KMAN PUBLISHING INSTITUTE
Journal Website

Article history:
Received 19 March 2026
Revised 30 May 2026
Accepted 13 June 2026
Initial Publish 25 June 2026
Published online 01 July 2026

Journal of Assessment and Research in Applied Counseling

Volume 8, Issue 3, pp 1-14

E-ISSN: 3041-8518

Support Vector Machine Classification of High-Risk University Students Using Academic Stress, Sleep Quality, Self-Efficacy, and Depression

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A r t i c l e I n f o

Article type:
Original Research

How to cite this article:
Moreno, M., & Barbosa, J.C. (2026). Support Vector Machine Classification of High-Risk University Students Using Academic Stress, Sleep Quality, Self-Efficacy, and Depression. *Journal of Assessment and Research in Applied Counseling, 8*(3), 1-14.
http://dx.doi.org/10.61838/kman.jarac.5482

A B S T R A C T

Objective: This study aimed to develop and evaluate a Support Vector Machine classification model for identifying high-risk university students in Colombia using academic stress, sleep quality, self-efficacy, and depression as predictive indicators.

Methods and Materials: This quantitative cross-sectional predictive study was conducted among 1,248 undergraduate students from five public and private universities in Colombia. Data were collected using standardized self-report instruments measuring academic stress, sleep quality, general self-efficacy, and depressive symptoms. Students were classified into high-risk and lower-risk groups according to predefined criteria combining depressive symptoms, severe academic stress, and poor sleep quality. Data were analyzed using descriptive statistics, correlation analysis, and a Support Vector Machine algorithm with a radial basis function kernel. The dataset was divided into training and testing subsets using stratified sampling, and hyperparameter optimization was performed through grid search and ten-fold cross-validation. Model performance was evaluated using accuracy, precision, recall, specificity, F1-score, balanced accuracy, Matthews correlation coefficient, ROC-AUC, and Brier score. SHAP analysis was applied to interpret the relative contribution of each predictor.

Findings: Correlation analysis showed that academic stress was positively associated with depression and poor sleep quality, while self-efficacy was negatively associated with academic stress, poor sleep quality, and depression. The optimized Support Vector Machine model demonstrated strong classification performance, achieving 92.4% testing accuracy, 90.6% precision, 89.1% recall, 93.7% specificity, an F1-score of 89.8%, balanced accuracy of 91.4%, Matthews correlation coefficient of 0.81, ROC-AUC of 0.951, and Brier score of 0.074.

SHAP analysis identified depression as the strongest predictor of high-risk classification, followed by academic stress, sleep quality, and self-efficacy.
Conclusion: The findings indicate that Support Vector Machine classification can accurately and interpretably identify high-risk university students based on psychological and behavioral indicators. Integrating depression, academic stress, sleep quality, and self-efficacy into predictive screening may support early detection and targeted student mental health interventions.
Keywords: *Support Vector Machine; university students; academic stress; sleep quality; self-efficacy; depression; machine learning; psychological risk*

1. Introduction

University students constitute a population exposed to a complex combination of developmental, academic, social, technological, and psychological demands that may increase vulnerability to mental health problems and academic maladjustment. The transition to higher education commonly involves increased autonomy, new interpersonal expectations, financial pressure, competitive academic environments, and uncertainty about future professional identity. These demands may become particularly harmful when students lack adequate coping resources or when institutional conditions intensify stress rather than buffer it. In Latin American university contexts, recent research has increasingly emphasized that student well-being cannot be understood only as the absence of psychopathology, but must be examined through the interaction of emotional symptoms, lifestyle habits, academic functioning, perceived quality of life, resilience, coping strategies, and institutional support systems. Studies on student health and well-being have shown that psychological discomfort among university populations is connected to broader educational conditions and that universities must consider mental health as a core dimension of academic success rather than as an external or secondary concern (Brito et al., 2024; Garcés et al., 2023). This perspective is especially important in post-pandemic higher education, where many students continue to experience the residual psychological, behavioral, and academic effects of disrupted learning environments, social isolation, and increased dependence on digital technologies (Javes et al., 2024; Monzón et al., 2022).

Academic stress is one of the most frequently studied determinants of student vulnerability and represents a central predictor of both psychological distress and academic impairment. It emerges when students perceive that educational demands exceed their available personal, cognitive, emotional, or temporal resources. Academic stress may include pressure related to examinations, workload, deadlines, performance expectations, fear of failure, interpersonal competition, and adaptation to institutional norms. Evidence from Latin American university samples indicates that academic stress is strongly associated with poorer academic outcomes, reduced motivation, and emotional exhaustion, making it a critical indicator for identifying students who may be at risk of maladjustment (Castillo, 2024). In the context of virtual and hybrid education during and after COVID-19, academic stress became even more salient because students were required to manage technological barriers, reduced face-to-face interaction, uncertainty about assessment, and blurred boundaries between academic and personal life (Campas et al., 2022; Vilca et al., 2022). Systematic review evidence has further confirmed that academic stress among university students during the COVID-19 context was not an isolated response to temporary educational disruption, but part of a broader pattern of psychological strain requiring sustained institutional attention (Tejada et al., 2024).

