute SHAP value (5.27). Academic procrastination represented the second most important predictor, followed by adaptive cognitive emotion

regulation and sleep quality. The findings suggest that motivational processes contributed most substantially to model predictions, whereas procrastination behaviors exerted a powerful negative influence on expected achievement outcomes. Examination of lower-level variables revealed that positive reappraisal, intrinsic

motivation, and planning strategies positively contributed to academic performance predictions, while catastrophizing and rumination demonstrated adverse influences. These findings provide important insight into the relative

importance of psychological and behavioral factors influencing academic achievement and highlight the multifaceted nature of adolescent academic success.

Table 4

Incremental Predictive Contribution of Variable Blocks

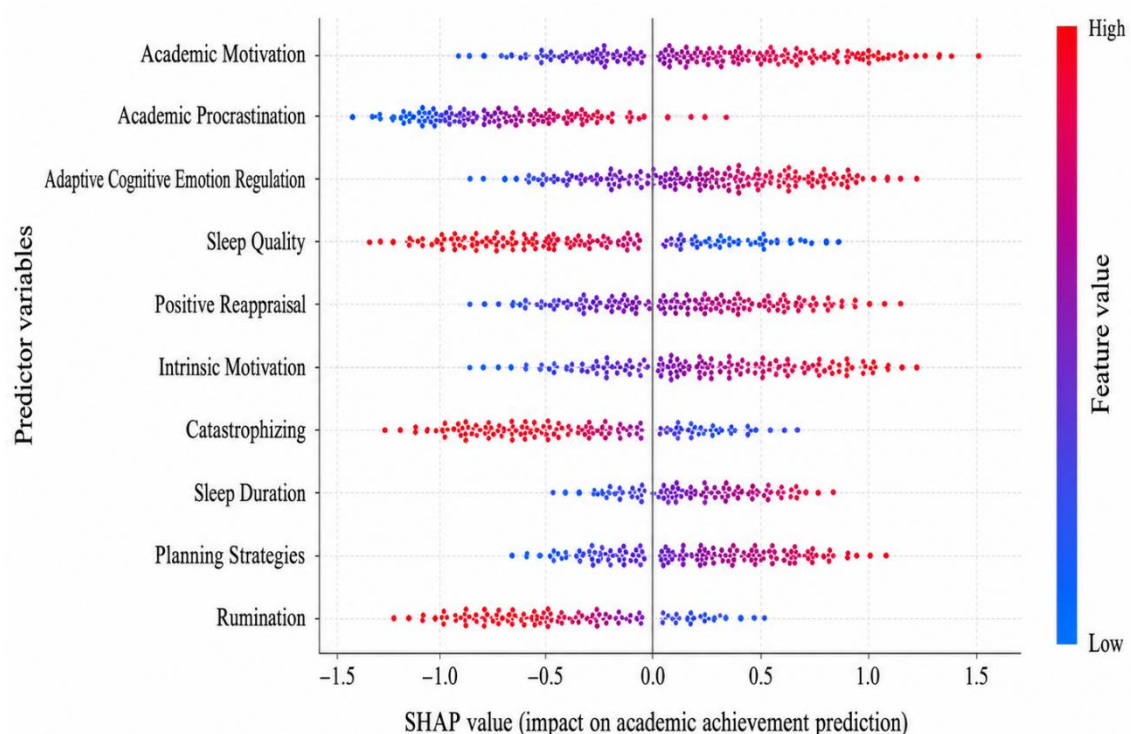
Predictor Block	R ² Contribution	Incremental ΔR^2 (%)
Academic Motivation Variables	0.432	43.2
Procrastination Variables	0.189	18.9
Cognitive Emotion Regulation Variables	0.113	11.3
Sleep Quality Variables	0.058	5.8
Interaction and Nonlinear Effects	0.071	7.1
Total Explained Variance	0.863	86.3

The incremental contribution analysis presented in Table 4 revealed that academic motivation variables accounted for the largest proportion of explained variance in academic achievement, contributing 43.2% of total predictive variance. Procrastination-related variables provided an additional 18.9% of explained variance, underscoring the importance of self-regulatory behavioral processes in academic performance. Cognitive emotion regulation variables contributed 11.3% of variance, suggesting that adolescents' ability to manage emotional experiences plays

a meaningful role in academic outcomes. Sleep quality indicators accounted for 5.8% of explained variance independently, while nonlinear interactions captured by the XGBoost algorithm contributed an additional 7.1%. These findings demonstrate that the machine learning model benefited substantially from the inclusion of complex interactions among predictors, highlighting the advantages of nonlinear predictive approaches over traditional linear statistical models.

