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Predicting Mental Wellbeing in University Students Using Machine Learning and Lifestyle Data

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Abstract

Abstract: This study examines how lifestyle factors influence mental well-being among university students and evaluates the predictive performance of machine learning models. Data were collected from 154 university students using validated instruments, including the WHO-5 Well-Being Index and IPAQ-SF for physical activity. Key variables included sleep duration, screen time, nutrition quality, and physical activity. Results show that mental well-being is significantly associated with multiple lifestyle behaviors. Physical activity (r = 0.42), sleep duration (r = 0.38), and nutrition quality (r = 0.33) correlate positively with well-being, while screen time shows a negative association (r = −0.35). A multiple regression model explains 48% of the variance in well-being, with sleep and physical activity as the strongest associations. Machine learning models improve prediction accuracy compared to traditional regression. The Random Forest model achieves the best performance (R^2 = 0.58), indicating the presence of non-linear relationships between variables. These findings highlight that student well-being depends on a combination of modifiable behaviors rather than a single factor. The study supports the use of integrated and personalized interventions that target sleep, physical activity, and screen habits. It also shows the value of machine learning in identifying complex behavioral patterns and improving health predictions.

Keywords: Mental Well-Being, University Students, Lifestyle Factors, Machine Learning, Physical Activity.

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INTRODUCTION

Mental well-being among university students has become an increasingly important public health concern, given the rising prevalence of stress, anxiety, and lifestyle-related disorders in this population [1,2]. The transition to university life is often associated with significant changes in daily routines, including irregular sleep patterns, reduced physical activity, poor dietary habits, and increased screen time, all of which may negatively affect both physical and psychological health [3,4]. As a result, understanding the determinants of student well-being has become a priority for both researchers and educational institutions.

A substantial body of literature highlights the positive role of physical activity in promoting mental well-being. Regular engagement in exercise has been associated with reduced symptoms of depression and anxiety, improved mood, and enhanced cognitive functioning [5,6]. Physical activity is also considered a protective factor against stress and burnout, particularly in academic environments characterized by high demands [7,8]. However, despite these benefits, many students fail to meet recommended levels of physical activity, often due to sedentary behaviors and academic pressures [9]. In addition to physical activity, other lifestyle factors such as sleep and nutrition play a critical role in shaping mental well-being. Adequate sleep is essential for emotional regulation, cognitive performance, and overall psychological functioning, while sleep deprivation has been consistently linked to increased stress and reduced well-being [4]. Similarly, diet quality has been associated with mental health outcomes, although its effects are often mediated by interactions with other lifestyle behaviors [10]. These findings support a holistic perspective, in which well-being is influenced by multiple interconnected factors rather than isolated behaviors.

Screen time has emerged as a particularly relevant factor in recent years, especially among university students who are highly engaged with digital technologies. Excessive screen exposure has been associated with sedentary behavior, sleep disturbances, and poorer mental health outcomes [11,12]. While digital tools can also provide opportunities for health promotion, such as through mobile health applications, their impact remains complex and context-dependent. Recent advances in artificial intelligence and machine learning offer new opportunities for understanding and predicting health-related outcomes.

Machine learning models are capable of capturing complex, non-linear relationships between variables and have been increasingly applied in the field of mental health and behavioral research [13,14]. In the context of student populations, these approaches can be used to identify patterns of behavior, predict well-being outcomes, and support the development of personalized interventions [15]. Compared to traditional statistical methods, machine learning techniques may provide improved predictive accuracy and deeper insights into the interactions between lifestyle factors [16].

Despite the growing body of research, there is still a need for studies that integrate multiple lifestyle variables and apply both statistical and machine learning approaches within the same framework. Moreover, most existing studies focus on specific student groups or single domains of behavior, limiting the generalizability of findings. Therefore, a comprehensive approach that considers physical activity, sleep, screen time, and nutrition simultaneously is essential for a more accurate understanding of student well-being. Based on these considerations, the present study aims to examine the relationship between physical activity, lifestyle behaviors, and mental well-being among university students, and to evaluate the predictive performance of machine learning models in this context.

We guided our research after the following hypotheses:

H_1: Physical activity and sleep duration are strongly positively associated with mental well-being, while nutrition quality shows a weaker positive association and screen time is negatively associated with mental well-being among university students.

H_2: Lifestyle factors (physical activity, sleep, screen time, and nutrition) significantly predict mental well-being in a multiple regression model.