Sleep quality is another major determinant of university student functioning and is closely related to academic stress, mental health, and learning efficiency. Poor sleep quality may involve delayed sleep onset, insufficient sleep duration, frequent awakenings, low sleep efficiency, daytime fatigue, and impaired concentration. Among students, sleep disturbance is especially relevant because academic schedules, late-night study habits, excessive screen exposure, social demands, and emotional rumination may collectively disrupt regular sleep patterns. Research on sleep and academic performance among medical students has shown that sleep quality is associated with educational functioning, suggesting that sleep is not merely a biological variable but a key component of academic adaptation (Maria del Mar Duque, 2022). Similar findings have been reported in studies examining sleep habits, mental health, and physical activity in students participating in virtual education, where poor sleep was linked to broader patterns of psychological and behavioral vulnerability (Mora et al., 2022). Recent evidence has also emphasized the connection between sleep quality, academic stress, and performance,

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E-ISSN: 3041-8518

indicating that students with poorer sleep may experience greater stress and reduced academic effectiveness (Villasboa et al., 2025). Moreover, studies conducted with adolescent and student populations have demonstrated that sleep problems and academic stress are mutually reinforcing, with stress disturbing sleep and poor sleep reducing students' capacity to cope with academic demands (Buri & Zumbaña, 2023).

Depression represents one of the most clinically significant outcomes and predictors of high-risk status among university students. Depressive symptoms in higher education may manifest as persistent sadness, loss of interest, fatigue, feelings of worthlessness, concentration problems, sleep disturbance, appetite changes, and reduced academic engagement. These symptoms may directly impair students' capacity to attend classes, complete assignments, maintain social relationships, and sustain motivation toward long-term goals. Research among Colombian university students during the pandemic documented depressive and anxious symptomatology as a relevant mental health concern, highlighting the need for early detection strategies in higher education contexts (Restrepo et al., 2022). Studies from other Latin American university populations have similarly shown that depression, anxiety, and stress are prevalent and meaningful indicators of student distress (Huamani-Calloapaza et al., 2024). In addition, post-pandemic research has linked anxiety, depression, and stress to academic performance, suggesting that emotional symptoms may have persistent consequences for students' educational trajectories (Merchán-Villafuerte et al., 2024). Comparative work among medical students has also identified psychological distress as a variable associated with academic functioning and emphasized that sex-based differences may influence the experience and academic consequences of distress (Jaimes-Medrano et al., 2024).

Self-efficacy is a protective psychological factor that may buffer the negative effects of academic stress, sleep disturbance, and depressive symptoms. In the university context, self-efficacy refers to students' belief in their capacity to organize actions, regulate effort, solve problems, persist through challenges, and succeed in academic tasks. Students with higher self-efficacy are more likely to interpret academic demands as manageable challenges rather than uncontrollable threats. They may also demonstrate stronger persistence, more adaptive coping, better study regulation, and greater resilience in the face of failure or uncertainty. Intervention research on study skills has shown that improving academic skills may reduce stress and enhance academic self-efficacy among first-year university students, suggesting that self-efficacy is both a predictor of adjustment and a modifiable target for prevention (Chust-Hernández et al., 2024). The role of resilience among undergraduate nursing students further supports the importance of protective psychological resources in demanding academic environments (Kelly Liset De la Cruz, 2024). Likewise, studies on psychological well-being and coping strategies during the pandemic indicate that students' adaptive coping resources are crucial for maintaining mental health under conditions of educational uncertainty (Everly & Monsivais, 2022). Therefore, the assessment of self-efficacy alongside risk variables may provide a more balanced and clinically useful framework for identifying vulnerable students.

The psychological condition of university students should also be understood in relation to lifestyle, physical activity, technology use, and broader quality-of-life indicators. Multivariate research has shown that psychological factors and lifestyle variables jointly predict university students' perceived quality of life, supporting the need for analytic models capable of integrating multiple interacting predictors rather than examining isolated variables independently (Martins et al., 2024). Physical activity and healthy university initiatives have been identified as important strategies for strengthening mental and physical health among young people, suggesting that preventive models should consider health-promoting behaviors alongside psychological symptoms (Sanchís-Soler et al., 2022). Research on physical exercise in the treatment of depression among university students also indicates that behavioral interventions may contribute to reducing depressive symptoms and improving emotional functioning (González, 2024). At the same time, the increasing use of mobile devices in university contexts may influence academic performance and daily functioning, demonstrating that digital behaviors can function as either resources or risks depending on their pattern of use (Enríquez-Mayanger et al., 2024). These findings collectively suggest that high-risk classification in university students should be multidimensional and sensitive to the interplay of emotional, behavioral, academic, and self-regulatory factors.

The pandemic and post-pandemic literature has further demonstrated that the psychological risk profile of students is heterogeneous rather than uniform. Some students may primarily experience academic stress, others may present sleep-related impairment, others may show depressive symptoms, and others may be protected by high self-efficacy despite exposure to difficult academic conditions.

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E-ISSN: 3041-8518

Systematic review evidence on psychological factors and academic performance during COVID-19 has shown that students' educational outcomes were shaped by multiple psychological mechanisms, including stress, motivation, emotional symptoms, and adaptation difficulties (Cabezas et al., 2023). Research on mental health alterations and university adaptation among Honduran students also suggests that students may form distinct groups with different academic performance profiles, emphasizing the importance of classification-based approaches rather than relying only on average group comparisons (Castillo-Díaz et al., 2022). Similarly, narrative evidence on psychological distress among nursing students indicates that distress is associated with multiple personal, educational, and contextual factors, reinforcing the need for integrative assessment models (Silva et al., 2023). Studies of personal and contextual predictors of mental health among adolescents further support the view that stress, anxiety, depression, and impulsivity operate together in shaping psychological risk (Rodríguez & Barajas, 2022).

