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Predicting Depression Among College Students Through Academic, Lifestyle, and Smartphone Factors

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Abstract

Purpose: This study examines how academic, lifestyle, and smartphone usage factors jointly predict depression severity among college students in Nepal, with the aim of identifying key risk and protective determinants of mental health.

Design/methodology/approach: A quantitative, cross-sectional survey was administered to 394 college students. The questionnaire captured academic stress, lifestyle behaviors, and smartphone habits, alongside the Patient Health Questionnaire (PHQ-9) to measure depressive symptoms. Data were analyzed using Python through descriptive, correlational, and multiple regression techniques to identify significant predictors.

Findings and conclusion: Results showed that 62% of students experienced mild to moderate depression. Multiple regression analysis ($R^2 = 0.56$) identified sleep quality ($\beta = -0.37$), academic stress ($\beta = 0.29$), and social support ($\beta = -0.23$) as the strongest predictors. Nighttime smartphone use ($\beta = 0.21$) and low physical activity ($\beta = -0.18$) also had significant effects. The study concludes that poor sleep, academic overload, and weak social ties elevate depressive symptoms, while social support and healthy lifestyle behaviors act as protective factors.

Implications: The findings underscore the importance of holistic student mental health strategies combining stress management, digital hygiene, and lifestyle promotion.

Originality/value: This research provides one of the first integrative, data-driven analyses in Nepal linking academic, behavioral, and technological domains to student depression, offering actionable insights for higher education institutions to strengthen well-being initiatives.

Keywords: depression, college students, academic stress, lifestyle factors, smartphone use, mental health

1. Introduction

Depression is a pervasive mental health disorder characterized by persistent sadness, loss of interest in daily activities, and impaired cognitive and emotional functioning (Wuthrich et al., 2020). Globally, over 1 billion people live with a mental disorder, with depression and anxiety being the most prevalent, and nearly half of all mental disorders begin before the age of 18 (World Mental Health Today, 2025). Within this context, college students constitute a particularly susceptible group, as they experience the multifaceted transition from adolescence to adulthood, an important developmental stage often accompanied by intensified academic demands, evolving social relationships, and growing personal independence (Jafarlou et al., 2022). These combined pressures substantially increase the risk of developing depressive symptoms, which, if left untreated, can profoundly affect students' academic performance, interpersonal relationships, and overall psychological well-being.

The college environment exposes students to a variety of psychological and situational pressures. Academic expectations, including heavy workloads, examinations, and uncertainty about future careers, are among the most frequently cited sources of stress (Saleh et al., 2017). While manageable stress can enhance motivation and performance, chronic or excessive academic pressure often overwhelms students' coping mechanisms, leading to anxiety, sleep disturbances, and depressive symptoms. Furthermore, academic stress seldom operates in isolation, it often interacts with lifestyle behaviors such as sleep quality, physical activity, and social engagement, amplifying its negative impact on mental health (Zara & Monteiro, 2021). Lifestyle factors play a crucial role in shaping psychological resilience and vulnerability (Zaman et al., 2019). Adequate sleep, regular physical activity, and balanced nutrition are well-established protective factors against depression. Conversely, poor sleep quality and physical inactivity are consistently linked to emotional dysregulation, reduced cognitive performance, and heightened depressive symptomatology (Kvelde et al., 2013). Social support also emerges as a vital determinant of mental health, serving as a buffer against psychological distress (Tindle et al., 2022). Students with strong emotional and interpersonal support networks typically exhibit greater coping capacity and lower levels of depression compared to those with limited social connections.

In recent years, digital technology, particularly smartphone use, has introduced a new dimension to student mental health (Haidt & Allen, 2020). Smartphones provide convenience and connectivity but can also contribute to psychological strain. Excessive or maladaptive use, such as prolonged screen exposure or nighttime phone use, disrupts sleep patterns, reduces physical activity, and fosters social comparison, all of which have been associated with depressive symptoms (Wang et al., 2017). While moderate use for academic and social purposes may be neutral or even beneficial, problematic usage patterns, especially passive engagement with social media, have been shown to exacerbate feelings of loneliness, anxiety, and low mood (Jensen et al., 2019).

Despite the growing body of research examining depression among college students, relatively few studies have adopted an integrative approach that considers demographic, academic, lifestyle, and smartphone usage factors simultaneously. Most prior investigations have focused on isolated domains, limiting understanding of how these factors interact to predict depression risk (Joormann & Stanton, 2016). There remains a need for empirical models that quantify the combined predictive power of these variables, enabling early identification of at-risk students and the design of targeted, evidence-based interventions.

Addressing this gap, the present study employs a quantitative, cross-sectional design to analyze the interplay of demographic, academic, lifestyle, and smartphone usage variables in predicting depression among college students. Specifically, the study aims to: (1) determine the prevalence and severity of depressive symptoms, (2) identify key demographic, academic, lifestyle, and smartphone-related predictors, (3) evaluate their combined predictive power using multiple regression analysis, Uyanık and Güler (2013), and (4) highlight protective factors that mitigate depressive symptoms (Dejonckheere et al., 2018). By integrating these domains, this research contributes to a comprehensive understanding of depression among students and provides actionable insights for educators, mental health professionals, and policymakers in developing holistic well-being strategies within academic environments.

