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ORIGINAL RESEARCH

An Artificial Intelligence Platform to Stratify the Risk of Experiencing Sleep Disturbance in University Students After Analyzing Psychological Health, Lifestyle, and Sports: A Multicenter Externally Validated Study

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Background: Sleep problems are prevalent among university students, yet there is a lack of effective models to assess the risk of sleep disturbance. Artificial intelligence (AI) provides an opportunity to develop a platform for evaluating the risk. This study aims to develop and validate an AI platform to stratify the risk of experiencing sleep disturbance for university students.

Methods: A total of 2243 university students were included, with 1882 students from five universities comprising the model derivation group and 361 students from two additional universities forming the external validation group. Six machine learning techniques, including extreme gradient boosting machine (eXGBM), decision tree (DT), k-nearest neighbor (KNN), random forest (RF), neural network (NN), and support vector machine (SVM), were employed to train models using the same set of features. The models' prediction performance was assessed based on discrimination and calibration, and feature importance was determined using Shapley Additive exPlanations (SHAP) analysis.

Results: The prevalence of sleep disturbance was 44.69% in the model derivation group and 49.58% in the external validation group. Among the developed models, eXGBM exhibited superior performance, surpassing other models in metrics such as area under the curve (0.779, 95% CI: 0.728–0.830), accuracy (0.710), precision (0.737), F1 score (0.692), Brier score (0.193), and log loss (0.569). Calibration and decision curve analyses demonstrated favorable calibration ability and clinical net benefits, respectively. SHAP analysis identified five key features: stress score, severity of depression, vegetable consumption, age, and sedentary time. The AI platform was made available online at https://sleepdisturbancestudents-xakgzwectsw85cagdgkax9.streamlit.app/, enabling users to calculate individualized risk of sleep disturbance.

Conclusion: Sleep disturbance is prevalent among university students. This study presents an AI model capable of identifying students at high risk for sleep disturbance. The AI platform offers a valuable resource to guide interventions and improve sleep outcomes for university students.

Keywords: university students, sleep disturbance, machine learning, artificial intelligence, feature importance

Introduction

Sleep disturbance is a significant health concern among university students, with high prevalence rates[1–3] and potential adverse effects on various aspects of their well-being.[4–7] Epidemiological studies have shown that a substantial proportion of university students experienced sleep disturbance, including insomnia, drowsiness, and poor sleep quality. To elaborate, 33%

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to 60% of university students were categorized as poor-quality sleepers.[1–3] In addition, sleep disturbance has been associated with a range of negative outcomes, including impaired cognitive function, decreased academic performance,[4,5] mental health issues,[6] compromised physical health,[1] and even elevated suicide risk of suicidal thoughts and behaviours.[7]

Generally, sleep disturbance refers to a disruption in the quality of sleep, which can be assessed using the Pittsburgh Sleep Quality Index (PSQI),[8] and a PSQI score exceeding five is indicative of sleep disturbance.[3] Notably, insomnia, a common sleep problem, is a specific sleep disorder characterized by persistent difficulty falling asleep or staying asleep, and it can be regarded as a specific form of sleep disturbance. Accurately predicting the risk of sleep disturbance in university students is very importance for early intervention and targeted prevention strategies. Identifying individuals who are at a higher risk of experiencing sleep disturbance can help healthcare professionals and educators implement appropriate interventions to improve sleep quality and overall well-being.[9,10] Traditionally, risk assessment for sleep disturbance has relied on self-report questionnaires and subjective evaluations, which may be limited by recall bias and subjective interpretation. In recent years, the emergence of artificial intelligence (AI) has provided new opportunities for developing predictive models in various fields, including sleep research.[11–13] By leveraging machine learning algorithms and analyzing a wide range of lifestyle factors, sports activities, and psychological health indicators, AI has the potential to accurately predict the risk of sleep disturbance in university students. Previous studies have demonstrated the effectiveness of AI in predicting various health outcomes,[14–16] and its application in the sleep domain holds promise for improving sleep health in the university student population.

Therefore, the main objective of this study is to develop an AI model for predicting sleep disturbance in university students based on lifestyle, sports, and psychological health factors. By analyzing a large dataset of university students, we employed six different machine learning techniques to train models and assess their prediction performance. The optimal model, as determined by its superior performance in discrimination and calibration metrics, was then deployed as an internet-based AI platform. This platform enables users to calculate their individualized risk of sleep disturbance and provides valuable insights for interventions and improving sleep outcomes in university students.

Methods

Participants

A total of 2243 university students were recruited for this study between September 2021 and June 2023. The model derivation group consisted of 1882 students from five esteemed universities, namely Xiamen University of Technology (Xiamen), Chongqing Normal University (Chongqing), Harbin Sport University (Harbin), Sichuan Normal University (Chengdu), and North China University of Water Resources and Electric Power (Zhengzhou). Additionally, 361 students from two additional universities constituted the external validation group. Participants voluntarily responded and completed the survey, which was distributed using instant communication platforms such as telephone messages and WeChat software. The survey employed a non-probability snowball sampling strategy. It encompassed various aspects including participants' demographics, sports habits, eating habits, lifestyles, comorbidities, psychological health, and sleep quality. Completing all questionnaires typically takes around 10 minutes.

