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LightGBM Classification of Academic Procrastination Risk Among Adolescents Based on Executive Function, Motivation, Smartphone Use, and Learning Strategy Variables

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A B S T R A C T

Objective: The objective of this study was to develop and evaluate a LightGBM machine learning model for predicting academic procrastination risk among adolescents using cognitive, motivational, behavioral, and learning strategy variables.

Methods and Materials: A total of 1,248 adolescents aged 13–18 years from public secondary schools in Germany participated in this cross-sectional study. Participants completed standardized self-report instruments assessing executive function (Behavior Rating Inventory of Executive Function–Self-Report), academic motivation (Academic Motivation Scale), smartphone use patterns (Smartphone Addiction Scale–Short Version), and learning strategies (Motivated Strategies for Learning Questionnaire). Demographic information, including age, gender, grade, parental education, and academic achievement, was also collected. The dataset was preprocessed to handle missing data, outliers, and standardization, and academic procrastination scores were categorized into low, moderate, and high-risk groups. A LightGBM classification model was trained on 80% of the data using stratified sampling and five-fold cross-validation, with hyperparameter tuning performed to optimize model performance. Model evaluation was conducted on the remaining 20% of the data using accuracy, precision, recall, F1-score, AUC-ROC, and interpretability analysis via SHAP values.

Findings: Executive function difficulties, low academic motivation, problematic smartphone use, and ineffective learning strategies were significant predictors of academic procrastination. Metacognitive self-regulation, working memory difficulties, intrinsic motivation, smartphone dependence, and time management emerged as the most influential features. The LightGBM model achieved an overall accuracy of 88.7%, macro-averaged F1-score of 0.877, and an AUC-ROC of 0.931. Misclassifications primarily occurred between adjacent risk categories, indicating the model's robustness in distinguishing different levels of procrastination risk. SHAP analysis confirmed the relative contributions of cognitive, motivational, behavioral, and learning strategy factors in shaping predicted risk levels.

Conclusion: The study demonstrates that an interpretable LightGBM model can accurately classify adolescents according to academic procrastination risk based on executive function, motivation, smartphone use, and learning strategy variables, highlighting the critical roles of cognitive self-regulation, motivation, and digital behavior in academic outcomes.

Keywords: *Academic procrastination, Adolescents, Executive function, Motivation, Smartphone use, Learning strategies.*

1. Introduction

Academic procrastination, characterized by the voluntary delay of intended academic tasks despite anticipating negative outcomes, is a prevalent and multifaceted phenomenon among adolescents. Contemporary research indicates that procrastination is not merely a matter of poor time management but reflects complex interactions among cognitive, motivational, behavioral, and technological factors (B. Liu et al., 2025; Parmaksız, 2022). Adolescence is a critical developmental period during which self-regulatory capacities, executive functioning, and motivational orientations are still maturing, making young people particularly susceptible to procrastinatory behaviors that may compromise academic performance, psychological well-being, and future educational attainment (B. Liu et al., 2025; Mao et al., 2025).

A growing body of evidence identifies executive function deficits as core cognitive correlates of procrastination. Components such as working memory, inhibitory control, cognitive flexibility, and metacognitive self-regulation have been consistently linked with the likelihood of delaying academic tasks. Adolescents with limited executive functioning demonstrate difficulty planning, monitoring progress, and maintaining focus on long-term academic goals, thereby increasing vulnerability to procrastination (Asheri et al., 2024; Cherrier et al., 2023). Moreover, research suggests that deficiencies in warm executive functions, including self-initiated organization and emotional control, may exacerbate procrastinatory tendencies when combined with heightened impulsivity and intolerance of uncertainty (Asheri et al., 2024). Interventions targeting executive planning and self-regulatory strategies have been shown to reduce procrastination, underscoring the importance of cognitive factors in predicting adolescent academic behavior (Cherrier et al., 2023; Lobos et al., 2021).

Motivational constructs also play a pivotal role in understanding procrastination. Intrinsic and extrinsic academic motivation directly influence adolescents' engagement with learning tasks, persistence in the face of challenges, and utilization of self-regulated learning strategies (Atasever et al., 2023; Wang et al., 2022). Students with high intrinsic motivation are more likely to engage in proactive planning and adopt effective learning techniques, whereas low motivation or amotivation is associated with task avoidance and procrastination (Cherrier et al., 2023; B. Liu et al., 2025). The interplay between motivation and executive function is particularly salient; motivated students with intact executive capacities demonstrate higher academic self-regulation, whereas motivational deficits may amplify procrastination even among adolescents with relatively preserved cognitive abilities (Wang et al., 2022; Xu et al., 2021).