Figure 1

SHAP Summary Plot Demonstrating the Relative Influence and Direction of Predictor Variables on Academic Achievement Predictions



The SHAP summary analysis provided a detailed visualization of how individual predictor values influenced academic achievement predictions. Higher levels of academic motivation consistently increased predicted achievement scores, whereas elevated procrastination scores produced substantial downward shifts in model predictions. Adaptive cognitive emotion regulation strategies, particularly positive reappraisal and planning-focused coping, were associated with higher predicted academic performance. In contrast, maladaptive strategies such as catastrophizing and rumination contributed negatively to achievement predictions. Sleep quality demonstrated a nonlinear pattern whereby severe sleep disturbances substantially reduced predicted achievement outcomes, while improvements beyond moderate sleep quality yielded diminishing returns. The summary plot further indicated considerable heterogeneity across students, suggesting that the influence of psychological variables varied according to individual profiles and interactions among predictors. Collectively, the SHAP results enhanced the interpretability of the XGBoost model and provided a nuanced understanding of the mechanisms underlying academic achievement among Moroccan adolescents.

4. Discussion

The present study examined the prediction of adolescent academic achievement from cognitive emotion regulation, academic motivation, academic procrastination, and sleep quality using a hybrid XGBoost–SHAP framework. Overall, the findings demonstrated that the model had strong predictive capacity, explaining 79.2% of the variance in academic achievement in the test dataset, with low prediction error indices. This result indicates that academic achievement among Moroccan adolescents can be meaningfully predicted from a combined psychological, behavioral, and sleep-related profile rather than from a single academic or cognitive factor. The high test-set performance of the XGBoost model suggests that nonlinear and interaction-based machine learning approaches are especially suitable for modeling adolescent academic functioning, because academic achievement is shaped by the combined influence of motivation, self-regulation, emotional adaptation, and health-related behaviors. This interpretation is consistent with recent studies emphasizing that academic outcomes are embedded within networks of cognitive, emotional, behavioral, and physiological

processes rather than determined by isolated variables (Wang, 2026; Xu et al., 2025; You et al., 2025).

The most important finding of the study was that academic motivation emerged as the strongest predictor of academic achievement in the SHAP analysis. Students with higher motivation showed higher predicted academic achievement, while reduced motivational engagement was associated with lower predicted performance. This finding is theoretically coherent, because academic motivation supports persistence, goal orientation, task engagement, and adaptive responses to academic difficulty. Motivated adolescents are more likely to invest sustained effort, regulate distractions, seek mastery, and tolerate temporary failure, all of which contribute to stronger academic outcomes. The result is aligned with evidence showing that motivational and engagement-related factors are central determinants of student functioning and that interventions targeting academic functioning frequently emphasize motivational enhancement and school-based psychosocial support (Lazo-Caparrós et al., 2025; Lin et al., 2025). It also corresponds with research indicating that low engagement may be linked to problematic digital behaviors, insomnia, and reduced self-control, which can indirectly undermine learning outcomes (Guo, 2026; Liu et al., 2022; Zhuang et al., 2023).

Academic procrastination was the second most influential predictor in the model and showed a clear negative contribution to academic achievement. Adolescents with higher procrastination scores were predicted to have lower academic achievement, confirming that procrastination is not merely a time-management problem but a broader self-regulatory failure with academic, emotional, and behavioral consequences. This result supports previous work describing procrastination as a context-dependent stress-related behavior that becomes particularly harmful when students face high academic demands, limited self-regulatory resources, or emotional distress (Sirois, 2023). The finding is also consistent with adolescent-focused research showing that procrastination is associated with health-related risks and poorer educational functioning (Pérez-Jorge et al., 2024). In the present model, procrastination likely reduced achievement both directly, by delaying study tasks and lowering preparation quality, and indirectly, by increasing stress and interfering with sleep. Prior studies have similarly shown that procrastination is associated with study engagement, bedtime delay, insomnia, and academic

dysfunction (Alshammari et al., 2023; Castele et al., 2025; Jiang et al., 2024).