Traditional statistical methods have contributed substantially to understanding the associations among stress, sleep quality, self-efficacy, depression, and academic functioning; however, they may be limited when the research objective is to classify individual students into risk categories. Correlational and regression-based approaches are valuable for estimating linear relationships and identifying average effects, but they may not fully capture nonlinear patterns, threshold effects, or complex combinations of predictors that differentiate high-risk students from lower-risk students. In contrast, machine learning methods are designed to optimize prediction and classification by learning patterns from data. Among these methods, Support Vector Machine classification is particularly suitable for psychological risk classification because it can separate groups in high-dimensional feature spaces and can model nonlinear boundaries when used with kernels such as the radial basis function. This is important in student mental health research because the same symptom score may have different implications depending on the presence or absence of other variables, such as self-efficacy or sleep quality. For example, moderate academic stress may not indicate high risk when self-efficacy is strong, but the same level of stress may become more concerning when accompanied by poor sleep and depressive symptoms. Therefore, Support Vector Machine modeling offers an analytically rigorous approach for identifying students whose combined psychological profile indicates elevated risk.

Although growing research has examined academic stress, sleep quality, self-efficacy, depression, coping, and academic performance among university students, important gaps remain. Many existing studies focus on single predictors or use conventional association-based models, while fewer studies translate psychological indicators into predictive classification frameworks that can support early identification. Moreover, Latin American higher education contexts require context-sensitive predictive models because students' experiences are shaped by regional educational structures, socioeconomic variability, family expectations, post-pandemic adjustment, and digital learning conditions. Meta-analytic evidence on mindfulness interventions for affective disorders among university students indicates that psychological symptoms are modifiable and that early identification can support timely preventive or therapeutic responses (Obando & Peralta-Eugenio, 2023). However, early identification requires classification tools capable of distinguishing students who may benefit most from support. Therefore, integrating academic stress, sleep quality, self-efficacy, and depression into a Support Vector Machine model may offer a useful methodological advance by combining theoretically meaningful psychological variables with a predictive algorithm suitable for individualized risk detection.

The aim of this study was to develop and evaluate a Support Vector Machine classification model for identifying high-risk university students in Colombia using academic stress, sleep quality, self-efficacy, and depression as predictive indicators.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a quantitative, cross-sectional predictive research design to develop and validate a Support Vector Machine (SVM) model for the classification of high-risk university students based on psychological and behavioral characteristics. The study was conducted between September 2025 and February 2026 across five major public and private universities located in Bogotá, Medellín, Cali, Barranquilla, and Bucaramanga, Colombia. The primary objective was to determine the predictive utility of academic stress, sleep quality, self-efficacy, and depressive symptoms in identifying students at elevated psychological risk.

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A total of 1,248 undergraduate students participated in the study. Participants were recruited using a stratified random sampling strategy to ensure adequate representation from different academic disciplines, including health sciences, engineering, social sciences, business administration, education, and humanities. Students ranged in age from 18 to 29 years (Mean = 21.46 years, SD = 2.71), with representation from all years of undergraduate education. Approximately 56.2% of participants were female and 43.8% were male. Inclusion criteria consisted of current enrollment as a full-time undergraduate student, age of at least 18 years, sufficient Spanish language proficiency to complete the questionnaires independently, and willingness to provide informed consent. Students with documented severe neurological disorders, active psychotic disorders, or incomplete questionnaire responses exceeding 10% of total items were excluded from the final analyses.

The dependent variable consisted of students' overall psychological risk status. Risk classification was established by combining clinically validated cut-off scores for depressive symptoms with indicators of severe academic stress and poor sleep quality. Participants meeting predetermined high-risk criteria were coded as belonging to the high-risk group, whereas all remaining participants were categorized as lower-risk students. This binary classification served as the target variable for the machine learning model. Independent variables included academic stress, sleep quality, self-efficacy, and depression, each represented by standardized total scores. Prior to model development, all predictor variables were examined for missing values, distributional characteristics, and outliers. Missing data constituted less than 2% of all observations and were handled using multiple imputation procedures. Continuous variables were standardized using z-score normalization to improve model convergence and optimize the performance of the Support Vector Machine algorithm.

2.2. Measures

Academic stress was assessed using the Student-Life Stress Inventory (SSI), a multidimensional instrument specifically developed to measure stressors and stress reactions experienced within higher education settings. The questionnaire contains 51 items distributed across several domains evaluating frustrations, conflicts, pressures, changes, emotional responses, physiological reactions, behavioral reactions, and cognitive appraisals associated with academic demands. Responses are recorded using a five-point Likert scale ranging from strongly disagree to strongly agree, with higher scores indicating greater perceived academic stress. Previous international studies have demonstrated excellent psychometric properties, including high internal consistency, construct validity, and cross-cultural applicability among university student populations. In the present study, Cronbach's alpha coefficient for the overall scale was .93, indicating excellent internal reliability.