In parallel, the pervasive use of smartphones and digital media has introduced novel behavioral risk factors for academic procrastination. Problematic smartphone use, characterized by compulsive checking, overdependence, and interference with daily responsibilities, has been linked to both reduced academic engagement and increased procrastination (Guo, 2026; Kabir et al., 2023; Sánchez-Fernández & María de las Mercedes Borda, 2022). Empirical studies demonstrate that excessive time spent on social networking, short video platforms, and instant messaging can displace study time, disrupt sleep patterns, and fragment attention, thereby promoting task delay (Bottaro & Faraci, 2022; Cherrier et al., 2023; Ziye, 2025). Moreover, constructs such as fear of missing out (FoMO), digital addiction, and parental phubbing have been shown to exacerbate adolescents' susceptibility to procrastinatory behaviors by interfering with cognitive resources and self-regulatory capacities (Guan et al., 2023; Y. K. Liu et al., 2025; Parmaksız, 2022).

Learning strategies, encompassing both cognitive and metacognitive approaches, constitute another critical determinant of academic procrastination. Strategies such as rehearsal, elaboration, organization, metacognitive monitoring, time management, and effort regulation enable adolescents to structure their study activities effectively, sustain focus, and maintain task completion despite competing distractions (Lobos et al., 2021; Wang et al., 2022; Ziye, 2025). In contrast, ineffective or inconsistent use of learning strategies has been associated with higher procrastination, lower academic achievement, and reduced engagement (Mao et al., 2025; Xu et al., 2021). Notably, learning strategies may mediate the relationship between motivational and cognitive variables and procrastination, highlighting the interconnected nature of these predictors (B. Liu et al., 2025; Wang et al., 2022).

Emerging studies also emphasize the role of psychological resilience and self-regulation in buffering the effects of technology overuse on procrastination. Adolescents with higher resilience and stronger self-regulatory capacities demonstrate lower susceptibility to digital distractions and exhibit more adaptive study behaviors (B. Liu et al., 2025; Mao et al., 2025). Similarly, interventions aimed at scaffolding metacognition through digital tools or artificial intelligence–supported task management have shown promising effects in reducing procrastinatory behavior and enhancing executive planning (Zhu et al., 2023; Zhu et al., 2026). These findings underscore the importance of considering both individual cognitive and motivational characteristics, as well as contextual and technological factors, in predictive models of academic procrastination.

Traditional correlational analyses provide valuable insights into the relationships among executive function, motivation, smartphone use, and learning strategies; however, they often fail to capture complex, nonlinear interactions that may more accurately reflect real-world behavior (Cherrier et al., 2023; Tagliaferri et al., 2025). Machine learning techniques, particularly gradient boosting methods such as LightGBM, allow for sophisticated modeling of such interactions and provide both predictive accuracy and interpretable measures of feature importance (Crowhurst & Hosseinzadeh, 2024; Zhu et al., 2026). Recent applications of LightGBM and SHAP (Shapley Additive Explanations) in educational research have demonstrated the ability to classify students according to risk levels and identify the most influential cognitive, behavioral, and environmental predictors of academic outcomes (Cherrier et al., 2023; Zhu et al., 2026).

Given the multifactorial nature of academic procrastination among adolescents, a comprehensive predictive approach that integrates executive function, motivation, smartphone use, and learning strategies is warranted. Such an approach may inform targeted interventions, facilitate early identification of at-risk students, and enhance educational outcomes. Furthermore, the use of interpretable machine learning models enables educators and researchers to understand which variables contribute most strongly to procrastinatory behaviors, supporting evidence-based decision-making and personalized educational support (Cherrier et al., 2023; B. Liu et al., 2025; Xu et al., 2021).