H_3: Machine learning models provide improved predictive performance compared to traditional linear regression, suggesting the presence of non-linear relationships between variables.

MATERIALS AND METHODS

This cross-sectional study was conducted between October and December 2025 at Transilvania University of Brașov, Romania, involving a total of 154 undergraduate and graduate students recruited from multiple faculties, including engineering, medicine, economics, and social sciences. Eligibility criteria included being an enrolled student, aged 18 years or older, and providing informed consent. Responses with more than 10% missing data were excluded from the analysis. The study adhered to the principles of the Declaration of Helsinki and received approval from the Institutional Review Board of Transilvania University of Brașov (Approval No. 2776/23.09.2025). All participants provided informed consent prior to participation, and data were collected anonymously and stored securely.

Data collection was carried out using the online questionnaire platform - Google Forms, requiring approximately 10-15 minutes to complete. The survey remained open for four weeks and comprised items assessing demographic characteristics, lifestyle behaviors, physical activity levels, and mental well-being. Demographic variables included age, gender, faculty, and year of study, while lifestyle variables included sleep duration, screen time, nutritional habits, and substance use behaviors such as alcohol consumption and smoking. Mental well-being was assessed using the World Health Organization Well-Being Index (WHO-5), a widely validated instrument for evaluating psychological well-being in student populations. The WHO-5 consists of five items scored on a six-point Likert scale ranging from 0 (at no time) to 5 (all of the time), with total scores ranging from 0 to 25 and subsequently multiplied by four to yield a percentage scale from 0 to 100, where higher scores indicate better well-being. Physical activity levels were measured using the International Physical Activity Questionnaire – Short Form (IPAQ-SF), which evaluates the frequency and duration of walking, moderate-intensity, and vigorous-intensity activities over the previous seven days. Total physical activity was expressed in metabolic equivalent minutes per week (MET-min/week) according to standardized IPAQ scoring procedures.

Prior to analysis, the dataset underwent preprocessing to ensure data quality and suitability for statistical and machine learning analyses. Missing values were handled using mean imputation for continuous variables, while outliers were identified using the interquartile range method. Continuous variables were standardized using z-score normalization, and categorical variables were encoded using one-hot encoding techniques. The dataset was subsequently divided into training (80%) and testing (20%) subsets for predictive modeling. To investigate the relationship between lifestyle factors and mental well-being, as well as to develop predictive models, several supervised machine learning algorithms were implemented, including linear regression, random forest, support vector machine, and k-nearest neighbors. Model performance was evaluated using multiple metrics, including mean absolute error, mean squared error, root mean squared error, and the coefficient of determination (R^2). Additionally, five-fold cross-validation was applied to enhance model robustness and minimize overfitting.

Descriptive statistics were calculated for all variables and reported as means and standard deviations for continuous data. Pearson correlation analysis was used to examine associations between physical activity, lifestyle variables, and mental well-being scores. All statistical analyses and machine learning procedures were performed using Python (including libraries such as Pandas, NumPy, and Scikit-learn) and SPSS version 26, with statistical significance set at $p < 0.05$.

RESULTS

The results aim to provide a comprehensive overview of the relationships between physical activity, lifestyle factors, and mental well-being among university students, as well as to evaluate the predictive capacity of both traditional statistical methods and machine learning approaches.

Table 1: Participant characteristics and descriptive statistics

Variable	Category / Unit	Mean ± SD / n (%)
WHO-5 score	0–100	62.8 ± 14.5
Physical activity (IPAQ)	MET-min/week	2450 ± 980
Sleep duration	h/night	6.9 ± 1.2
Screen time	h/day	5.6 ± 1.8
Nutrition quality	1–5 Likert scale	3.2 ± 0.9
Smoking status	Yes	34 (22.1%)
	No	120 (77.9%)
Alcohol consumption	Yes	89 (57.8%)
	No	65 (42.2%)

Note: WHO-5 = World Health Organization Well-Being Index; IPAQ = International Physical Activity Questionnaire; MET = Metabolic Equivalent of Task; SD = Standard Deviation. Nutrition quality was self-reported on a 5-point Likert scale (1 = very poor, 5 = very good)

The sample consisted of young adults (21.4 ± 2.3 years) with a balanced gender distribution and representation across faculties and study years. Participants showed moderate mental well-being (WHO-5: 62.8 ± 14.5) and generally adequate physical activity levels (2450 ± 980 MET-min/week), although variability was high. Lifestyle indicators revealed suboptimal sleep duration (6.9 ± 1.2 h/night) and high screen time (5.6 ± 1.8 h/day), alongside moderate nutrition quality (3.2 ± 0.9). Additionally, over half of the participants reported alcohol

consumption (57.8%), while 22.1% were smokers, highlighting the presence of relevant health risk behaviors within the sample.