1.1 Research Objective

To examine how demographic, academic, lifestyle, and smartphone factors influence and predict depression among college students, and identify protective elements to support mental health.

1.2 Research Questions

How do various personal, academic, lifestyle, and smartphone related factors predict depression severity and identify protective strategies for improving college students' mental health?

2. Literature Review

Depression among college students has become a growing global concern, as it significantly affects their emotional stability, academic performance, and overall quality of life (Wuthrich et al., 2021). Numerous studies worldwide have investigated the causes and correlates of depression, identifying academic stress, poor lifestyle habits, and excessive smartphone use as major contributing factors. However, most existing research tends to focus on these factors independently, thereby overlooking the complex interactions that jointly influence students' mental health. This limited approach has left an important gap in understanding how academic, lifestyle, and technological behaviors collectively predict depressive symptoms, particularly among young adults navigating the challenges of college life.

Academic pressure has been identified as one of the most consistent predictors of student depression. Saleh et al. (2017) found that students facing continuous academic workload, examinations, and performance expectations often experience chronic stress that can lead to emotional exhaustion and depressive moods. Similarly, Zara and Monteiro (2021) emphasized that unmanaged academic stress weakens students' coping mechanisms, leading to higher anxiety and mental fatigue. Yet, while such studies clearly highlight the impact of academic challenges, they often fail to account for how these pressures interact with lifestyle factors like sleep, exercise, and social support - factors that could either intensify or alleviate depression risk.

Lifestyle behaviors are another crucial determinant of mental health, with prior studies showing that adequate sleep, regular physical activity, and strong social connections act as protective buffers against depression. John et al. (2019) and Kvelde et al. (2013) reported that insufficient sleep and physical inactivity contribute to emotional instability and cognitive decline, while supportive relationships enhance psychological resilience. Miloseva et al. (2017) further demonstrated that social support serves as a key moderator, reducing the likelihood of depression among students who face academic or personal difficulties. Despite these insights, many prior investigations have treated lifestyle variables as secondary concerns rather than as core predictive elements. As a result, there is limited evidence on how lifestyle patterns combine with academic and digital factors to influence depression severity.

In recent years, smartphone usage has also emerged as an influential behavioral factor linked to mental health outcomes. Dissing et al. (2022) observed that excessive smartphone use, especially during nighttime, disrupts sleep and increases psychological distress. Thorisdottir et al. (2019) similarly noted that passive use of social media fosters comparison, isolation, and lower mood. However, the literature presents mixed findings-some studies suggest that moderate or purpose-driven smartphone use can enhance communication and emotional support, indicating that not all forms of digital engagement are harmful (Kushlev, 2015). This inconsistency underscores the need for more comprehensive models that distinguish between adaptive and maladaptive smartphone behaviors when assessing their impact on depression.

Despite this growing body of international evidence, such integrative studies remain scarce in the Nepalese context. Most prior research conducted in Nepal has primarily focused on limited demographic or academic stress variables, often neglecting the combined role of lifestyle and smartphone usage patterns. Moreover, Nepal’s unique socio-cultural and educational environment, coupled with increasing digital dependence among youth, may shape depression differently compared to Western contexts (Khatiwada, 2024). Therefore, a holistic approach that examines these interrelated factors simultaneously is crucial for generating context-specific insights into student mental health.

The present study addresses this critical gap by integrating academic, lifestyle, and smartphone usage variables within a single predictive framework to understand depression among Nepalese college students. By employing quantitative analysis techniques such as correlation and multiple regression, the study identifies which factors most strongly predict depressive symptoms and which serve as protective elements (Sedgwick, 2012; Uyanık & Güler, 2013). This integrated approach not only builds upon the existing international literature but also contributes new, localized evidence relevant to Nepal’s higher education context. Ultimately, this study holds significant importance as it advances both theoretical understanding and practical application, offering a foundation for developing evidence-based interventions and mental health strategies tailored to the needs of Nepalese students.

3. Methodology

3.1 Research Design

This study employed a quantitative, cross-sectional survey design to examine the relationships between academic, lifestyle, and smartphone usage factors and depressive symptoms among college students. The design allowed for the analysis of both predictive and associative relationships between multiple independent variables and depression severity, as measured by the Patient Health Questionnaire (PHQ-9) (Urtasun et al., 2019). A structured online questionnaire was utilized to collect self-reported data, ensuring broad accessibility and participant anonymity.

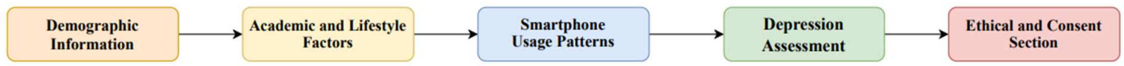
3.2 Population and Sampling

The target population consisted of students enrolled in higher education institutions, including those pursuing undergraduate programs, higher secondary (+2) studies, and various skill enhancement courses. A stratified sampling technique (Singh & Masuku, n.d.) was employed to group participants based on academic level and discipline, ensuring proportional representation across different study years. Data were collected through online student forums, academic networks, and institutional groups. In total, 394 valid responses were obtained for analysis. This sample size was deemed adequate to ensure statistical reliability and representativeness of the broader student population.