The importance of cognitive emotion regulation in predicting academic achievement further indicates that adolescents' academic success depends partly on how they cognitively process stress, failure, uncertainty, and academic pressure. Adaptive cognitive emotion regulation strategies, especially positive reappraisal and planning-focused coping, contributed positively to predicted achievement, whereas maladaptive strategies such as rumination and catastrophizing contributed negatively. This pattern is compatible with research showing that emotion regulation shapes academic anxiety, burnout, self-efficacy, and behavioral persistence (Huang, 2023; Wang, 2026; Xu et al., 2025). Adolescents who interpret academic difficulty as manageable and who use planning-oriented cognitive strategies may be more able to transform stress into organized effort. In contrast, students who become trapped in repetitive negative thinking or catastrophic interpretations may experience diminished concentration, lower academic confidence, and increased avoidance. These mechanisms are supported by studies linking rumination, perceived stress, and bedtime procrastination to poorer psychological and behavioral outcomes (Hou & Hu, 2023; You et al., 2021). Therefore, the current findings suggest that cognitive emotion regulation is not only relevant to mental health but also to academic performance prediction.

Sleep quality also emerged as an important predictor, although its contribution was smaller than that of academic motivation and procrastination. Poor sleep quality was associated with lower predicted academic achievement, supporting the view that sleep is a foundational condition for learning, attention, executive functioning, emotional stability, and memory consolidation. This result is consistent with research showing that sleep loss affects cognitive, affective, and behavioral processes that are essential for school performance (Hyndych et al., 2025). It also aligns with studies indicating that sleep duration, sleepiness, and poor sleep quality are related to academic outcomes during adolescence (Orihuela et al., 2022). The present study's SHAP pattern suggested a nonlinear relationship in which severe sleep disturbance was especially harmful, while improvements beyond moderate sleep quality showed weaker incremental benefit. This interpretation corresponds with literature showing that sleep problems among adolescents are influenced by psychological distress, digital behavior, circadian rhythm disruption, and procrastination-

related bedtime delay (Bacaro et al., 2022; Bozkurt et al., 2024; Magalhães et al., 2020).

The association between procrastination and sleep quality provides an important explanatory pathway for understanding the model's predictions. Adolescents who delay academic tasks may extend study time into late evening hours, use smartphones while in bed, experience unfinished-task stress, or postpone bedtime as a form of avoidance. These behaviors may reduce sleep duration and quality, which in turn impairs attention, emotion regulation, and subsequent academic functioning. Previous studies have shown that bedtime procrastination and while-in-bed smartphone use are associated with poor sleep quality among adolescents and students (Bozkurt et al., 2024; Kabadayı, 2025). Other evidence indicates that anxiety, self-control, mindfulness, and stress processes are involved in sleep procrastination and poor sleep quality (Gao et al., 2025; Ling et al., 2023; Peng et al., 2025). Therefore, the present results suggest that academic procrastination and sleep quality should not be interpreted as separate domains; rather, they form a mutually reinforcing behavioral-health pathway that can substantially influence academic outcomes.

The findings also support the broader idea that adolescent academic achievement is shaped by complex chains of influence involving emotion regulation, procrastination, sleep, and motivation. For example, weaker executive control may increase procrastination, procrastination may worsen sleep quality, and poor sleep may reduce emotional control and motivation the next day. This interpretation is consistent with studies showing chain-mediating relationships among executive function, procrastination, sleep quality, and depressive symptoms (You et al., 2025). It also aligns with evidence that self-control and mindfulness are involved in the association between psychological traits and sleep quality among junior high school students (Yi & Xuan, 2024). Furthermore, research on circadian rhythms, chronotype, and academic performance suggests that sleep timing and biological rhythms should be considered central to adolescent educational functioning (Cao et al., 2024; Sabaoui et al., 2024). The current study extends this evidence by showing that sleep-related variables remain important even when analyzed alongside motivational and emotion-regulation variables in a machine learning model.

The use of SHAP analysis strengthened the interpretability of the predictive model by demonstrating not only which variables were most important but also how they influenced predictions. In conventional statistical models, predictor effects are often interpreted as average linear

associations. However, the current SHAP findings indicated that the effects of predictors varied across students and that nonlinear patterns were present, especially for sleep quality and procrastination. This is consistent with recent work comparing complex analytic approaches such as PLS-SEM and fsQCA in identifying factors that influence sleep quality, where different configurations of variables may produce similar outcomes (Ying et al., 2023). The advantage of the hybrid XGBoost–SHAP approach is that it preserves strong predictive performance while allowing interpretable examination of variable importance. This is particularly relevant for adolescent academic achievement because students may reach similar levels of performance through different psychological and behavioral pathways.