Sleep quality was measured using the Pittsburgh Sleep Quality Index (PSQI), one of the most widely validated instruments for assessing subjective sleep quality during the previous month. The PSQI evaluates seven components including subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. Component scores are combined to generate a global score ranging from 0 to 21, with higher scores reflecting poorer sleep quality. The Spanish-language version of the PSQI has demonstrated excellent reliability and validity across Latin American populations. In this study, the overall internal consistency coefficient reached .88, confirming satisfactory reliability for the Colombian university student sample.

General self-efficacy was evaluated using the General Self-Efficacy Scale (GSES), a 10-item instrument measuring individuals' confidence in their ability to cope successfully with challenging situations and overcome obstacles. Participants responded using a four-point Likert scale ranging from "not at all true" to "exactly true." Total scores ranged from 10 to 40, with higher values representing stronger perceived self-efficacy. The scale has consistently demonstrated strong psychometric properties across different cultural contexts and educational settings. Within the current sample, Cronbach's alpha was .91, indicating excellent internal consistency.

Depressive symptoms were assessed using the Patient Health Questionnaire-9 (PHQ-9), a brief self-report measure designed to evaluate depressive symptom severity during the preceding two weeks. The questionnaire consists of nine items corresponding directly to the diagnostic criteria for major depressive disorder, with responses scored from 0 (not at all) to 3 (nearly every day). Total scores range from 0 to 27, with higher scores indicating greater depressive symptom severity. The PHQ-9 has been extensively validated among university students worldwide and has demonstrated excellent diagnostic sensitivity and specificity. In the present investigation, Cronbach's alpha coefficient was .90, confirming high internal reliability.

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In addition to the principal psychological instruments, participants completed a demographic questionnaire collecting information regarding age, gender, academic year, faculty, grade point average, living arrangements, employment status, socioeconomic status, weekly study hours, physical activity, smoking behavior, alcohol consumption, and previous mental health treatment. These variables were included to characterize the sample and to explore potential confounding influences during preliminary analyses.

2.3. Data analysis

Data analysis was conducted using Python version 3.12 and IBM SPSS Statistics version 29. Initial analyses included descriptive statistics for all demographic and psychological variables. Means, standard deviations, frequencies, percentages, skewness, kurtosis, and correlation coefficients were calculated to summarize participant characteristics and examine associations among study variables. Internal consistency reliability for each questionnaire was evaluated using Cronbach's alpha coefficients. Prior to predictive modeling, predictor variables were examined for multicollinearity using tolerance statistics and variance inflation factors, while standardized z-scores were inspected to identify influential outliers.

The predictive classification model was developed using a Support Vector Machine algorithm with a radial basis function (RBF) kernel because of its ability to capture complex nonlinear relationships between predictor variables and classification outcomes. Hyperparameter optimization was performed using an exhaustive grid-search strategy combined with stratified ten-fold cross-validation. Candidate values for the regularization parameter (C) and kernel parameter (gamma) were systematically evaluated to identify the model demonstrating the highest average validation accuracy while minimizing overfitting. Class imbalance between high-risk and lower-risk students was addressed using Synthetic Minority Oversampling Technique (SMOTE) exclusively within the training dataset to prevent information leakage into validation samples.

The complete dataset was randomly divided into training and testing subsets using an 80:20 ratio while preserving the proportional distribution of the outcome classes through stratified sampling. Feature standardization was performed independently within the training data and subsequently applied to the testing data using identical scaling parameters.

Model performance was evaluated using multiple complementary classification metrics including accuracy, precision, recall, specificity, F1-score, balanced accuracy, Matthews correlation coefficient, and the area under the receiver operating characteristic curve (AUC-ROC). Precision-recall curves were also generated because of the relatively lower prevalence of high-risk cases.

To improve model interpretability, permutation feature importance analysis and SHapley Additive exPlanations (SHAP) were employed to quantify the relative contribution of each psychological predictor to the classification decisions. SHAP summary plots, dependence plots, and individual force plots were generated to illustrate the direction and magnitude of each variable's influence on predicted risk probabilities. Model calibration was further evaluated using calibration curves and Brier scores to assess agreement between predicted probabilities and observed outcomes. Statistical significance for conventional analyses was established at $p < .05$ using two-tailed tests. The overall analytical framework was designed to maximize predictive accuracy while maintaining transparency and clinical interpretability, thereby supporting the identification of university students at elevated psychological risk through an evidence-based machine learning approach.

3. Findings and Results

A total of 1,248 undergraduate students from five Colombian universities completed all study measures and were included in the final analyses. Participants ranged in age from 18 to 29 years ($M = 21.46$, $SD = 2.71$). Of the total sample, 701 students (56.2%) were female and 547 (43.8%) were male. Regarding academic level, 18.9% were first-year students, 20.5% were second-year students, 22.1% were third-year students, 20.4% were fourth-year students, and 18.1% were fifth-year or higher students. Students represented diverse academic disciplines, including health sciences (24.6%), engineering (22.8%), social sciences (19.7%), business administration (14.9%), education (10.8%), and humanities (7.2%). Based on the predefined classification criteria combining depressive symptoms, academic stress, and sleep quality, 342 students (27.4%) were classified as belonging to the high-risk group, whereas 906 students (72.6%) were categorized as lower-risk. Missing data accounted for less than 2% of all observations and were successfully imputed prior to analysis. Examination of skewness and kurtosis values indicated acceptable univariate normality for all predictor variables,

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E-ISSN: 3041-8518

while variance inflation factors ranged from 1.18 to 2.06, demonstrating the absence of problematic multicollinearity among the independent variables.