In light of the growing evidence linking cognitive, motivational, behavioral, and technological factors with adolescent academic procrastination, this study aims to develop a predictive LightGBM model to classify the risk of academic procrastination among adolescents based on executive function, motivation, smartphone use, and learning strategy variables.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional predictive research design using a supervised machine learning approach to classify adolescents according to their risk level for academic procrastination. The primary objective was to develop and evaluate a Light Gradient Boosting Machine (LightGBM) classification model capable of identifying students at high risk of academic procrastination based on a set of psychological, behavioral, and educational predictors, including executive function, academic motivation, smartphone use patterns, and learning strategy variables. The study was conducted in Germany during the 2025–2026 academic year. Participants were recruited from public secondary schools located in the federal states of North Rhine-Westphalia, Bavaria, Baden-Württemberg, and Lower Saxony through a multistage cluster sampling procedure. School administrators granted permission for data collection, and informed consent was obtained from both adolescents and their parents or legal guardians prior to participation.

The final sample consisted of 1,248 adolescents aged between 13 and 18 years (M = 15.62, SD = 1.47). Of the participants, 628 were female (50.3%) and 620 were male (49.7%). Inclusion criteria included enrollment in secondary education, adequate German language proficiency, and regular smartphone use. Students with diagnosed intellectual disabilities or severe psychiatric conditions that could interfere with questionnaire completion were excluded. Data collection was carried out during regular school hours under the supervision of trained research assistants. Participants completed a comprehensive battery of standardized self-report instruments designed to assess executive functioning, academic motivation, smartphone use behaviors, learning strategies, and academic procrastination tendencies.

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2.2. *Measures*

Academic procrastination was assessed using the Procrastination Assessment Scale–Students (PASS) developed by Solomon and Rothblum (1984). The instrument is one of the most widely used measures of academic procrastination and evaluates delays in completing academic tasks across several domains, including writing assignments, studying for examinations, reading activities, and administrative academic responsibilities. The scale contains 44 items rated on a Likert-type format, with higher scores indicating greater procrastination tendencies. Previous research has demonstrated satisfactory psychometric properties across adolescent and student populations, including strong internal consistency and construct validity.

Executive function was measured using the Behavior Rating Inventory of Executive Function–Self-Report Version (BRIEF-SR), developed by Guy, Isquith, and Gioia (2004). This instrument assesses multiple dimensions of executive functioning, including inhibition, emotional control, working memory, task monitoring, planning and organization, initiation, shifting, and organization of materials. The BRIEF-SR consists of 80 items scored on a three-point Likert scale ranging from never to often. Higher scores indicate greater executive functioning difficulties. Numerous studies have reported excellent reliability coefficients and strong evidence of convergent and discriminant validity among adolescent populations.

Academic motivation was assessed using the Academic Motivation Scale (AMS) developed by Vallerand and colleagues (1992). The scale measures intrinsic motivation, extrinsic motivation, and amotivation through 28 items rated on a seven-point Likert scale. Intrinsic motivation is assessed across dimensions of knowledge acquisition, accomplishment, and stimulation, while extrinsic motivation encompasses identified, introjected, and external regulation. Higher scores on the respective subscales reflect stronger motivational orientations. Previous investigations have consistently demonstrated the scale's reliability and validity in educational settings and adolescent samples.

Smartphone use patterns were evaluated using the Smartphone Addiction Scale–Short Version (SAS-SV) developed by Kwon and colleagues (2013). The instrument consists of 10 items assessing problematic smartphone behaviors, including compulsive use, withdrawal symptoms, tolerance, daily-life disturbances, and overdependence. Responses are recorded on a six-point Likert scale, with higher scores indicating more problematic smartphone use. The SAS-SV has demonstrated excellent psychometric performance and has been validated across multiple cultural contexts and adolescent populations.

Learning strategies were measured using the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich, Smith, Garcia, and McKeachie (1991). Selected subscales relevant to learning strategy utilization were employed, including rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, effort regulation, time management, and study environment management. The questionnaire uses a seven-point Likert response format and provides a comprehensive assessment of cognitive and metacognitive learning processes. Prior studies have reported strong reliability estimates and robust evidence supporting the instrument's factorial validity.

2.3. *Data Analysis*

Data analysis was conducted using Python 3.12 and relevant machine learning libraries, including LightGBM, Scikit-learn, NumPy, Pandas, and SHAP. Initial data preprocessing involved examination of missing values, detection of outliers, assessment of variable distributions, and standardization of continuous predictors where appropriate. Cases with substantial missing data were removed, while minor missing values were imputed using median-based procedures. Academic procrastination scores were transformed into categorical risk groups based on percentile-based classification thresholds. Participants scoring below the 50th percentile were classified as low risk, those between the 50th and 75th percentiles as moderate risk, and those above the 75th percentile as high risk for academic procrastination.