3.3 Research Instrument

Data were collected through a structured questionnaire designed in Google Forms, consisting of five major sections:

Figure 1: *Questionnaire Sections*



Demographic Information **-** Age, gender, year of study, living arrangement, and prior diagnosis or treatment for depression.

Academic and Lifestyle Factors **-** Average weekly study hours, perceived academic stress, average sleep duration, sleep quality, weekly physical activity, and perceived social support.

Smartphone Usage Patterns **-** Average daily screen time (weekdays and weekends), duration of continuous usage sessions, frequency of nighttime smartphone use, and primary purpose of use (e.g., study, social media, entertainment).

Depression Assessment **-** The Patient Health Questionnaire (PHQ-9) was used to measure depressive symptoms. Each item was scored from 0 ("not at all") to 3 ("nearly every day"), with total scores ranging from 0 to 27 and categorized into standard severity levels.

Ethical and Consent Section **-** Participants provided informed digital consent before proceeding, confirming voluntary participation and understanding of confidentiality. Mental health helpline information (1166 National Suicide Prevention Helpline, TPO Nepal, and 1145 Khabar Garaun Helpline) was provided at the end of the survey to support participants experiencing emotional distress.

3.4 Data Analysis

Data were analyzed using Python, employing libraries such as pandas, scipy, seaborn, matplotlib, and statsmodels (Stancin & Jovic, 2019). The analysis followed a structured procedure.

First, data preparation involved cleaning the dataset, removing incomplete responses, and coding categorical variables for analysis.

Second, descriptive statistics, including frequencies, percentages, means, and standard deviations, were computed for all demographic, academic, lifestyle, smartphone usage, and PHQ-9 variables.

Third, inferential tests were conducted: Chi-square tests (Pandis, 2016), assessed associations between categorical predictors (e.g., gender, living situation, social support) and depression severity.

Fourth, Pearson's correlation coefficients were calculated to explore linear relationships between lifestyle variables and PHQ-9 scores. Finally, multiple linear regression analysis was conducted to identify significant predictors of depression severity. Prior to interpretation, all regression assumptions-including linearity, homoscedasticity, independence of residuals, and absence of multicollinearity-were verified.

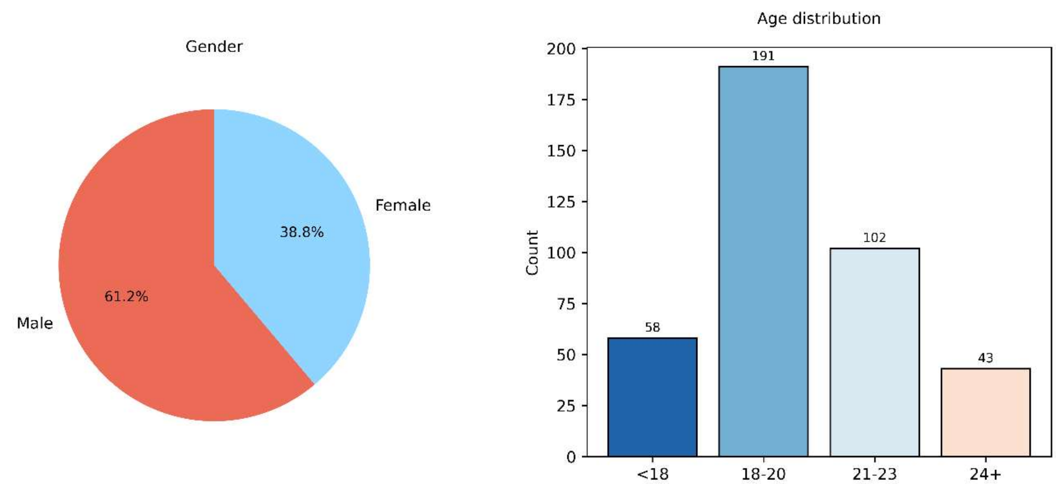
3.5 Ethical Considerations

The study ensured ethical compliance by obtaining digital informed consent, maintaining anonymity, and allowing voluntary participation. Participants were informed of their right to withdraw at any time, and mental health resources were provided to support those experiencing distress.