The inclusion criteria comprised university students who were present on campus, willing to participate in the survey, and completed all survey questions. The exclusion criteria encompassed individuals who had postponed their graduation, been previously diagnosed with sleep disorders or psychological illnesses in a hospital setting, or declined to participate. The study design is depicted in Figure 1, and participant's flowchart is summarized in Supplementary Figure 1. Ethical approval for this study was obtained from the Academic Committee and Ethics Board of Xiamen University of Technology (no. 202,001). Written informed consent was obtained online by the participants before they formally fill out the survey, ensuring their identifiable personal information was not collected. The study was conducted in accordance with the Declaration of Helsinki, and its reporting adhered to the TRIPOD Checklist.[17]

Data Collection

The study collected data on participants' demographics (age, gender, grade, and marital status), sports habits (frequency of engagement in physical activity per week and types of sports), eating habits (consumption of fatty meal, vegetables, and fruits), lifestyles (drinking habits, smoking habits, daily sedentary time, naps at noon, and monthly expenses),

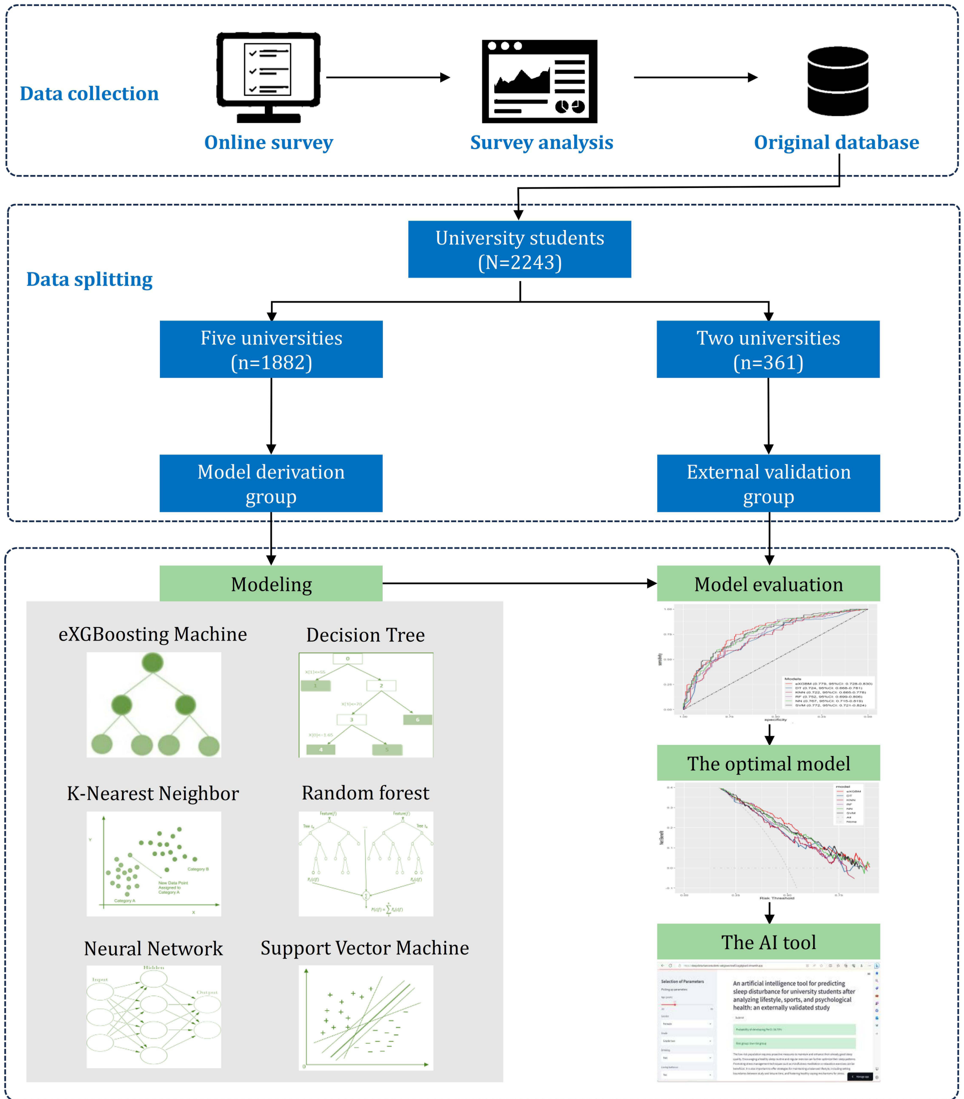

Figure 1 Machine learning techniques and study design.