The dataset was randomly divided into training and testing subsets using an 80:20 ratio while preserving class distributions through stratified sampling. Hyperparameter optimization was performed using grid search combined with five-fold cross-validation on the training dataset. Key parameters optimized included learning rate, maximum tree depth, number of leaves, feature fraction, bagging fraction, and minimum data per leaf. Model performance was evaluated using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC-ROC), and confusion matrix indices.

Feature importance analysis was conducted using both the built-in LightGBM gain-based importance metrics and Shapley Additive Explanations (SHAP) values to identify the relative contribution of executive function dimensions, motivation factors, smartphone use behaviors, and learning strategy variables to academic procrastination risk classification. Cross-validation procedures were employed to minimize overfitting and enhance model generalizability. Statistical analyses and descriptive summaries of participant characteristics were additionally conducted using IBM SPSS Statistics version 29. Statistical significance was evaluated at the 0.05 level for preliminary analyses, while machine learning model performance was assessed through predictive accuracy and classification metrics derived from the testing dataset.

3. Findings and Results

A total of 1,248 adolescents participated in the study. The sample included 628 females (50.3%) and 620 males (49.7%). Participants ranged in age from 13 to 18 years, with a mean age of 15.62 years (SD = 1.47). Students were enrolled across grades 8 through 12, with relatively balanced representation from each grade level. Based on the academic procrastination classification criteria, 512 participants (41.0%) were categorized as low-risk, 423 participants (33.9%) as moderate-risk, and 313 participants (25.1%) as high-risk for academic procrastination. Preliminary analyses indicated that students classified in the high-risk group reported significantly greater executive functioning difficulties, higher levels of problematic smartphone use, lower academic motivation, and less effective learning strategy utilization compared with students in the low-risk category. Data screening demonstrated acceptable distributions for all study variables, with skewness and kurtosis values within recommended ranges. Missing data accounted for less than 2% of responses and were successfully handled through median imputation procedures.

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4	5
1. Academic Procrastination	53.84	11.92	1.00				
2. Executive Function Difficulties	97.61	18.74	.64	1.00			
3. Academic Motivation	118.53	21.38	-.58	-.49	1.00		
4. Smartphone Use Problems	31.47	8.19	.55	.51	-.43	1.00	
5. Learning Strategies	102.84	17.62	-.61	-.56	.68	-.41	1.00

Table 1 presents the descriptive statistics and bivariate correlations among the major study variables. Academic procrastination demonstrated a strong positive association with executive function difficulties ($r = .64$, $p < .001$) and problematic smartphone use ($r = .55$, $p < .001$), indicating that adolescents who experienced greater difficulties with planning, inhibition, working memory, and self-monitoring, as well as excessive smartphone engagement, tended to report higher levels of procrastination. Conversely, academic procrastination was negatively correlated with academic motivation ($r = -.58$, $p < .001$) and learning strategies ($r = -.61$, $p < .001$), suggesting that highly motivated students who regularly employed cognitive and metacognitive learning strategies exhibited lower tendencies toward delaying academic tasks. Learning strategies showed the strongest positive relationship with academic motivation ($r = .68$, $p < .001$), highlighting the close connection between motivational processes and effective self-regulated learning behaviors.

Table 2

LightGBM Classification Performance on the Test Dataset

Metric	Value
Accuracy	0.887
Precision (Macro Average)	0.881
Recall (Macro Average)	0.874
F1-Score (Macro Average)	0.877
AUC-ROC	0.931
Cohen's Kappa	0.822
Matthews Correlation Coefficient	0.819

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The performance indicators of the LightGBM classifier are presented in Table 2. Results demonstrated excellent predictive performance across all evaluation criteria. The model achieved an overall classification accuracy of 88.7%, indicating that nearly nine out of every ten students were correctly assigned to their respective academic procrastination risk category. The macro-averaged precision, recall, and F1-score values all exceeded .87, reflecting strong performance across all three risk groups and suggesting balanced classification capability without substantial bias toward any specific category. The AUC-ROC value of .931 further demonstrated outstanding discriminative ability, indicating that the model effectively distinguished between adolescents at different levels of procrastination risk. Additionally, the Cohen's Kappa coefficient (.822) and Matthews Correlation Coefficient (.819) indicated substantial agreement between observed and predicted classifications, supporting the robustness and reliability of the predictive model.