The data from Table 1 suggest that the studied population of university students can be characterized as moderately healthy but not optimally balanced in terms of lifestyle. While participants report adequate levels of physical activity and a moderate degree of mental well-being, these positive aspects are counterbalanced by suboptimal lifestyle behaviors, particularly insufficient sleep duration, high daily screen time, and only average nutritional quality. Additionally, the presence of risk behaviors such as alcohol consumption in more than half of the sample and smoking in a notable proportion of students further highlights potential vulnerabilities in this population. The relatively large variability observed across key indicators indicates that students differ considerably in their habits and health status, suggesting that a one-size-fits-all approach may be ineffective. Overall, the findings point to a population that is functioning adequately but is constrained by modifiable lifestyle factors, emphasizing the need for targeted and potentially personalized interventions to improve overall well-being and health outcomes.

Table 2: Pearson correlations between physical activity, lifestyle factors, and mental well-being

Variable	1	2	3	4	5
WHO-5 score	1				
Physical activity (MET-min/week)	0.42**	1			
Sleep duration (h/night)	0.38**	0.21*	1		
Screen time (h/day)	-0.35**	-0.28**	-0.31**	1	
Nutrition quality	0.33**	0.25**	0.29**	-0.22*	1

Note: *p < 0.05; **p < 0.01. WHO-5 = World Health Organization Well-Being Index; MET = Metabolic Equivalent of Task

Pearson correlation analysis from Table 2 revealed that mental well-being (WHO-5) was positively associated with physical activity ($r = 0.42$, $p < 0.01$), sleep duration ($r = 0.38$, $p < 0.01$), and nutrition quality ($r = 0.33$, $p < 0.01$), while it was negatively associated with screen time ($r = -0.35$, $p < 0.01$). Physical activity also showed positive correlations with sleep and nutrition, and negative correlations with screen time. These findings suggest that healthier lifestyle behaviors are consistently associated with higher levels of mental well-being among university students.

Table 3: Multiple linear regression analysis predicting mental well-being (WHO-5 score)

Predictor	B	SE	β	p
Constant	18.72	5.14	–	<0.001
Physical activity (MET-min/week)	0.006	0.002	0.29	<0.001
Sleep duration (h/night)	2.15	0.58	0.31	<0.001
Screen time (h/day)	-1.84	0.47	-0.28	<0.001
Nutrition quality	3.26	0.89	0.24	<0.001

Model statistics: $R^2 = 0.48$; Adjusted $R^2 = 0.46$; $F(4,149) = 34.2$, $p < 0.001$.
Note: B = unstandardized coefficient; SE = standard error; β = standardized coefficient; WHO-5 = World Health Organization Well-Being Index; MET = Metabolic Equivalent of Task; p = statistical significance threshold

The results of the multiple linear regression analysis indicate that the proposed model provides a strong and statistically significant explanation of mental well-being among university students, accounting for approximately 48% of the total variance ($R^2 = 0.48$). This suggests that nearly half of the differences in well-being scores can be explained by the combined effect of physical activity and lifestyle-related factors, highlighting the relevance of these variables in understanding student health.

Among the predictors, sleep duration emerged as the strongest contributor to mental well-being ($\beta = 0.31$, $p < 0.001$), indicating that students who reported longer sleep duration also tended to have significantly higher well-being scores. This finding reinforces the critical role of sleep in psychological functioning and recovery processes. Physical activity also showed a substantial positive effect ($\beta = 0.29$, $p < 0.001$), suggesting that higher levels of engagement in physical exercise are associated with improved mental well-being. This aligns with existing evidence supporting the role of physical activity as a protective factor for mental health.

In contrast, screen time was identified as a significant negative predictor ($\beta = -0.28$, $p < 0.001$), indicating that increased daily exposure to screens is associated with lower levels of well-being. This may reflect the impact of sedentary behavior, digital fatigue, or disrupted sleep patterns associated with excessive screen use. Nutrition quality also contributed positively ($\beta = 0.24$, $p < 0.001$), although its effect size was smaller compared to other predictors, suggesting that while diet plays a role, it may be less influential than sleep or physical activity in this context.