comorbidities (presence of chronic diseases), and psychological health (levels of anxiety, depression, and stress). Chronic diseases considered in the study included hypertension, diabetes, congenital heart disease, chronic kidney disease, chronic lung disease, chronic liver disease, and others. Participants' anxiety severity was assessed using the General Anxiety Disorder-7 (GAD-7) questionnaire,[18] while the severity of depression was evaluated using the Patient Health Questionnaire-9 (PHQ-9).[19] Both scales are widely employed self-report measures with several items scored on a scale from 0 to 3, with higher scores indicating greater symptom severity. In the GAD-7 scale, scores ranging from 0 to 4 denote no anxiety, 5–9 indicate mild anxiety, 10–14 signify moderate anxiety, and 15–21 represent severe anxiety. Similarly, in the PHQ-9 scale, scores between 0 and 4 indicate no depression, 5–9 suggest mild depression, 10–14 point towards moderate depression, 15–19 indicate moderate-to-severe depression, and scores from 20 to 27 represent severe depression. The Cronbach α values of GAD-7 and PHQ-7 were 0.93 and 0.92, respectively.

Definition of Sleep Disturbance

Sleep disturbance refers to a disruption in the quality of sleep experienced by college students, which can be assessed using the Pittsburgh Sleep Quality Index (PSQI).[8] The PSQI is a widely used tool for assessing sleep quality and disturbances, and it measures various aspects of sleep, including sleep duration, sleep disturbances, sleep latency, sleep efficiency, sleep medication usage, and daytime dysfunction. Each item on the questionnaire is scored on a scale from 0 to 3, with a higher total score indicating poorer overall sleep quality. A score exceeding five is indicative of sleep disturbance.[3] The Cronbach α value of PSQI was 0.90, indicating a high level of internal consistency among the items in the PSQI questionnaire.

Data Preparation

To ensure the successful development and validation of machine learning models, a comprehensive data preprocessing pipeline was implemented in this study. This pipeline employed the scikit-learn library (version 1.1.3) to standardize the data. Furthermore, to address imbalanced data distribution and enhance model robustness, the Synthetic Minority Oversampling Technique (SMOTE) was combined with Tomek Links Undersampling techniques. This resampling technique, known as SMOTETomek, effectively balanced the proportions of outcome classes within the training and validation groups.[20]

Modeling

A diverse range of machine learning techniques were utilized in this study for the purpose of modeling. These techniques included the Extreme Gradient Boosting Machine (eXGBM), Decision Tree (DT), K-Nearest Neighbor (KNN), Random Forest (RF), Neural Network (NN), and Support Vector Machine (SVM). The introduction and characteristics of these machine learning-based techniques were summarized in Supplementary Table 1. All models were trained and optimized using the same input features identified through subgroup analysis of participants with and without sleep disturbance. To determine the optimal hyperparameters for each model, grid and random hyperparameter searches were conducted, with the area under the curve (AUC) serving as the optimization metric. Wide ranges were set as upper and lower bounds for the hyperparameters during the search to account for potential performance variability. For instance, the decision tree depth range was set from 2 to 100. This approach ensured the selection of well-performing models while avoiding both underfitting and overfitting. Furthermore, learning curves were employed to mitigate the risks of overfitting and underfitting. The machine learning algorithms were implemented using Python (version 3.9.7), and hyperparameter tuning was conducted using scikit-learn (version 1.2.2).

Validation

To evaluate the performance of our models, we employed internationally recognized metrics commonly used in machine learning studies. These metrics included the area under the curve (AUC), accuracy, precision, recall, specificity, F1 score, Brier score, log loss, and discrimination slope. Accuracy measures the model's ability to correctly classify instances by dividing the number of correctly classified instances (true positives and true negatives) by the total number of instances. Precision calculates the proportion of instances accurately predicted as positive out of all instances predicted as positive. It is obtained by dividing the number of true positive predictions by the sum of true positives and false positives. Recall, also known as sensitivity or the true positive rate, quantifies the proportion of correctly predicted positive instances out of all actual positive instances. It is calculated by dividing the number of true positive predictions by the sum of true positives and false negatives.

Discrimination slope evaluates how effectively a predictive model can differentiate between individuals with different outcomes. It measures the change in predicted probabilities or scores as the risk levels increase, indicating the model's ability to discriminate between high-risk and low-risk individuals. A steeper discrimination slope suggests better discrimination, indicating that the model effectively distinguishes between individuals with varying risks. Calibration curve is a graphical representation that assesses the calibration of a predictive model by comparing the predicted probabilities with the observed probabilities of the outcome. Decision curve analysis (DCA) evaluates the clinical utility or net benefit of a predictive or diagnostic model. It compares the use of a particular model or test with alternative strategies or no testing at all. DCA involves plotting the net benefit gained from using a specific model or test against a range of threshold probabilities. To gain interpretability in clinical applications, we utilized the Shapley Additive Explanation (SHAP) method to understand the contributions of each feature.[21]

Establishment of the AI Model

The establishment of the AI model involved the development of a web-based AI platform, which offered a user-friendly interface for researchers, university managers, and healthcare providers. The codebase was stored and version-controlled on GitHub. Streamlit, a cloud infrastructure platform, facilitated the hosting of the internet calculator, ensuring reliable and scalable performance. The user interface was thoughtfully designed to allow users to input relevant participant data and obtain predicted probabilities efficiently. The internet AI platform was deployed on a publicly accessible website. An example to show how to use the AI platform was presented using the real data from a student. Written informed consent was obtained from the student to have the response published. This survey is anonymous, and no personally identifiable information was collected.