Table 3

Confusion Matrix for Academic Procrastination Risk Classification

Actual Class	Predicted Low Risk	Predicted Moderate Risk	Predicted High Risk
Low Risk	95	8	3
Moderate Risk	10	71	6
High Risk	4	9	44

Analysis of the confusion matrix presented in Table 3 revealed that the LightGBM algorithm accurately classified the majority of participants across all risk categories. Among adolescents who were actually categorized as low risk, 95 of 106 participants were correctly identified. Similarly, 71 of 87 moderate-risk students and 44 of 57 high-risk students were accurately classified. Misclassification patterns were relatively limited and primarily occurred between adjacent risk categories rather than between low- and high-risk groups, suggesting that the model effectively captured meaningful distinctions in procrastination severity. The small number of extreme classification errors indicates strong discriminative performance and supports the practical utility of the model for educational screening purposes.

Table 4

Feature Importance Rankings Generated by LightGBM

Rank	Predictor Variable	Importance Score
1	Metacognitive Self-Regulation	847
2	Working Memory Difficulties	798
3	Academic Motivation (Intrinsic)	752
4	Smartphone Dependence	713
5	Time Management Strategy	689
6	Inhibitory Control Difficulties	643
7	Effort Regulation	615
8	Organization Skills	584
9	Academic Achievement	491
10	External Motivation	443

Table 4 presents the relative importance of predictors used in the LightGBM model. Metacognitive self-regulation emerged as the most influential predictor of academic procrastination risk, followed closely by working memory difficulties and intrinsic academic motivation. These findings suggest that adolescents’ ability to monitor, regulate, and organize their learning processes constitutes the strongest determinant of procrastination behavior. Smartphone dependence also demonstrated considerable predictive value, highlighting the role of digital distractions in academic delay behaviors. Executive function components, particularly working memory and inhibitory control, consistently appeared among the highest-ranking variables, underscoring the importance of cognitive self-regulation mechanisms. Collectively, the top predictors accounted for the majority of model decision-making processes, indicating that both cognitive and motivational

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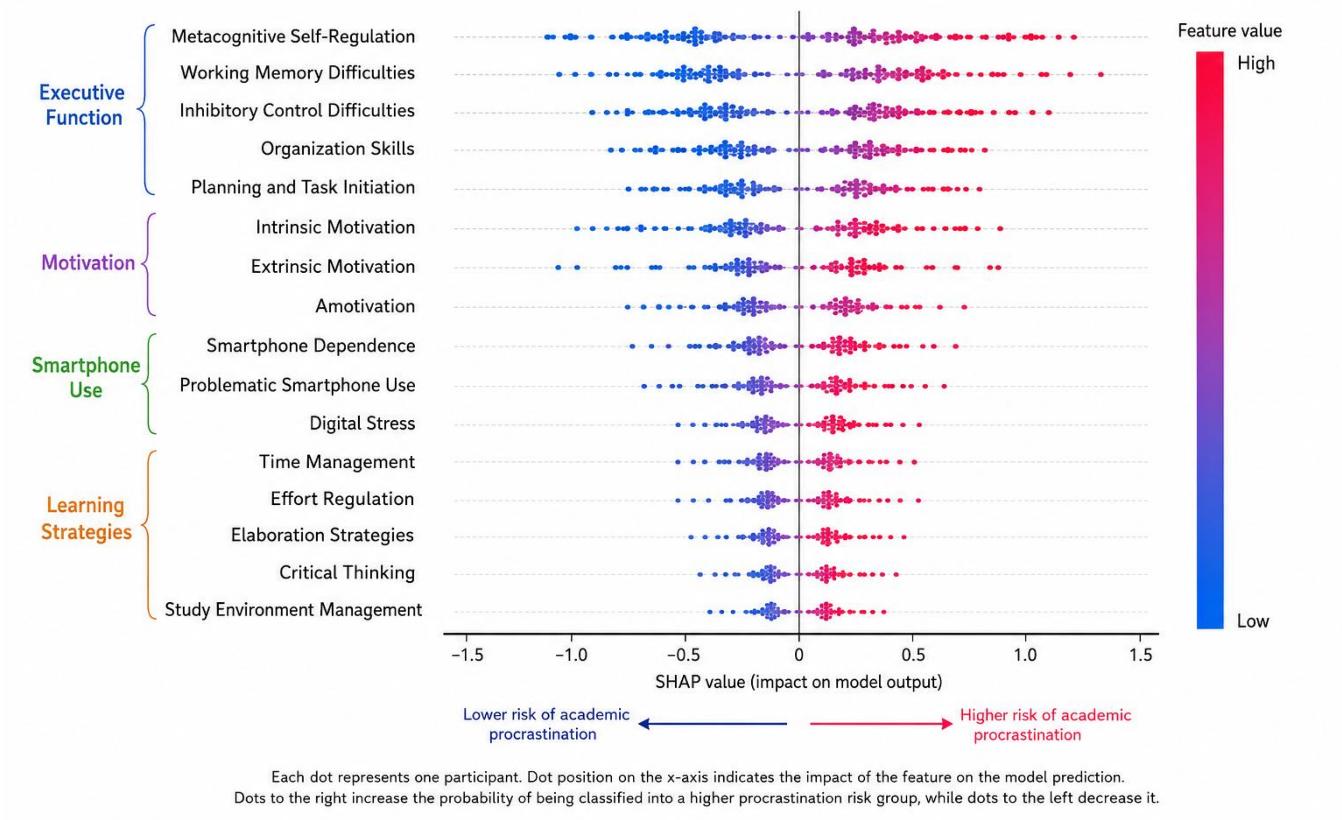
factors are central to understanding academic procrastination risk among adolescents.