4. Results

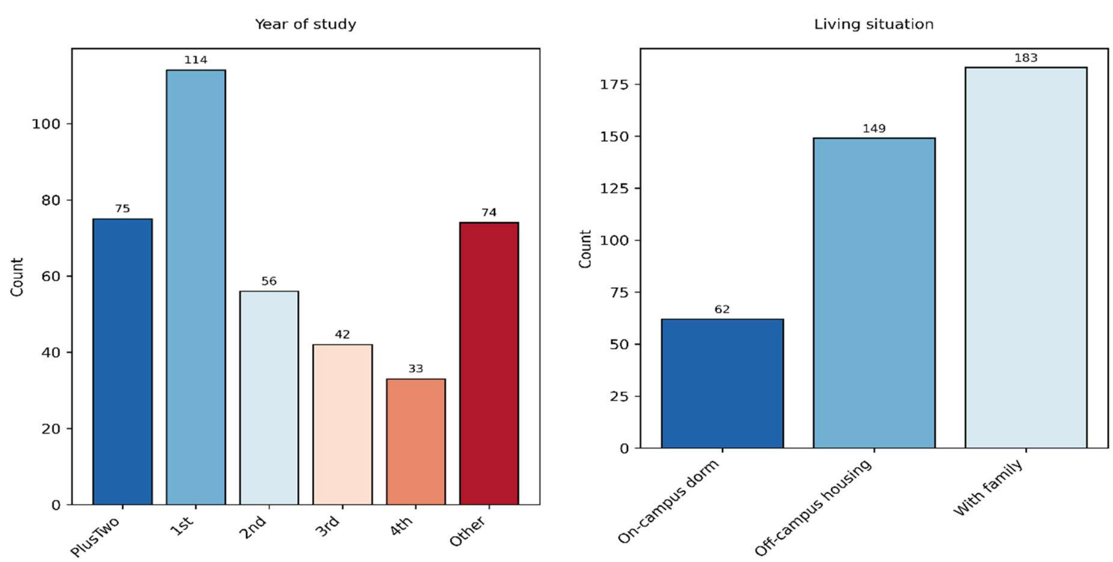
4.1 Descriptive Statistics

Figure 2: *Gender and Age Distribution*



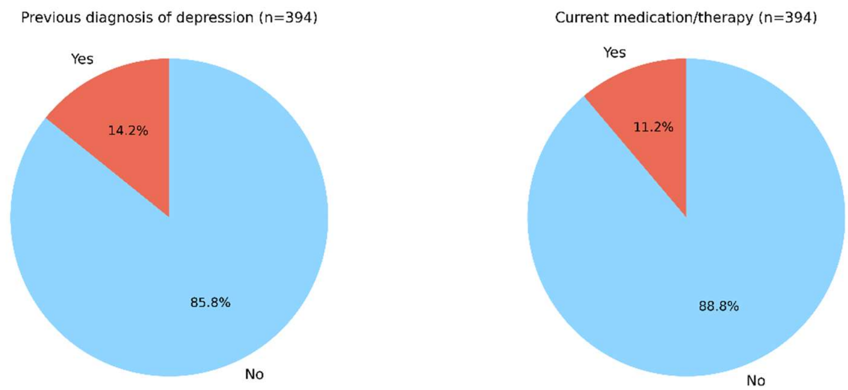
A total of 394 valid responses were analyzed in this study, which aimed to examine the impact of academic, lifestyle, and smartphone usage factors on depressive symptoms among college students. The sample included 61.2% male and 38.8% female participants, reflecting a slight male predominance. Participants' ages ranged from 16 to 25 years, with the majority (48.5%) aged 18-20 years, followed by 25.9% aged 21-23, 14.7% under 18, and 10.9% aged 24 and above, representing a typical college-age distribution.

Figure 3: *Year of study and Living situation*



In terms of academic standing, the majority of respondents were undergraduate students (62.2%), followed by those enrolled in higher secondary (+2) programs (19.0%), and a smaller proportion categorized as "Other" (18.8%), representing individuals participating in nondegree or skill-based courses. Regarding living arrangements, 46.4% of participants resided with their families, 37.9% lived in off-campus housing, and 15.7% stayed in on-campus dormitories. Additionally, 14.2% of respondents reported having a previous diagnosis of depression, while 11.2% indicated that they were currently receiving treatment through medication or psychotherapy.

Figure 4: *Previous Diagnosis and Current Medication*



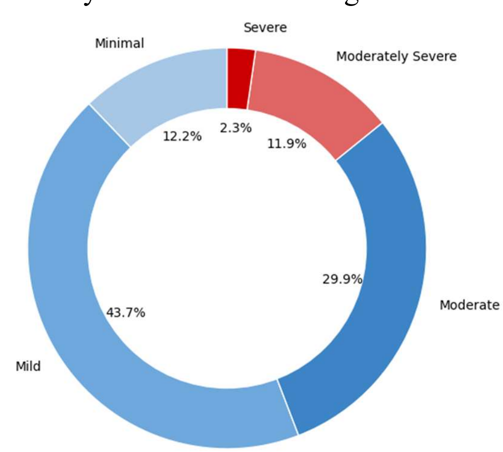
Lifestyle variables indicated moderate risk factors for depressive symptoms. Participants reported an average sleep duration of 6.4 hours per night (SD = 1.3), with a mean sleep quality rating of 3.1 on a 1-5 scale. Weekly physical activity averaged 105 minutes (SD = 67.2), and the mean perceived academic stress score was 3.7 (SD = 1.0), reflecting moderate to high stress levels.

Smartphone usage patterns revealed that participants spent an average of 6.8 hours per weekday (SD = 2.4) and 8.2 hours per weekend day (SD = 2.8) on their devices. Nighttime use after 10 PM was common, with 63% reporting "often" or "always" using their smartphones at night.

4.2 Distribution of Depression Severity (PHQ-9)

Figure 5: *Distribution of Depression Severity (PHQ-9)*

Depression severity was measured using the Patient Health Questionnaire (PHQ-9),



with total scores categorized as follows: *0-4 (Minimal)*, *5-9 (Mild)*, *10-14 (Moderate)*, *15-19*

(Moderately Severe), and *20-27 (Severe)*. The majority of students scored within the *Mild* to *Moderate* range, suggesting that depressive symptoms were relatively common among participants, though not always at clinical severity levels.

4.3 Bivariate Inferential Analysis

Chi-square tests were conducted to assess associations between categorical predictors and depression severity levels.