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4
Academic Stress	126.81	22.45	—			
Sleep Quality	7.94	3.41	.58**	—		
Self-Efficacy	28.16	5.39	-.55**	-.46**	—	
Depression	10.27	5.86	.69**	.61**	-.63**	—

Table 1 presents the descriptive statistics and Pearson correlation coefficients for all study variables. Students reported moderate-to-high levels of academic stress ($M = 126.81$, $SD = 22.45$), while the average Pittsburgh Sleep Quality Index score ($M = 7.94$, $SD = 3.41$) exceeded the conventional clinical threshold for poor sleep quality, suggesting that sleep disturbances were common within the sample. Mean self-efficacy scores indicated moderate perceived confidence in coping with academic demands ($M = 28.16$, $SD = 5.39$), whereas depression scores reflected considerable variability across participants ($M = 10.27$, $SD = 5.86$). Correlation analyses demonstrated that academic stress exhibited the strongest positive association with depression ($r = .69$, $p < .001$), indicating that students experiencing greater academic stress also reported substantially higher depressive symptoms. Poor sleep quality was positively associated with both academic stress ($r = .58$, $p < .001$) and depression ($r = .61$, $p < .001$), supporting the close relationship between sleep disturbances and psychological distress. Conversely, self-efficacy demonstrated significant negative correlations with academic stress ($r = -.55$, $p < .001$), poor sleep quality ($r = -.46$, $p < .001$), and depression ($r = -.63$, $p < .001$), suggesting that greater confidence in personal abilities may serve as an important protective factor against psychological vulnerability. None of the correlations exceeded .80, confirming that the predictor variables contributed unique information suitable for machine learning model development.

Table 2

Performance of the Support Vector Machine Classification Model

Performance Metric	Training Set	Testing Set
Accuracy	94.7%	92.4%
Precision	92.8%	90.6%
Recall (Sensitivity)	91.5%	89.1%
Specificity	95.8%	93.7%
F1-Score	92.1%	89.8%
Balanced Accuracy	93.7%	91.4%
Matthews Correlation Coefficient	0.86	0.81
ROC-AUC	0.972	0.951
Brier Score	0.058	0.074

The Support Vector Machine classifier demonstrated excellent predictive performance across both training and independent testing datasets. The optimized radial basis function model achieved an overall classification accuracy of 94.7% during training and maintained a high testing accuracy of 92.4%, indicating strong generalizability and minimal evidence of overfitting. Precision reached 90.6% within the testing dataset, demonstrating that the vast majority of students identified as high-risk were correctly classified. Similarly, recall of 89.1% indicated that the model successfully detected nearly nine out of every ten genuinely high-risk students. The specificity value of 93.7% reflected excellent discrimination of lower-risk students, minimizing false-positive classifications. The testing F1-score of 89.8% further confirmed an optimal balance between sensitivity and precision. The ROC-AUC value of

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0.951 demonstrated outstanding discriminatory ability, indicating that the model could accurately distinguish between high-risk and lower-risk students across a broad range of classification thresholds. Furthermore, the low Brier score (0.074) suggested excellent calibration, meaning that predicted probabilities closely matched observed classification outcomes. Collectively, these findings indicate that the Support Vector Machine algorithm achieved robust and clinically meaningful predictive accuracy for identifying psychologically vulnerable university students.

Table 3

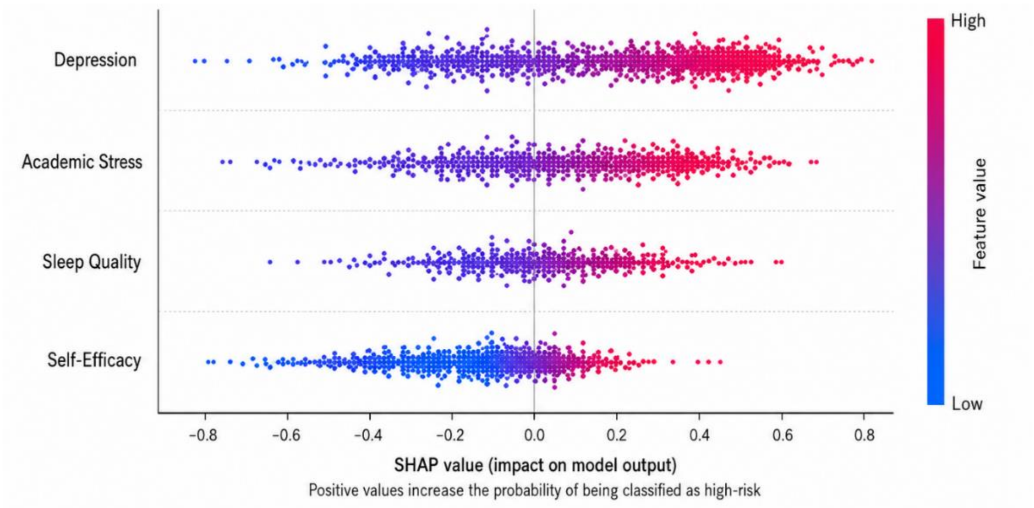
Feature Importance Based on SHAP Analysis