Figure 1

SHAP Summary Plot Illustrating the Relative Contributions of Executive Function, Motivation, Smartphone Use, and Learning Strategy Variables to Academic Procrastination Risk Classification



The SHAP analysis provided additional insights into the internal decision-making processes of the LightGBM model. The summary plot revealed that lower levels of metacognitive self-regulation, weaker time management skills, greater working memory difficulties, elevated smartphone dependence, and reduced intrinsic motivation were consistently associated with increased probabilities of classification into higher academic procrastination risk groups. Positive SHAP values indicated features contributing toward high-risk predictions, whereas negative SHAP values reflected characteristics associated with lower procrastination risk. The visualization further demonstrated substantial interactions among executive functioning variables and learning strategy measures, suggesting that deficits in cognitive control mechanisms frequently co-occurred with ineffective learning behaviors. Overall, the SHAP findings supported the feature importance results and provided interpretable evidence that academic procrastination among adolescents is driven by a complex interplay of executive, motivational, technological, and self-regulatory learning factors.

4. Discussion

The present study aimed to develop and evaluate a LightGBM classification model capable of identifying adolescents at risk for academic procrastination using executive function, academic motivation, smartphone use, and learning strategy variables. The findings demonstrated that the proposed model achieved high predictive performance, with an overall classification accuracy of 88.7% and an AUC value exceeding .93. Furthermore, the results revealed that executive function difficulties, problematic smartphone use, academic motivation, and learning strategies were all significantly associated with academic procrastination. Feature importance analyses

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indicated that metacognitive self-regulation, working memory difficulties, intrinsic motivation, smartphone dependence, and time-management skills represented the most influential predictors of procrastination risk.

One of the most important findings of the present study was the substantial contribution of executive function variables to the classification of academic procrastination risk. Working memory difficulties and inhibitory control emerged among the strongest predictors in the LightGBM model, while executive function difficulties also demonstrated the strongest positive correlation with procrastination. These findings are consistent with previous theoretical and empirical evidence suggesting that procrastination is fundamentally a self-regulation failure rooted in deficits in executive control processes (Asheri et al., 2024; Cherrier et al., 2023). Executive functions are responsible for planning, goal maintenance, attention allocation, impulse inhibition, and behavioral monitoring. Adolescents who struggle with these cognitive processes may find it difficult to initiate academic tasks, sustain concentration, and resist competing distractions, thereby increasing the likelihood of postponing academic responsibilities. The prominence of executive function variables in the present study also aligns with intervention research demonstrating that improvements in planning skills and executive functioning are associated with reductions in procrastination behaviors (Cherrier et al., 2023). Moreover, evidence from studies examining ADHD-related executive functioning challenges further supports the notion that weaknesses in cognitive control significantly impair task management and academic persistence (Doulou et al., 2022; Shuai et al., 2021).