Prediction Evaluation Between Human and the AI Platform

To compare the performance of the AI platform, a comparative study was conducted between the AI platform and psychologists who had extensive experience in the field. Five psychologists participated in the study and independently provided their predictions of the risk of sleep disturbance based on their assessments. By comparing the predicted and actual mental status of college students, the AUC value was used to evaluate the prediction performance of each psychologist.

Statistical Analysis

Statistical analysis involved summarizing continuous variables using mean and standard deviation (SD) and presenting categorical variables as proportions. The Chi-square test was used to compare the distribution of categorical variables, and the Student's *t*-test or Wilcoxon rank test was employed to compare continuous variables based on the nature of the data. Spearman correlation analysis was conducted to investigate the association between model features, correlation coefficients were calculated, and a correlation matrix was presented. All statistical analyses were performed using the R language program (version 4.1.2). Statistical significance was determined using a two-tailed P-value of less than 0.05.

Results

Participant Characteristics

In this study, a total of 2243 university students were enrolled, with 1882 students from five universities comprising the model derivation group (Table 1). In this group, the average age of the participants in this group was 19.64 (SD: 1.71), with females accounting for 54.9% of the group. The majority of university students were single (77.0%), non-smokers (92.5%), and non-drinkers (81.9%). In terms of eating habits, 28.9% enjoyed fatty meals, while 49.1% and 57.9% preferred vegetables and fruits, respectively. The most popular type of sport among the participants was aerobic exercise (44.4%). In terms of psychological status, 30.1% of participants experienced anxiety symptoms, 36.5% experienced depressive symptoms. To further elaborate, 24.0% of participants experienced mild anxiety, 4.5% experienced moderate

Table 1 Participant's Baseline Characteristics

Characteristics	Overall	Sleep Disturbance		P
		No	Yes	
n	1882	1041	841	
Age (years, mean (SD))	19.64 (1.71)	19.50 (1.62)	19.82 (1.80)	<0.001
Gender (male/female, %)	848/1034 (45.1/54.9)	494/547 (47.5/52.5)	354/487 (42.1/57.9)	0.023
Grade (%)				<0.001
First	462 (24.5)	305 (29.3)	157 (18.7)	
Second	892 (47.4)	488 (46.9)	404 (48.0)	
Third	316 (16.8)	146 (14.0)	170 (20.2)	
Fourth	212 (11.3)	102 (9.8)	110 (13.1)	

(*Continued*)

Table 1 (Continued).

Characteristics	Overall	Sleep Disturbance		P
		No	Yes	
Marital status (%)				0.281
Single	1450 (77.0)	793 (76.2)	657 (78.1)	
Dating	423 (22.5)	241 (23.2)	182 (21.6)	
Married	9 (0.5)	7 (0.7)	2 (0.2)	
Smoking (%)				0.077
No	1740 (92.5)	965 (92.7)	775 (92.2)	
Abstained from smoking	53 (2.8)	22 (2.1)	31 (3.7)	
Yes	89 (4.7)	54 (5.2)	35 (4.2)	
Drinking (%)				0.008
No	1541 (81.9)	878 (84.3)	663 (78.8)	
Abstained from drinking	87 (4.6)	43 (4.1)	44 (5.2)	
Yes	254 (13.5)	120 (11.5)	134 (15.9)	
Monthly expense (%)				0.417
<2000	1491 (79.2)	836 (80.3)	655 (77.9)	
≧2000 and <5000	378 (20.1)	200 (19.2)	178 (21.2)	
≧5000 and <10,000	7 (0.4)	3 (0.3)	4 (0.5)	
≧10,000	6 (0.3)	2 (0.2)	4 (0.5)	
Loving eating fatty meal (no/yes, %)	1339/543 (71.1/28.9)	767/274 (73.7/26.3)	572/269 (68.0/32.0)	0.008
Loving eating vegetable (no/yes, %)	957/925 (50.9/49.1)	489/552 (47.0/53.0)	468/373 (55.6/44.4)	<0.001
Loving eating fruit (no/yes, %)	793/1089 (42.1/57.9)	428/613 (41.1/58.9)	365/476 (43.4/56.6)	0.341
Naps at noon (yes/no, %)	1484/398 (78.9/21.1)	817/224 (78.5/21.5)	667/174 (79.3/20.7)	0.703
Sedentary time (hours, %)				0.001
<1	95 (5.0)	54 (5.2)	41 (4.9)	
≧1 and <3	349 (18.5)	218 (20.9)	131 (15.6)	
≧3 and <6	628 (33.4)	363 (34.9)	265 (31.5)	
≧6	810 (43.0)	406 (39.0)	404 (48.0)	
Frequency of sports per week (%)				0.067
0	399 (21.2)	206 (19.8)	193 (22.9)	
1–2	688 (36.6)	379 (36.4)	309 (36.7)	
3–4	398 (21.1)	215 (20.7)	183 (21.8)	
≧5	397 (21.1)	241 (23.2)	156 (18.5)	

(*Continued*)

Table 1 (Continued).