Predictor	Mean Absolute SHAP Value	Relative Importance (%)	Rank
Depression	0.421	34.9	1
Academic Stress	0.357	29.6	2
Sleep Quality	0.265	21.9	3
Self-Efficacy	0.164	13.6	4

Feature importance analysis using SHAP values revealed that depression was the strongest contributor to the Support Vector Machine classification model, accounting for approximately 34.9% of the model's overall predictive contribution. This finding indicates that depressive symptom severity exerted the greatest influence on determining whether a student was classified as high-risk. Academic stress emerged as the second most influential predictor, contributing 29.6% of the model's predictive information, emphasizing the critical role of academic demands and educational pressures in psychological vulnerability among university students. Sleep quality represented the third strongest predictor, accounting for 21.9% of model importance, suggesting that persistent sleep disturbances substantially increased the probability of high-risk classification. Although self-efficacy demonstrated the lowest relative importance among the four predictors, it nevertheless contributed 13.6% of the overall predictive capacity, indicating that positive psychological resources remain meaningful protective factors within the classification framework. The relatively balanced distribution of feature importance demonstrates that the machine learning algorithm relied upon the combined influence of all psychological variables rather than depending exclusively on a single predictor. This multidimensional pattern supports the conceptualization of psychological risk as a complex phenomenon arising from interactions among emotional distress, academic burden, behavioral health, and personal coping resources.

Figure 1

SHAP Summary Plot Illustrating the Relative Contribution of Academic Stress, Sleep Quality, Self-Efficacy, and Depression to Support Vector Machine Classification of High-Risk University Students



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E-ISSN: 3041-8518

The SHAP summary plot demonstrated clear differences in the influence of individual predictor variables on classification outcomes. Higher depression scores consistently shifted predictions toward the high-risk category and showed the largest absolute SHAP values across participants. Elevated academic stress similarly increased the likelihood of high-risk classification, particularly among students simultaneously reporting poor sleep quality. Poor sleep quality exerted a moderate but consistent positive influence on predicted risk, whereas higher self-efficacy scores shifted predictions toward the lower-risk category, reflecting their protective role within the classification model. The distribution of SHAP values further illustrated considerable inter-individual variability, suggesting that although depression was generally the strongest predictor, different combinations of psychological characteristics contributed to classification decisions across individual students. The visualization also confirmed that the Support Vector Machine model captured complex nonlinear relationships among predictors, with depression and academic stress exhibiting stronger effects at higher values, while self-efficacy showed progressively greater protective influence as scores increased. Overall, the explainability analysis demonstrated that the machine learning model produced clinically interpretable predictions grounded in meaningful psychological constructs, thereby supporting its potential application for early identification and targeted intervention among university students at elevated mental health risk.

4. Discussion

The present study developed and evaluated a Support Vector Machine classification model for identifying high-risk university students in Colombia using academic stress, sleep quality, self-efficacy, and depression as predictors. The findings showed that 27.4% of the students were classified as high-risk according to the combined criteria of depressive symptoms, severe academic stress, and poor sleep quality. This proportion indicates that psychological vulnerability is not a marginal phenomenon in the university context, but a substantial issue affecting more than one quarter of the sample. The descriptive results further demonstrated that students reported moderate-to-high academic stress, clinically relevant sleep difficulties, moderate self-efficacy, and considerable variability in depressive symptoms. These findings are consistent with the growing body of Latin American research showing that university students experience significant psychological burden, particularly in contexts shaped by academic pressure, post-pandemic educational changes, and increasing psychosocial demands (Huamani-Calloapaza et al., 2024; Merchán-Villafuerte et al., 2024; Restrepo et al., 2022). The observed prevalence of risk also aligns with studies emphasizing that student well-being must be considered a central component of academic adaptation and institutional quality rather than a peripheral health concern (Brito et al., 2024; Garcés et al., 2023). Therefore, the present findings reinforce the need for universities to move beyond reactive counseling models and toward systematic, data-informed early identification strategies.

The correlation results showed a coherent pattern among the psychological variables. Academic stress was strongly and positively associated with depression, indicating that students who perceived greater academic pressure also reported more severe depressive symptoms. This finding supports prior evidence suggesting that academic stress is a central factor in student maladjustment and may negatively affect both emotional functioning and educational performance (Castillo, 2024; Tejada et al., 2024). Academic stress may contribute to depression through several mechanisms, including persistent rumination about performance, perceived lack of control, chronic fatigue, reduced reward from academic engagement, and repeated exposure to evaluation-related failure or fear of failure. In virtual or hybrid learning contexts, these mechanisms may be intensified by uncertainty, reduced interpersonal support, and greater responsibility for self-regulation (Campas et al., 2022; Vilca et al., 2022). The positive association between academic stress and poor sleep quality also supports previous findings indicating that stress and sleep disturbance frequently co-occur among students (Buri & Zumbaña, 2023; Villasboa et al., 2025). Stress may delay sleep onset, increase physiological arousal, and promote intrusive academic thoughts at night, while insufficient sleep may reduce attention, emotional regulation, and coping capacity, thereby increasing vulnerability to further academic stress.