The results additionally highlighted the importance of metacognitive self-regulation as the strongest predictor identified by the LightGBM algorithm. This finding is theoretically meaningful because metacognition enables learners to monitor progress, evaluate strategies, and adjust behavior according to academic goals. Students who effectively regulate their learning activities are more capable of organizing tasks, setting priorities, and overcoming barriers to task completion. Previous studies have consistently reported that self-regulated learning competencies serve as protective factors against procrastination and academic disengagement (Lobos et al., 2021; Wang et al., 2022). Similarly, emerging technological interventions designed to scaffold metacognitive functioning through artificial intelligence have shown promise in improving task management and reducing delays in academic work (Zhu et al., 2026). Therefore, the central role of metacognitive self-regulation identified in the present model supports existing theories that conceptualize procrastination as a failure of self-regulated learning rather than merely poor time management.

Academic motivation also emerged as a major predictor of procrastination risk. Both the correlation analyses and machine learning findings demonstrated that lower motivation was associated with higher levels of academic procrastination. In particular, intrinsic motivation ranked among the most influential features within the predictive model. These results support motivational theories suggesting that students who perceive academic activities as personally meaningful and enjoyable are more likely to engage consistently with learning tasks and less likely to postpone them. Conversely, reduced motivation may undermine persistence and increase susceptibility to avoidance behaviors (Atasever et al., 2023; B. Liu et al., 2025). Previous research has demonstrated that academic motivation is closely linked to self-regulation, learning engagement, and psychological well-being, all of which contribute to academic productivity (Atasever et al., 2023; Guo, 2026). The present findings further extend this literature by demonstrating that motivational variables contribute substantially to the accurate classification of procrastination risk among adolescents. The results also support evidence showing that motivational deficits often coexist with digital addictions and problematic technology use, creating a cycle of disengagement and task avoidance (Atasever et al., 2023; Mao et al., 2025).

A particularly noteworthy finding concerns the significant role of smartphone dependence in predicting academic procrastination. Problematic smartphone use ranked among the strongest predictors in the LightGBM model and showed a substantial positive relationship with procrastination. This finding is highly consistent with the growing body of literature identifying smartphone addiction as a major threat to academic functioning among adolescents and young adults (Crowhurst & Hosseinzadeh, 2024; Sánchez-Fernández & María de las Mercedes Borda, 2022). Smartphones provide immediate access to entertainment, social interaction, and information, making them powerful sources of distraction during academic activities. Excessive smartphone engagement may consume cognitive resources, reduce attention span, disrupt concentration, and increase task-switching behaviors, all of which contribute to procrastination. Previous studies have reported significant associations between problematic smartphone use and

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reduced academic performance, impaired psychological well-being, and increased behavioral avoidance (Kabir et al., 2023; Rodríguez et al., 2020). The current findings support these observations and further demonstrate that smartphone-related behaviors can be leveraged within machine learning frameworks to identify students at elevated risk of procrastination.

The relationship between smartphone use and procrastination may also operate through several indirect mechanisms. Research has demonstrated that problematic smartphone use is associated with sleep disturbances, bedtime procrastination, depressive symptoms, anxiety, and impaired self-control (Cui et al., 2021; Deng, 2025; Guo, 2026). These consequences may reduce students' cognitive resources and increase vulnerability to task avoidance. Furthermore, digital stress, social comparison, fear of missing out, and continuous online connectivity have been identified as important contributors to problematic technology use and psychological distress (Guan et al., 2023; Ren et al., 2025; Throuvala et al., 2021). The present findings suggest that these technology-related challenges may ultimately manifest as academic procrastination when students prioritize digital engagement over educational responsibilities.

Learning strategy variables represented another highly influential category of predictors. Time management, effort regulation, organization, and metacognitive strategy use all contributed substantially to model performance. These findings are consistent with extensive evidence linking effective learning strategies to improved academic outcomes and lower procrastination tendencies (Lobos et al., 2021; Wang et al., 2022). Learning strategies facilitate goal-directed behavior by helping students organize information, allocate study time efficiently, and monitor progress toward objectives. Adolescents who lack these skills may experience greater difficulty initiating tasks, maintaining momentum, and completing assignments within deadlines. The strong predictive value of learning strategies identified in the current study is also supported by research demonstrating that interventions aimed at strengthening self-regulated learning can significantly reduce academic delays and increase academic engagement (Lobos et al., 2021; Xu et al., 2021; Ying & Wang, 2022).