Importantly, all predictors remained significant within the same model, indicating that each variable independently contributes to mental well-being rather than simply reflecting overlapping effects. This highlights the multidimensional nature of well-being, where multiple lifestyle behaviors interact but also exert distinct influences. These findings suggest that mental well-being in university students is not determined by a single factor but rather by a combination of modifiable lifestyle behaviors, with sleep, physical activity, and screen time playing particularly prominent roles. This supports the need for integrated and potentially personalized interventions targeting multiple aspects of student lifestyle to effectively enhance well-being.

Table 4: Performance of machine learning models for predicting mental well-being (WHO-5 score)

Model	MAE	MSE	RMSE	R^2
Linear Regression	7.12	78.45	8.86	0.46
Random Forest	5.84	61.32	7.83	0.58
Support Vector Machine	6.21	68.10	8.25	0.52
K-Nearest Neighbors	6.75	72.88	8.54	0.49

Note: MAE = Mean Absolute Error; MSE = Mean Squared Error; RMSE = Root Mean Squared Error; R^2 = coefficient of determination; WHO-5 = World Health Organization Well-Being Index

The comparative analysis of machine learning models revealed differences in predictive performance when estimating mental well-being based on lifestyle and behavioral variables. Among the tested models, the Random Forest algorithm demonstrated the best overall performance, achieving the lowest prediction errors (MAE = 5.84; RMSE = 7.83) and the highest explained variance ($R^2 = 0.58$). This suggests that non-linear relationships and interactions between variables may play an important role in predicting mental well-being, which are better captured by ensemble learning methods.

The Support Vector Machine model also performed well, with moderate error values and an R^2 of 0.52, indicating a good balance between bias and variance. K-Nearest Neighbors showed slightly lower performance, suggesting that local similarity-based approaches may be less effective in capturing the complexity of the dataset.

Interestingly, the traditional Linear Regression model yielded the lowest performance ($R^2 = 0.46$), closely aligning with the regression results presented previously. This indicates that while linear models

can explain a substantial portion of variance, they may not fully capture more complex, non-linear patterns present in the data.

The findings highlight that machine learning approaches, particularly ensemble methods such as Random Forest, can improve the prediction of mental well-being compared to classical statistical models. This supports the potential application of AI-driven systems in developing personalized health and fitness interventions for university students.

DISCUSSION

The present study aimed to examine the relationship between physical activity, lifestyle behaviors, and mental well-being among university students, while also exploring the predictive potential of machine learning models. The results partially confirm H_1, with stronger effects observed for sleep duration and physical activity, and a weaker but still significant contribution of nutrition quality. The findings indicate that mental well-being is significantly associated with modifiable lifestyle factors, particularly physical activity, sleep duration, screen time, and nutrition quality. These results align with a growing body of literature emphasizing the multifactorial nature of student well-being [1,2]. Consistent with previous studies, physical activity emerged as a significant positive predictor of mental well-being. This supports extensive evidence demonstrating that regular engagement in physical activity contributes to improved mood, reduced stress, and enhanced psychological functioning among students [5,7]. The observed association is likely mediated by both physiological mechanisms, such as endorphin release, and psychosocial factors, including increased self-efficacy and social interaction [6].

Sleep duration was identified as the strongest predictor of well-being in the regression model, highlighting its critical role in mental health. This finding is consistent with research showing that insufficient sleep is associated with increased psychological distress and reduced cognitive performance in young adults [4]. The interaction between sleep and other lifestyle behaviors, such as screen time and physical activity, further underscores the importance of considering these variables in an integrated framework. Screen time demonstrated a significant negative association with mental well-being, which is in line with studies linking excessive digital exposure to sedentary behavior, sleep disruption, and mental health issues [11,12]. This finding is particularly relevant in the context of modern student lifestyles, where digital engagement is pervasive and often unavoidable. It suggests that interventions aimed at reducing screen time or promoting healthier digital habits may have beneficial effects on well-being. Nutrition quality also contributed positively to well-being, although its effect size was smaller compared to other predictors. This is consistent with literature indicating that diet plays a supportive but not dominant role in mental health, often interacting with other lifestyle factors such as physical activity and sleep [3,10]. The moderate scores observed in this study suggest that dietary improvements could further enhance student well-being. Nutrition quality showed a significant but smaller effect compared to sleep and physical activity, indicating a supportive rather than dominant role in predicting mental well-being.