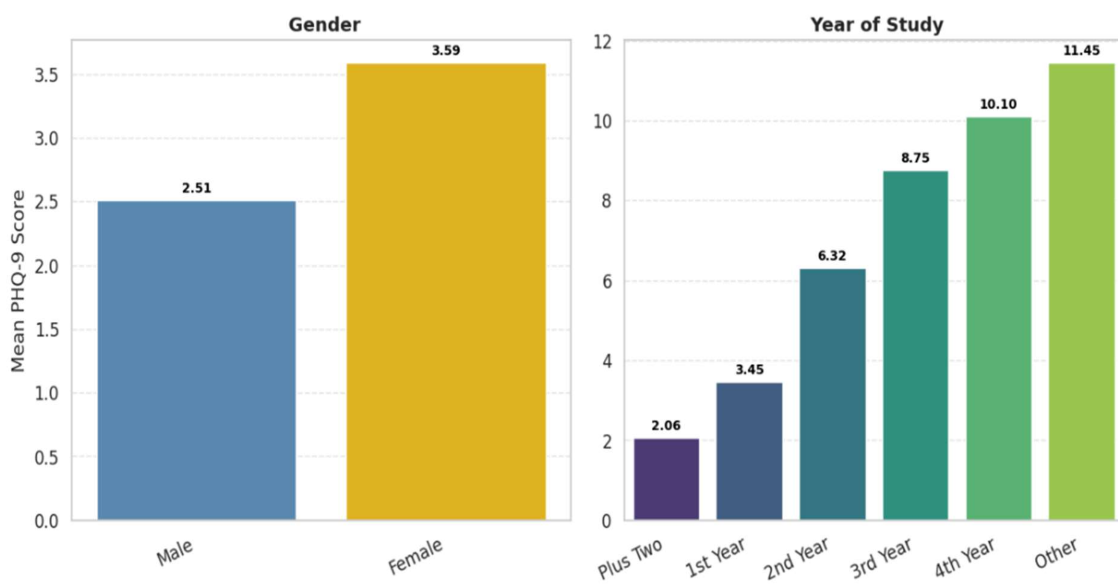
Table 1: *Chi-square Test*

Variable	p-value	Interpretation
Gender vs Depression_Level	0.077	No significant association between gender and depression levels, though slight differences may exist.
Year_of_Study vs Depression_Level	0.016	Statistically significant**.** This suggests that depression severity varies across academic years, with certain years showing higher prevalence than others.
Living_Situation vs Depression_Level	0.038	Statistically significant**.** This indicates that students' living arrangements are associated with depression severity, with some living situations potentially increasing risk.
Social_Support vs Depression_Level	0.041	Statistically significant**.** This implies that social support is associated with depression severity, with higher support likely reducing depressive symptoms.

4.4: Mean PHQ-9 scores Across Variables

Further examination of continuous PHQ-9 scores provided additional insight into the patterns of depressive symptoms among students:

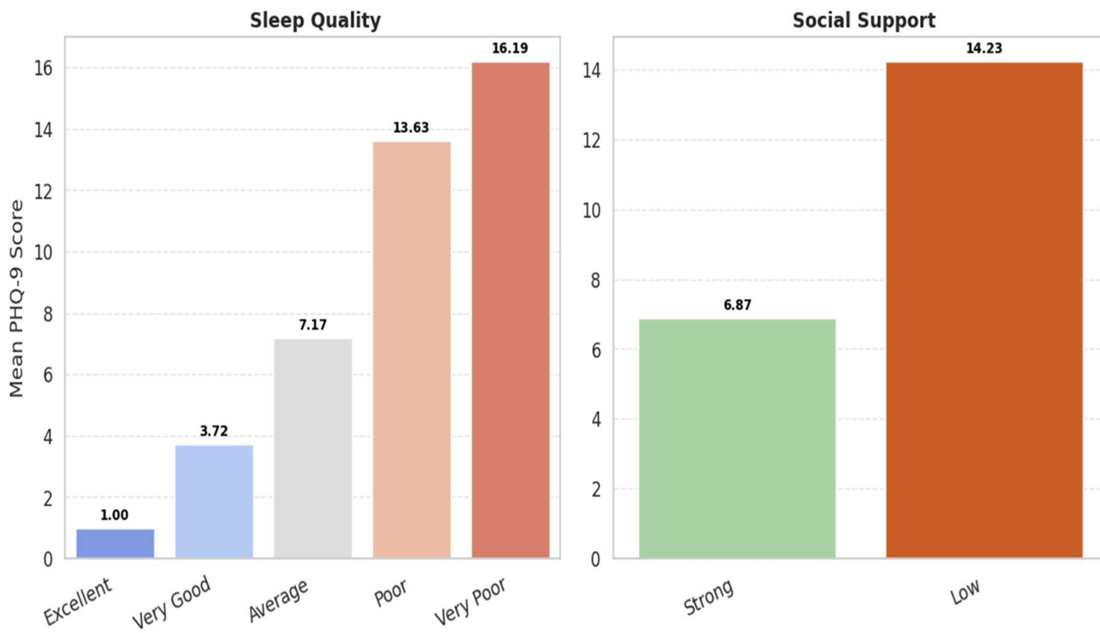
Figure 6: *Mean PHQ-9 Score of Gender and Year of Study*



Gender: Female students reported higher mean PHQ-9 scores (M = 3.59) compared to male students (M = 2.51), suggesting a gender-related difference in depressive symptoms.