Poor sleep quality was also positively related to depression, confirming the importance of sleep as both a behavioral and psychological risk marker among university students. Sleep problems may directly worsen mood through fatigue, reduced cognitive control, irritability, and impaired emotion regulation. At the same time, depression may disrupt sleep through negative rumination, low motivation, and altered daily routines. Previous studies have similarly demonstrated that sleep quality is closely related to academic

JARAC Assessment and Research in Applied Counseling E-ISSN: 3041-8518

functioning and psychological health among medical and university students (Maria del Mar Duque, 2022; Mora et al., 2022). The present findings extend this evidence by showing that sleep quality is not only associated with distress but also contributes meaningfully to predictive classification of high-risk students. This is important because sleep problems are often normalized in university culture as a consequence of academic commitment, despite their potential role in psychological deterioration. The current results suggest that poor sleep should be interpreted as an early warning indicator rather than as a routine feature of student life. This interpretation is consistent with studies showing that lifestyle factors, mental health indicators, and perceived quality of life interact in determining student well-being (Martins et al., 2024).

Self-efficacy demonstrated significant negative correlations with academic stress, poor sleep quality, and depression. This pattern indicates that students with stronger confidence in their ability to manage challenges were less likely to report psychological and behavioral indicators of risk. The protective role of self-efficacy may be explained by its influence on appraisal, persistence, coping, and problem-solving. Students with higher self-efficacy may interpret academic tasks as demanding but manageable, whereas students with lower self-efficacy may perceive the same tasks as threatening, overwhelming, or uncontrollable. This finding is consistent with intervention research showing that strengthening academic skills can reduce stress and improve self-efficacy among university students (Chust-Hernández et al., 2024). It also aligns with evidence emphasizing resilience and adaptive coping as important protective resources in higher education, particularly among students in demanding disciplines such as nursing and health sciences (Everly & Monsivais, 2022; Kelly Liset De la Cruz, 2024). In the context of the present study, self-efficacy did not eliminate the effects of stress, sleep disturbance, or depression, but it contributed unique protective information to the classification model. This suggests that prevention programs should not only reduce symptoms but also enhance perceived competence and academic agency.

The Support Vector Machine model demonstrated strong classification performance, with a testing accuracy of 92.4%, precision of 90.6%, recall of 89.1%, specificity of 93.7%, F1-score of 89.8%, and ROC-AUC of 0.951. These results indicate that the model achieved excellent discrimination between high-risk and lower-risk students. The high recall value is particularly important because, in mental health screening, failure to identify genuinely high-risk students may delay support and increase the probability of academic failure, emotional deterioration, or withdrawal. The high specificity also indicates that the model was able to minimize unnecessary false-positive classifications, which is relevant for institutional settings where counseling resources may be limited. These findings support the value of machine learning methods for student mental health screening because psychological risk is rarely determined by one isolated variable. Instead, risk emerges from nonlinear combinations of symptoms, stressors, lifestyle factors, and protective resources. This interpretation is supported by previous studies showing that student mental health and academic outcomes are influenced by multiple psychological, personal, contextual, and behavioral factors (Cabezas et al., 2023; Rodríguez & Barajas, 2022; Silva et al., 2023). The present results therefore suggest that SVM classification can complement traditional statistical models by translating multidimensional psychological data into individualized risk predictions.

The SHAP explainability analysis showed that depression was the most influential predictor in the classification model, followed by academic stress, sleep quality, and self-efficacy. The dominance of depression is theoretically expected because depressive symptoms directly reflect emotional suffering and functional impairment. Prior research among Colombian university students and other Latin American student populations has documented the relevance of depressive symptoms during and after the pandemic (Huamani-Calloapaza et al., 2024; Restrepo et al., 2022). Furthermore, studies have shown that depression, anxiety, and stress may negatively affect academic performance and student functioning, supporting the role of depression as a primary risk indicator (Jaimes-Medrano et al., 2024; Merchán-Villafuerte et al., 2024). However, the model did not rely exclusively on depression. Academic stress contributed almost one third of the model's predictive information, indicating that students' perception of academic burden was central to risk classification. This finding is consistent with evidence that academic stress predicts poorer educational outcomes and psychological vulnerability (Castillo, 2024; Tejada et al., 2024). It also suggests that depression among students should not be interpreted only as an individual clinical problem, but partly as a response to academic environments that may exceed students' coping resources.

Sleep quality emerged as the third most important predictor, confirming that behavioral health indicators provide substantial information in student risk classification.

This result is consistent with studies showing that sleep is associated with academic performance, stress, and student health (Maria del Mar Duque, 2022; Mora et al., 2022; Villasboa et al., 2025). In practical terms, the inclusion of sleep quality improves the ecological validity of the model because sleep is closely tied to daily academic routines, technology use, physical activity, and emotional regulation. Research on technology use in university contexts has shown that digital behaviors may influence academic performance and daily functioning, and excessive or poorly regulated mobile device use may contribute to sleep disruption and reduced academic effectiveness (Enríquez-Mayanger et al., 2024; Monzón et al., 2022). In addition, evidence on healthy university initiatives and physical activity suggests that lifestyle-oriented interventions can improve mental and physical health among young people (Sanchís-Soler et al., 2022). The present findings therefore support the view that university mental health screening should not focus exclusively on symptoms but should also include modifiable health behaviors such as sleep routines, digital habits, and physical activity.