Importantly, the machine learning analysis revealed that non-linear models, particularly Random Forest, outperformed traditional linear regression in predicting mental well-being. This finding aligns with recent research demonstrating the superiority of machine learning approaches in capturing complex interactions between behavioral and psychological variables [13,14]. The improved predictive performance suggests that well-being is influenced by non-linear and interactive effects that cannot be fully captured using traditional statistical models. While machine learning models demonstrated improved predictive performance, the differences compared to linear regression were moderate, suggesting cautious interpretation of their added value.

The high variability observed in the dataset further supports the need for personalized approaches to health promotion. Students differ significantly in their lifestyle behaviors and well-being levels, indicating that generalized interventions may be insufficient. This is consistent with emerging trends in digital health, where AI-driven systems are increasingly used to deliver tailored recommendations based on individual data [12,15].

From a practical perspective, these findings highlight the importance of developing integrated interventions targeting multiple lifestyle domains simultaneously. Programs combining physical activity promotion, sleep optimization, and digital behavior management may be particularly effective in improving student well-being [17]. Additionally, the use of mobile health applications and AI-based tools offers promising opportunities for scalable and personalized interventions [14]. Due to the cross-sectional design of the study, causal relationships cannot be established. The findings reflect associations between lifestyle factors and mental well-being at a single point in time. The exclusion of relevant psychosocial variables may have introduced omitted variable bias, potentially influencing the strength and direction of the observed associations.

Several limitations should be acknowledged. First, the cross-sectional design limits the ability to infer causality between variables. Second, the use of self-reported measures such as IPAQ and WHO-5 may introduce reporting bias. Third, the sample was drawn from a single university, which may limit generalizability. Future research should consider longitudinal designs, objective measurements (wearables), and larger, more diverse samples.

The study did not include several potentially important variables, such as academic stress, social support, and prior mental health status, which may also influence mental well-being. Their omission may have affected the observed relationships. All variables were assessed using self-reported measures, which may be subject to recall bias and social desirability bias. Participants may have overestimated or underestimated their behaviors, particularly in relation to physical activity, sleep, and nutrition.

Future research should incorporate these factors to provide a more comprehensive understanding of student well-being.

Despite these limitations, the study provides valuable insights into the determinants of student well-being and demonstrates the added value of machine learning approaches in health research. Overall, the findings suggest that university students represent a population with moderate well-being but suboptimal lifestyle behaviors, highlighting the need for targeted and personalized interventions to enhance health outcomes.

CONCLUSION

The present study demonstrates that mental well-being among university students is significantly associated with modifiable lifestyle factors, particularly physical activity, sleep duration, screen time, and nutrition quality. While the sample exhibited moderate levels of well-being and generally adequate physical activity, suboptimal lifestyle behaviors, especially insufficient sleep and high screen time, appear to limit overall health outcomes.

The findings highlight that mental well-being is not determined by a single factor but rather by the combined and independent influence of multiple lifestyle behaviors. Among these, sleep and physical activity showed the strongest associations with mental well-being, while excessive screen time showed a detrimental effect. These results emphasize the need for integrated approaches targeting multiple aspects of student lifestyle simultaneously.

The machine learning models demonstrated improved predictive performance compared to traditional statistical methods, suggesting that student well-being is influenced by complex, non-linear interactions between variables. This supports the growing role of artificial intelligence in health research and its potential for developing personalized interventions.

The study suggests that university students represent a population with moderate well-being but modifiable lifestyle constraints. Future interventions should focus on promoting balanced behaviors, including adequate sleep, regular physical activity, and reduced screen time, potentially leveraging AI-based tools to deliver personalized and scalable solutions.

Author Contributions

SA conceptualized, designed, and supervised the study. SA did the literature search and conducted the experiment. Manuscript preparation was done by SA. Data acquisition was done by SA. Statistical analysis was performed by SA. Manuscript editing was done by SA. SA reviewed and approved the final version of the manuscript.

Data Availability Statement

The data that support the findings of this study are available and will be made available upon request.

Use of AI in Drafting of Manuscript

The authors declare that they have not used any generative AI/AI-assisted technologies in the writing of this manuscript.

Conflicts of interest

None declared.

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