Characteristics	Overall	Sleep Disturbance		P
		No	Yes	
Sport type (%)				0.127
None	399 (21.2)	206 (19.8)	193 (22.9)	
Aerobic exercise	836 (44.4)	470 (45.1)	366 (43.5)	
A middle between aerobic and anaerobic exercise	438 (23.3)	237 (22.8)	201 (23.9)	
Anaerobic exercise	209 (11.1)	128 (12.3)	81 (9.6)	
Chronic disease (no/yes, %)	1810/72 (96.2/3.8)	1015/26 (97.5/2.5)	795/46 (94.5/5.5)	0.001
Severity of anxiety (%)				<0.001
None	1315 (69.9)	866 (83.2)	449 (53.4)	
Mild	452 (24.0)	151 (14.5)	301 (35.8)	
Moderate	85 (4.5)	22 (2.1)	63 (7.5)	
Severe	30 (1.6)	2 (0.2)	28 (3.3)	
GAD-7 (mean (SD))	3.10 (3.84)	1.90 (2.84)	4.58 (4.37)	<0.001
Severity of depression (%)				<0.001
None	1196 (63.5)	818 (78.6)	378 (44.9)	
Mild	497 (26.4)	192 (18.4)	305 (36.3)	
Moderate	123 (6.5)	23 (2.2)	100 (11.9)	
Moderate-to-severe	47 (2.5)	8 (0.8)	39 (4.6)	
Severe	19 (1.0)	0 (0.0)	19 (2.3)	
PHQ-9 (mean (SD))	3.96 (4.65)	2.32 (3.21)	6.00 (5.30)	<0.001
Stress score (mean (SD))	7.65 (7.96)	4.85 (6.10)	11.12 (8.60)	<0.001

Abbreviation: SD, Standard deviation. The Chi-square test was used to compare the distribution of categorical variables, and the Student's *t*-test was employed to compare continuous variables.

anxiety, and 1.6% experienced severe anxiety. With respect to depression, 26.4% of participants experienced mild depression, 6.5% experienced moderate depression, 2.5% experienced moderate-to-severe depression, and 1.0% experienced severe depression. The prevalence of sleep disturbance was 44.69% in the model derivation group.

Subgroup Analysis of Participants in Terms of Sleep Disturbance

Subgroup analysis revealed that participants with sleep disturbance tended to be older (P<0.001), female (P=0.023), in higher grades (P<0.001), drinkers (P=0.008), individuals who preferred eating fatty meal (P=0.008), and those who did not prefer eating vegetables (P<0.001) (Table 1). They also had a higher sedentary time (P=0.001), higher prevalence of chronic disease (P=0.001), anxiety (P<0.001), depression (P<0.001), and stress (P<0.001). Thus, the above significant variables were used as input features for modeling. The Spearman correlation analysis revealed significant associations among several model factors (Supplementary Figure 2). For instance, age showed a significant association with grade (correlation coefficient: 0.58). Additionally, anxiety, depression, and stress score were correlated with each other, with correlation coefficients ranging between 0.75 and 0.76. It is noteworthy that all the correlation coefficients were lower than 0.80, suggesting the absence of significant multicollinearity among the variables. In addition, the ability of some variable in predicting sleep disturbance is evaluated using the AUC analysis and summarized in Supplementary Table 2.

External validation

External validation was conducted in 361 university students, and among these students the prevalence of sleep disturbance was 49.58%. The background information on the external validation group was summarized, and a comparison between the model derivation group and external validation group was conducted (Supplementary Table 3). It demonstrated that the background information in the external validation group was different from that in the model derivation group. In detail, age (P<0.001), gender (P=0.002), grade (P<0.001), loving eating fatty meal (P=0.001), loving eating fruit (P=0.035), sedentary time (P=0.005), and frequency of sports per week (P=0.004) were significantly different between the two groups.