Year of Study: Depression scores increased with academic level, ranging from Plus Two students (M = 2.06) to fourth-year students (M = 10.10) and those in other categories (M = 11.45), indicating that higher academic years may be associated with elevated depressive symptoms.

Figure 7: *Mean PHQ-9 Score of Sleep Quality and Social Support*



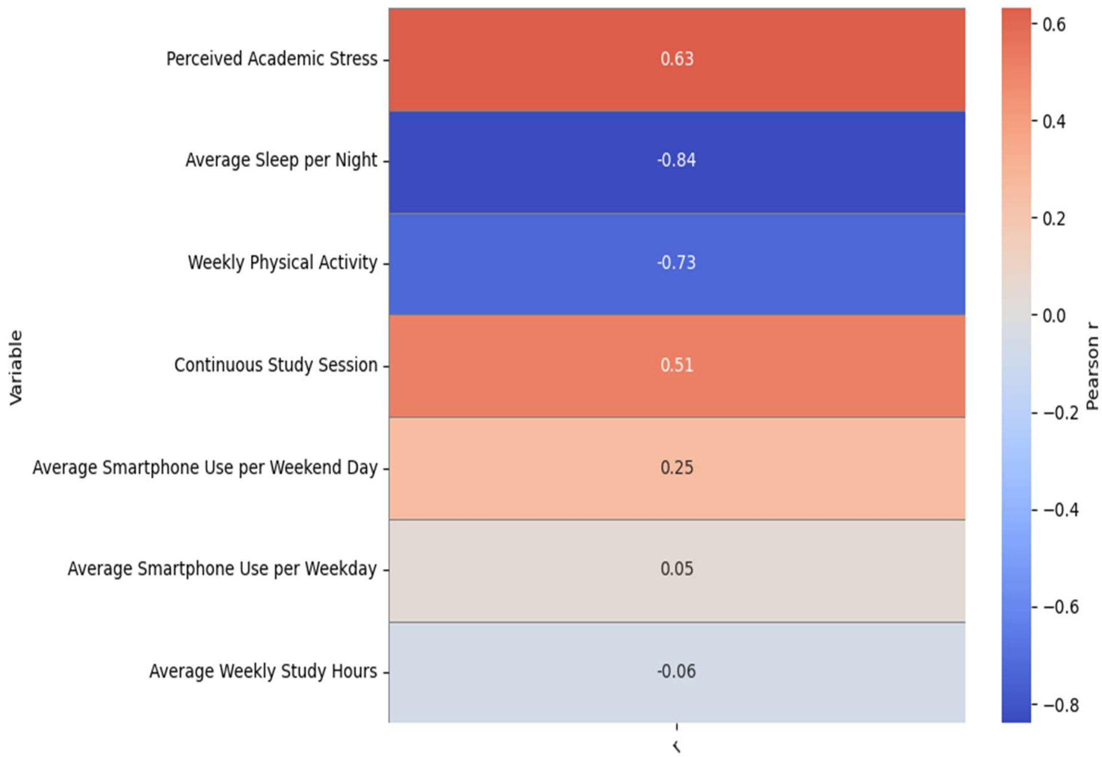
Sleep Quality: Depression scores showed a strong gradient across sleep quality levels: *Very Poor (M = 16.19) → Poor (M = 13.63) → Average (M = 7.17) → Very Good (M = 3.72) → Excellent (M = 1.00)*, demonstrating that poor sleep is closely associated with higher depression severity.

Social Support: Students reporting low social support had substantially higher depression scores (M = 14.23) than those who perceived having strong support networks (M = 6.87).
It seems like depression severity among college students was significantly associated with academic level, living situation, and social support. Students in higher academic years and those living away from family tended to report higher depressive symptoms, whereas students with stronger social support exhibited lower symptom levels. Gender showed a non-significant trend, with females tending toward higher depressive scores.

4.5 Correlation Analysis

Pearson correlation coefficients were computed to examine linear relationships between continuous predictors and PHQ-9 scores. as illustrated in the heatmap below. In the heatmap, colors represent both the strength and direction of correlations, with red indicating positive relationships and blue indicating negative relationships, while the intensity of the color reflects the magnitude of the correlation.