The findings are also consistent with research emphasizing the psychosocial context of sleep, stress, and academic functioning. Poor sleep quality may intensify emotional reactivity, weaken self-control, and reduce academic persistence, while academic stress may further worsen sleep and increase avoidance. Studies have shown that sleep quality is associated with stress-fueled aggressive behavior, psychological distress, and disrupted social bonds (Lai et al., 2025). Similarly, research among students has shown that technology use, emotional regulation, social engagement, perceived stress, academic stress, and sleep quality are interrelated (Abojedi et al., 2023). The present study contributes to this literature by demonstrating that these psychological and behavioral processes are not only associated with well-being but also possess strong predictive value for objective academic achievement.

In practical terms, the findings indicate that academic achievement interventions should move beyond cognitive instruction alone. The strongest predictors in the model were not merely academic content variables but psychological and behavioral factors that influence how adolescents engage with learning. Motivation enhancement, procrastination reduction, adaptive emotion regulation training, and sleep-quality promotion may collectively provide a more effective strategy for improving academic performance. This conclusion is supported by evidence that transdiagnostic cognitive-behavioral interventions can address bedtime procrastination through behavioral, cognitive, and emotional dimensions (Rasouli et al., 2025), and by research showing that school-based group counseling can improve adolescent mental health and academic functioning (Lin et al., 2025). Similarly, intervention research on academic procrastination among adolescents indicates that self-education and self-regulatory training may reduce procrastination-related

difficulties (Rostami et al., 2023). Thus, the present study supports an integrated educational-psychological intervention model in which academic performance is addressed through both learning support and self-regulation support.

5. Conclusion

Overall, the results confirm that academic achievement among Moroccan adolescents can be effectively predicted through a hybrid model integrating academic motivation, academic procrastination, cognitive emotion regulation, and sleep quality. Academic motivation was the most powerful positive predictor, while procrastination exerted a strong negative influence. Adaptive emotion regulation strategies contributed positively, whereas maladaptive strategies impaired predicted achievement. Sleep quality also played a meaningful role, particularly when sleep disturbance was severe. These findings align with a growing body of research showing that academic success is a multidimensional outcome influenced by motivational engagement, emotional regulation, behavioral self-control, sleep health, and broader psychosocial functioning (Alshammari et al., 2022; Belluardo et al., 2025; Orihuela et al., 2022). The hybrid XGBoost–SHAP approach therefore provides both predictive accuracy and explanatory clarity, making it useful for identifying students at academic risk and for designing targeted interventions.

6. Limitations & Suggestions

The present study has several limitations. First, the cross-sectional design does not allow causal conclusions about the relationships among academic motivation, procrastination, cognitive emotion regulation, sleep quality, and academic achievement. Second, although academic achievement was obtained from school records, the psychological and sleep-related variables were measured using self-report questionnaires, which may be affected by response bias, social desirability, or inaccurate recall. Third, the sample was restricted to Moroccan adolescents from selected regions, and the findings may not be fully generalizable to adolescents from other cultural, socioeconomic, or educational contexts. Fourth, although the XGBoost–SHAP framework provided strong predictive performance and interpretability, machine learning findings remain dependent on the quality of input variables, sampling procedures, and model specifications. Finally, the study did not include other potentially relevant predictors, such as parental education,

teacher support, socioeconomic status, digital media use patterns, school climate, physical activity, or mental health diagnoses.

Future research should use longitudinal designs to clarify the temporal ordering and causal pathways among motivation, procrastination, emotion regulation, sleep quality, and academic achievement. Future studies should also test the model across diverse countries, school systems, and age groups to determine whether the predictive structure remains stable across cultural and educational contexts. In addition, future research could compare multiple machine learning algorithms, such as random forest, LightGBM, support vector regression, neural networks, and elastic net models, to determine whether XGBoost provides consistently superior performance. It would also be valuable to incorporate objective sleep indicators, digital behavior logs, teacher ratings, parental reports, and school-level variables to improve ecological validity. Finally, future studies should examine whether SHAP-derived risk profiles can be used to design personalized interventions and whether such interventions produce measurable improvements in academic achievement over time.

The findings offer several implications for practice. Schools should consider academic achievement as a multidimensional outcome that requires attention to students' motivation, self-regulation, emotional coping, and sleep habits. Counselors and educational psychologists can use screening tools to identify students with low motivation, high procrastination, maladaptive emotion regulation, or poor sleep quality before academic decline becomes severe. Teachers can support students by encouraging structured planning, reducing avoidant task delay, promoting mastery-oriented motivation, and helping students interpret academic setbacks in more adaptive ways. Families can also contribute by supporting consistent sleep routines, limiting late-night technology use, and encouraging balanced study habits. At the institutional level, data-driven monitoring systems may help schools identify at-risk students and provide targeted academic and psychological support while ensuring confidentiality, fairness, and ethical use of predictive analytics.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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