Among the developed models, the eXGBM model exhibited superior performance in terms of AUC value (0.779, 95% CI: 0.728–0.830) (Figure 2), followed by the SVM model (0.772, 95% CI: 0.721–0.824) and NN model (0.767, 95% CI: 0.715–0.819). The AUC values for RF, DT, and KNN modes were 0.752 (95% CI: 0.699–0.806), 0.724 (95% CI: 0.668–0.781), and 0.722 (95% CI: 0.665–0.778), respectively. In addition, eXGBM model had best accuracy (0.710), precision (0.737), F1 score (0.692), Brier score (0.193), and log loss (0.569) (Table 2). The calibration curve demonstrated that these models, particularly the eXGBM model, had favorable calibration ability, as their curves closely aligned with the ideal calibration line (Figure 3). Probability density curve analysis showed that the models, including the eXGBM model, had favorable discrimination,

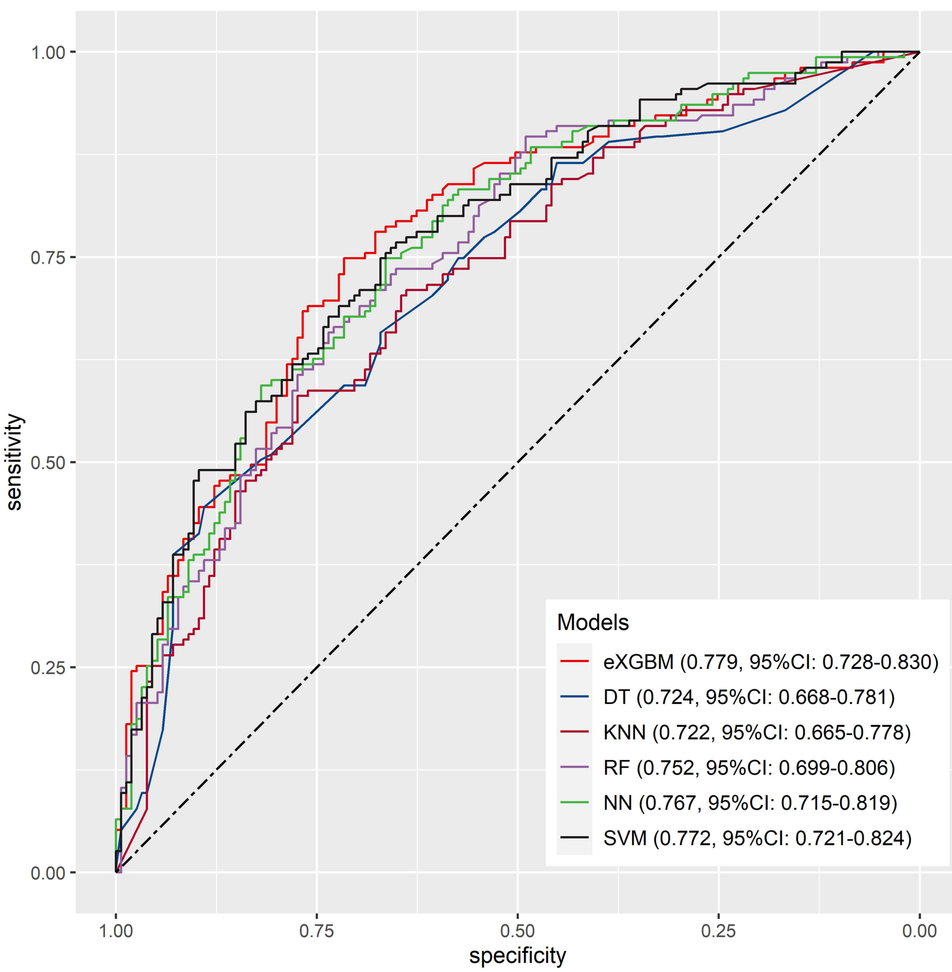

Figure 2 The area under the curve for each model.
Abbreviation: eXGBM, extreme gradient boosting machine; DT, decision tree; KNN, k-nearest neighbor; RF, random forest; NN, neural network; SVM, support vector machine.

Table 2 Prediction Performance of All Models in the External Validation Group

Metrics	Models					
	eXGBM	DT	KNN	RF	NN	SVM
AUC	0.779 (0.728–0.830)	0.724 (0.668–0.781)	0.722 (0.665–0.778)	0.752 (0.699–0.806)	0.767 (0.715–0.819)	0.772 (0.721–0.824)
Accuracy	0.710	0.655	0.674	0.694	0.687	0.694
Precise	0.737	0.636	0.711	0.714	0.713	0.727
Recall	0.652	0.723	0.587	0.645	0.626	0.619
F1 score	0.692	0.677	0.643	0.678	0.667	0.669
Brier score	0.193	0.210	0.228	0.204	0.198	0.196
Log loss	0.569	0.607	1.978	0.599	0.579	0.578
Discrimination slope	0.228	0.189	0.232	0.205	0.213	0.191

Abbreviation: eXGBM, extreme gradient boosting machine; DT, decision tree; KNN, k-nearest neighbor; RF, random forest; NN, neural network; SVM, support vector machine; AUC, area under the curve.

as the curves for participants without sleep disturbance shifted to the left side and the curves for participants with sleep disturbance shifted to the right side (Supplementary Figure 3). The calculation of discrimination slope demonstrated that the KNN model had the highest value of 0.232 (P<0.001), closely followed by the eXGBM model with a value of 0.228 (P<0.001) (Supplementary Figure 4). The decision curve analysis demonstrated favorable clinical net benefits for the eXGBM model (Figure 4). Thus, the eXGBM model was considered as the optimal model in this study.