Figure 8: *Correlation between Predictors and PHQ-9 scores*



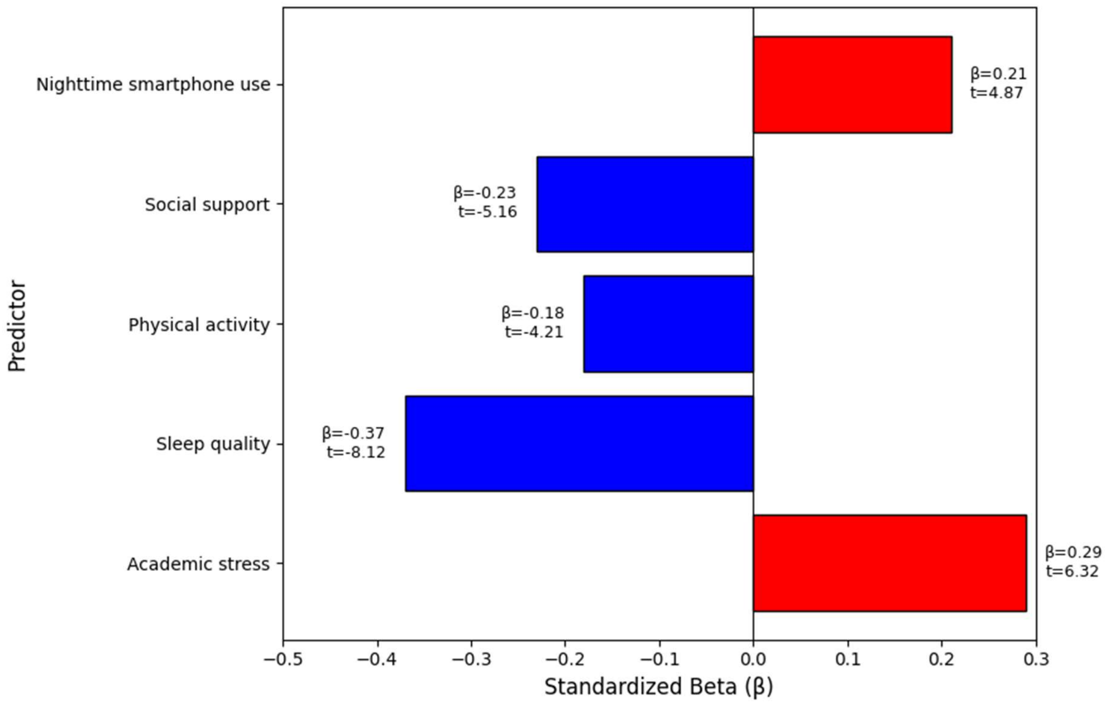
This analysis shows that a perceived academic stress was moderately to strongly positively correlated with depression scores (r = 0.63), indicating that higher stress levels were associated with greater depressive symptoms. In contrast, average sleep per night (r = -0.84) and weekly physical activity (r = -0.73) were strongly negatively correlated with depression, suggesting that longer sleep duration and more physical activity act as protective factors. Continuous study sessions without breaks also showed a moderate positive correlation (r = 0.51), implying that prolonged uninterrupted study may contribute to higher depression levels. Smartphone usage demonstrated weaker associations with depressive symptoms: average weekend use (r = 0.25) had a small positive correlation, while weekday use (r = 0.05) and average weekly study hours (r = -0.06) showed minimal influence.

This shows that relative importance of lifestyle and academic stress factors in predicting depression severity among college students, with sleep quality and physical activity serving as key protective factors, and academic stress and prolonged study sessions representing significant risk factors.

4.6 Predictive Modeling

A multiple linear regression analysis was conducted to identify the most influential predictors of depressive symptoms among college students. The PHQ-9 total score served as the dependent variable, while academic stress, sleep quality, physical activity, social support, and nighttime smartphone use were entered as independent variables.

Figure 9: *Standardized Beta Coefficients for PHQ-9 Predictors*



The overall regression model was statistically significant, $F(5, 388) = 97.62$, $p < .001$**,** explaining 56% of the variance in depressive symptoms ($R^2 = 0.56$, Adjusted $R^2 = 0.55$)**.** This indicates that the selected predictors collectively accounted for a substantial portion of the variability in depression severity among participants.

All predictors were statistically significant ($p < .001$). Among them, sleep quality ($\beta = -0.37$, $t = -8.12$) emerged as the strongest predictor, indicating that poorer sleep quality was strongly associated with higher depressive symptoms. Academic stress ($\beta = 0.29$, $t = 6.32$) was the next most influential factor, showing that greater perceived stress significantly elevated depression levels. Social support ($\beta = -0.23$, $t = -5.16$) was inversely related to depression, suggesting that strong interpersonal support buffered against depressive symptoms. Additionally, nighttime smartphone use ($\beta = 0.21$, $t = 4.87$) and physical activity ($\beta = -0.18$, $t = -4.21$) were significant contributors, with increased late-night phone use and reduced physical activity associated with higher depression scores.

It seems that, the regression findings highlight that sleep quality, academic stress, and social support are the most influential determinants of depression among college students, while nighttime smartphone use and low physical activity further exacerbate depressive symptoms. These results underscore the multifactorial nature of student mental health and emphasize the need for integrated interventions targeting both academic and lifestyle domains.

5. Discussion

The present study examined how academic, lifestyle, and smartphone usage factors collectively predict depression among college students. The results indicated a high prevalence of depressive symptoms, with most participants experiencing mild to moderate levels of depression. Consistent with prior research, the findings highlight that student mental health is influenced by the interplay of academic pressure, lifestyle behaviors, and social support. These factors jointly shape the psychological well-being of students, underscoring the multifactorial nature of depression in academic settings.

Academic stress emerged as one of the strongest positive predictors of depressive symptoms. Students experiencing higher levels of perceived academic pressure demonstrated significantly greater PHQ-9 scores, corroborating findings by Beiter et al. (2015) and Yangdon et al. (2021), who also identified academic workload and performance expectations as key sources of emotional distress. Furthermore, depression severity differed across academic years, with senior students reporting higher symptoms-possibly due to cumulative workload, thesis demands, and career uncertainty, aligning with Nahm and Chun (2021). These results affirm that unmanaged academic pressure remains a central risk factor for student depression. However, academic institutions can mitigate this through protective interventions**,** such as stress management workshops, flexible assessment systems, and counseling services to support emotional resilience during demanding academic phases.