The present findings further support recent studies emphasizing the interconnected nature of procrastination, technology use, and self-regulation. For example, procrastination has been identified as a predictor of future internet-related behavioral problems, suggesting that self-regulatory deficiencies may contribute to multiple forms of problematic digital behavior (Lardinoix et al., 2023). Similarly, procrastination has been found to mediate relationships between problematic social media use and adverse psychological outcomes such as depression (Rogowska & Cincio, 2024). Research examining phubbing behaviors has also demonstrated that academic self-efficacy and self-regulatory capacities play critical roles in explaining the relationship between digital distractions and procrastination (Parmaksız, 2022). The present study extends these findings by integrating multiple cognitive, motivational, and behavioral variables within a single predictive framework and demonstrating their combined utility for risk classification.

Another important contribution of the study lies in the application of LightGBM as a machine learning methodology. Traditional statistical approaches often focus on isolated relationships between variables and may struggle to capture complex nonlinear interactions. In contrast, LightGBM enabled the identification of intricate relationships among executive function, motivation, smartphone use, and learning strategy variables while maintaining high predictive accuracy. The SHAP analyses further enhanced interpretability by revealing how specific variables influenced classification decisions. Such approaches are increasingly recommended in educational and psychological research because they provide both predictive power and practical insights for intervention development (Crowhurst & Hosseinzadeh, 2024; Zhu et al., 2026). The high classification accuracy observed in the present study suggests that machine learning models may serve as valuable tools for early identification of students who are vulnerable to academic procrastination.

5. Conclusion

The findings should also be interpreted within the broader context of contemporary digital environments. Adolescents today are exposed to unprecedented levels of technological stimulation, social media engagement, and digital distraction. Recent investigations have highlighted concerns regarding problematic short-video consumption, digital dependency, boredom-driven technology use, and emerging phenomena such as "brain rot," all of which may negatively affect cognitive functioning and academic engagement (Mao et al., 2025; Özbay, 2026; Tagliaferri et al., 2025; Ziye, 2025). Consistent with these concerns, the present results indicate that technology-related factors constitute critical

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components of academic procrastination risk. Therefore, efforts to address procrastination among adolescents should consider not only traditional academic and motivational interventions but also strategies aimed at promoting healthy digital habits and reducing excessive smartphone dependence.

6. Limitations & Suggestions

Several limitations should be acknowledged when interpreting the findings of this study. First, the cross-sectional design limits causal inferences regarding the relationships among executive function, motivation, smartphone use, learning strategies, and academic procrastination. Second, all variables were assessed using self-report instruments, which may be influenced by response biases, social desirability effects, and inaccuracies in self-perception. Third, although the sample was relatively large and geographically diverse within Germany, the findings may not generalize to adolescents from different cultural, educational, or socioeconomic contexts. Fourth, the classification model was developed using psychological and behavioral variables only; additional factors such as family environment, teacher support, personality characteristics, and objective academic records may further improve predictive accuracy. Finally, despite the strong performance of the LightGBM model, machine learning predictions should complement rather than replace comprehensive psychological and educational assessments.

Future studies should employ longitudinal designs to examine how executive function, motivation, smartphone use, and learning strategies influence changes in procrastination over time. Researchers may also investigate whether intervention programs targeting self-regulation, metacognitive skills, or digital wellness can reduce procrastination risk as identified through machine learning models. Additional studies should explore other potential predictors, including personality traits, emotional regulation, academic self-efficacy, family relationships, peer influences, and school climate variables. Cross-cultural comparisons would help determine the generalizability of predictive models across different educational systems and cultural contexts. Furthermore, future investigations could compare the performance of LightGBM with other advanced machine learning approaches, such as XGBoost, CatBoost, Random Forest, and deep learning architectures, to identify optimal predictive frameworks for educational applications.

The findings suggest that schools should prioritize the development of students' executive functioning and self-regulated learning skills through structured educational programs. Educators can implement training focused on planning, time management, goal setting, self-monitoring, and metacognitive reflection to reduce procrastination tendencies. School counselors and psychologists may use screening procedures to identify students exhibiting high levels of smartphone dependence and self-regulation difficulties before academic problems become severe. Parents should also be encouraged to establish healthy technology-use practices and support adolescents in balancing digital engagement with academic responsibilities. Finally, educational institutions may benefit from integrating digital well-being initiatives, academic coaching programs, and technology-assisted self-management tools to foster adaptive learning behaviors and reduce the risk of academic procrastination among adolescents.

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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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