Feature Importance

The SHAP analysis revealed that age and stress score were important continuous factors in predicting sleep disturbance, as they had high SHAP values in both the model derivation group and the external validation group. This means that higher age and stress scores contribute more to the likelihood of experiencing sleep disturbance. Furthermore, the SHAP

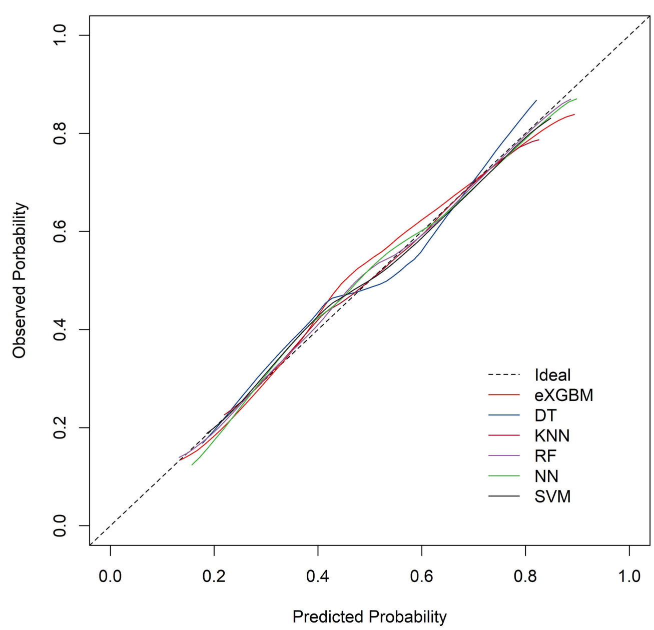

Figure 3 Calibration curve for each model.
Abbreviation: eXGBM, extreme gradient boosting machine; DT, decision tree; KNN, k-nearest neighbor; RF, random forest; NN, neural network; SVM, support vector machine.

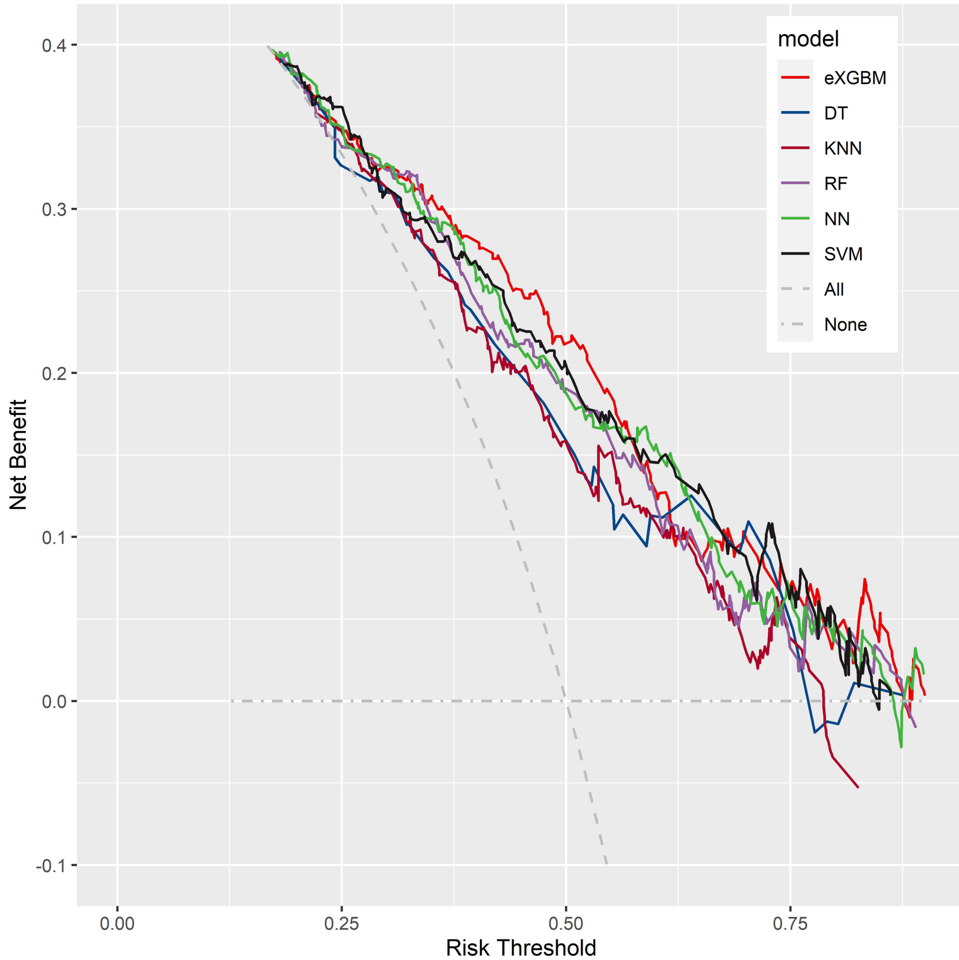

Figure 4 Decision curve analysis for each model.
Abbreviation: eXGBM, extreme gradient boosting machine; DT, decision tree; KNN, k-nearest neighbor; RF, random forest; NN, neural network; SVM, support vector machine.

analysis identified five key features that had significant influence on sleep disturbance. These features were stress score, severity of depression, vegetable consumption, age, and sedentary time. These factors were found to be important in predicting the risk of sleep disturbance (Figure 5).