Lifestyle related variables, particularly sleep quality and physical activity, were found to be critical determinants of depression. Poor sleep quality exhibited the strongest negative correlation with mental health, consistent with prior evidence linking sleep deprivation to affective instability and reduced cognitive performance (Carpenter et al., 2015; Hyndych et al., 2025). Similarly, reduced physical activity was associated with heightened depressive symptoms, echoing the findings of Pearce et al. (2022) and Creese et al. (2021) that regular exercise enhances psychological resilience and mood regulation. These results underscore that sleep hygiene and regular physical activity function as core protective strategies. Encouraging structured rest routines, campus sports programs, and wellness initiatives can serve as low-cost, high-impact methods to promote student well-being.

Social support also emerged as a powerful buffer against depression. Students with stronger interpersonal connections and emotional support networks reported substantially lower PHQ-9 scores, consistent with the social buffering hypothesis described by Cohen and McKay (2020). This finding directly addresses the research question concerning protective factors, demonstrating that social connectedness serves as one of the most potent defenses against psychological distress. Peer mentorship programs, student clubs, and group counseling can therefore play a crucial preventive role in campus mental health systems.

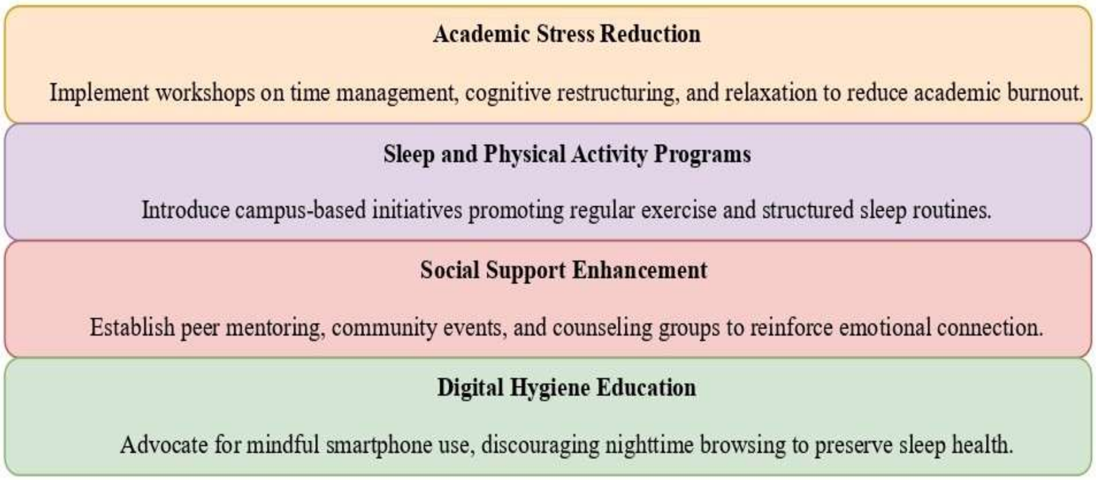
Smartphone-related behaviors, particularly nighttime use, demonstrated a moderate positive association with depression. Students frequently using smartphones after 10 p.m. reported higher PHQ-9 scores, indicating that late-night device engagement may disrupt sleep cycles and elevate fatigue, which is consistent with prior findings by Lemola et al. (2015) . However, total daily screen time exhibited a weaker relationship with depression, implying that how and when smartphones are used, rather than total duration, plays a more crucial role in psychological outcomes. Thus, interventions promoting digital well-being, such as device-free bedtime policies and awareness campaigns on mindful technology use, could significantly improve sleep and reduce depressive vulnerability.

The regression model explained 56% of the variance in depression severity, emphasizing the interconnected effects of academic, lifestyle, and technological factors. Sleep quality, academic stress, and social support were the strongest predictors, underscoring the need for multidimensional prevention strategies. Strengthening one area, such as social support, can buffer risks in others like academic stress, highlighting the value of integrated mental health approaches in higher education.

6. Implications for Mental Health Promotion

The study provides actionable insights into protective strategies that institutions can adopt:

Figure 10: *Protective Strategies*



Collectively, these measures align with a preventive, resilience-building approach to student well-being, transforming campuses into environments that nurture not only academic excellence but also emotional balance and psychological safety.

7. Limitations and Future Research

This cross-sectional, self-report study limits causal interpretation and generalizability. Future research should adopt longitudinal and intervention-based designs and include qualitative insights into students' coping experiences.

8. Conclusion

This study provides empirical evidence that depression among college students results from the combined effects of academic pressure, lifestyle behaviors, and digital habits. Sleep quality, academic stress, and social support emerged as the most influential predictors, jointly explaining over half of the variance in depression severity. Elevated academic stress, poor sleep, and nighttime smartphone use were linked to greater depressive symptoms, whereas strong social connections, adequate rest, and regular exercise acted as protective factors. These findings underscore the importance of multidimensional approaches to student well-being. Educational institutions should adopt holistic frameworks that integrate mental health literacy, flexible academic structures, physical activity promotion, and digital well-being education. Embedding such evidence-based strategies into campus life can cultivate supportive environments that enhance academic performance, psychological health, and overall resilience among students.

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