Self-efficacy had the lowest relative importance among the four predictors, but its contribution remained meaningful and theoretically important. Unlike depression, academic stress, and sleep quality, which primarily functioned as risk indicators, self-efficacy represented a protective resource. The SHAP pattern suggested that higher self-efficacy shifted predictions toward the lower-risk category, indicating that students' perceived capacity to cope may reduce the probability of high-risk classification even when other stressors are present. This finding is consistent with research emphasizing resilience, coping, and psychological well-being as important factors in student adjustment (Everly & Monsivais, 2022; Kelly Liset De la Cruz, 2024). It is also compatible with evidence that interventions targeting study skills and academic self-efficacy can reduce stress among first-year students (Chust-Hernández et al., 2024). Therefore, the relatively smaller importance of self-efficacy should not be interpreted as evidence of low relevance. Rather, it suggests that self-efficacy may operate as a buffering variable whose influence becomes especially important in interaction with academic stress, depressive symptoms, and sleep disturbance.

The findings also have implications for intervention design. Prior research has shown that affective symptoms among university students may respond to psychological interventions such as mindfulness-based approaches, while physical exercise may contribute to reducing depression and improving emotional functioning (González, 2024; Obando & Peralta-Eugenio, 2023). The present study contributes to this literature by suggesting that machine learning classification can help identify which students may need such interventions most urgently. Instead of offering general well-being programs without risk differentiation, universities could use predictive screening to direct resources toward students with specific profiles, such as those characterized by high depressive symptoms and academic stress, poor sleep and low self-efficacy, or combined emotional and behavioral risk. This is especially relevant in post-pandemic higher education, where student needs may be heterogeneous and institutional resources are often insufficient to provide intensive services to all students. Research on attitudes toward COVID-19 and student health further indicates that pandemic-related experiences continue to shape student well-being and should be considered in contemporary university health strategies (Javes et al., 2024). The present model therefore offers a practical framework for integrating psychological assessment, behavioral health monitoring, and preventive academic support.

5. Conclusion

Overall, the study advances the literature by demonstrating that academic stress, sleep quality, self-efficacy, and depression can be integrated into a high-performing SVM classification model for detecting high-risk university students in Colombia. The findings support a multidimensional understanding of student risk in which depressive symptoms serve as the strongest direct indicator, academic stress reflects contextual and educational burden, sleep quality captures behavioral and physiological vulnerability, and self-efficacy represents a protective psychological resource. The results are consistent with previous evidence showing that student mental health is shaped by complex interactions among emotional distress, academic functioning, lifestyle, technology use, coping, resilience, and institutional conditions (Cabezas et al., 2023; Castillo-Díaz et al., 2022; Garcés et al., 2023; Martins et al., 2024). By combining predictive accuracy with interpretability, the study provides an empirically grounded basis for early identification systems that are not only statistically robust but also meaningful for counseling, academic advising, and student support services.

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

6. Limitations & Suggestions

The present study has several limitations. First, the cross-sectional design prevents causal interpretation, meaning that the findings cannot determine whether academic stress, sleep quality, self-efficacy, or depression precede high-risk status or whether these variables develop simultaneously. Second, all variables were measured using self-report instruments, which may be affected by social desirability, recall bias, or individual differences in symptom awareness. Third, although the sample was large and included students from multiple Colombian universities, the findings may not be fully generalizable to students in rural institutions, technical programs, postgraduate education, or universities with different socioeconomic and cultural conditions. Fourth, the high-risk classification was based on predefined psychological criteria rather than structured clinical interviews, and therefore the model should be interpreted as a screening tool rather than a diagnostic instrument. Finally, the model included four theoretically important predictors, but other relevant factors such as social support, financial strain, substance use, physical activity, trauma history, academic performance, and access to counseling services were not incorporated.

Future research should use longitudinal designs to determine whether the identified predictors can forecast later deterioration in mental health, academic failure, dropout intention, or actual university withdrawal. Future studies should also validate the model across different Colombian regions and other Latin American countries to examine its cultural stability and institutional generalizability. Additional research could compare Support Vector Machine performance with other machine learning algorithms, including random forest, gradient boosting, logistic regression with regularization, neural networks, and ensemble models. Future models should also incorporate broader variables such as family support, socioeconomic status, digital technology use, physical activity, academic records, help-seeking behavior, and prior mental health history. Mixed-methods studies may also be valuable for understanding how students subjectively experience the combination of academic stress, sleep problems, depressive symptoms, and self-efficacy. Finally, future research should evaluate whether predictive screening followed by targeted intervention improves mental health and academic outcomes compared with usual university support services.

The findings suggest several practical implications for universities. Higher education institutions should implement routine psychological screening systems that assess academic stress, sleep quality, depressive symptoms, and self-efficacy at key points during the academic year, especially at entry, before examination periods, and after major academic transitions. Counseling centers should prioritize students whose profiles show combined emotional, academic, and sleep-related risk rather than relying only on students' voluntary help-seeking. Academic departments should also reduce avoidable stressors by improving assessment planning, workload coordination, academic advising, and early referral pathways. Interventions should combine symptom reduction with skills training, including sleep hygiene education, stress management, study planning, emotional regulation, self-efficacy enhancement, and referral to clinical care when needed. Finally, universities should use predictive models ethically and transparently, ensuring confidentiality, voluntary participation, human oversight, and the use of classification results for supportive rather than punitive purposes.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

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.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

Authors' Contributions

All authors equally contributed in this article.

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

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JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518