Establishment of the AI Model

To make the AI model accessible to users, it was made available online at https://sleepdisturbancestudents-xakgzwectsw85cagdgkax9.streamlit.app/. Users could input their information, such as age, dietary preferences, sedentary time, and mental health status, into the AI model interface. After clicking the "Submit" button, the model would calculate the individualized risk of sleep disturbance for the user (Figure 6). For example, a 21-year-old female university student who was in her second year of study, had a preference for fatty meal, did not like to consume alcohol or vegetables, had less than one hour of sedentary time per day, and did not have any chronic diseases or mental health issues such as anxiety, depression, or stress. After inputting the above information into the AI model, it calculated that the risk of experiencing sleep disturbance for this student was 34.79%, which classified her as belonging to the low-risk group. The AI model also provided therapeutic recommendations based on the calculated risk.

Prediction Evaluation Between Human and the AI Platform

In order to evaluate the prediction performance of the AI platform, a comparison was made between the predictions made by human experts and the AI model (Supplementary Figure 5). The results showed that the prediction performance of the

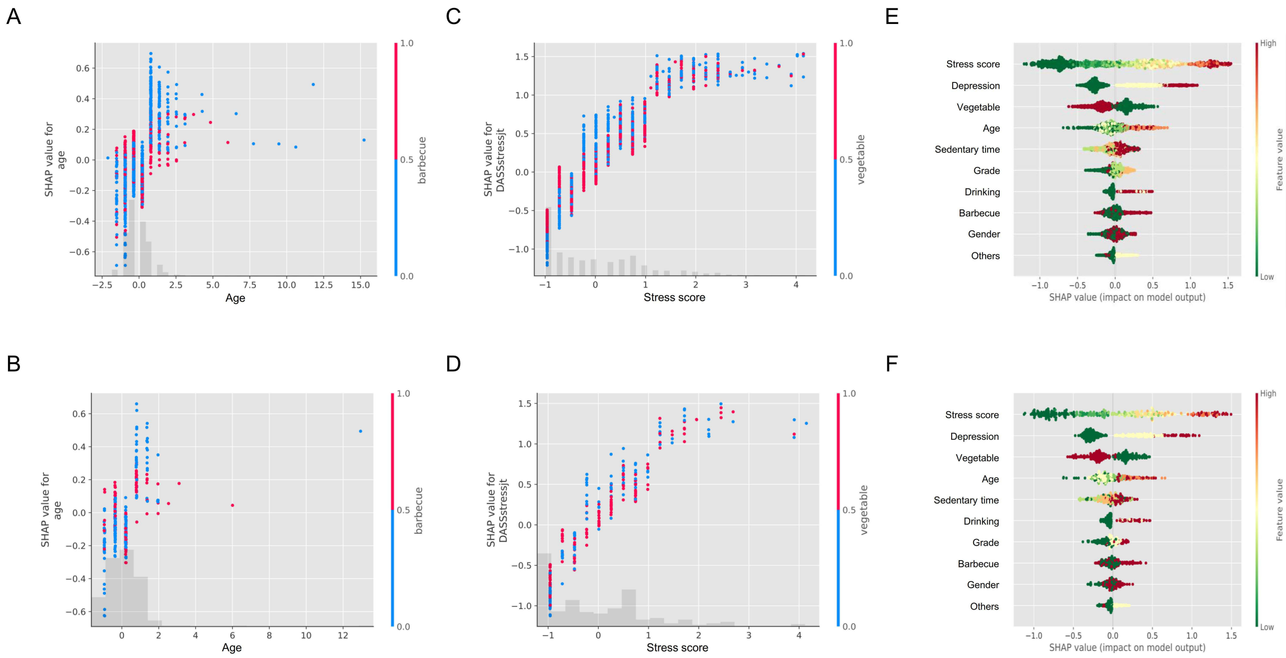

Figure 5 The Shapley Additive exPlanations (SHAP) analysis based on the eXGBM model. (**A**) The association between age and its SHAP value in the model derivation group; (**B**) The association between age and its SHAP value in the model external validation group; (**C**) The association between stress score and its SHAP value in the model derivation group; (**D**) The association between stress score and its SHAP value in the model external validation group; (**E**) Feature importance analysis in the model derivation group; (**F**) Feature importance analysis in the model external validation group.

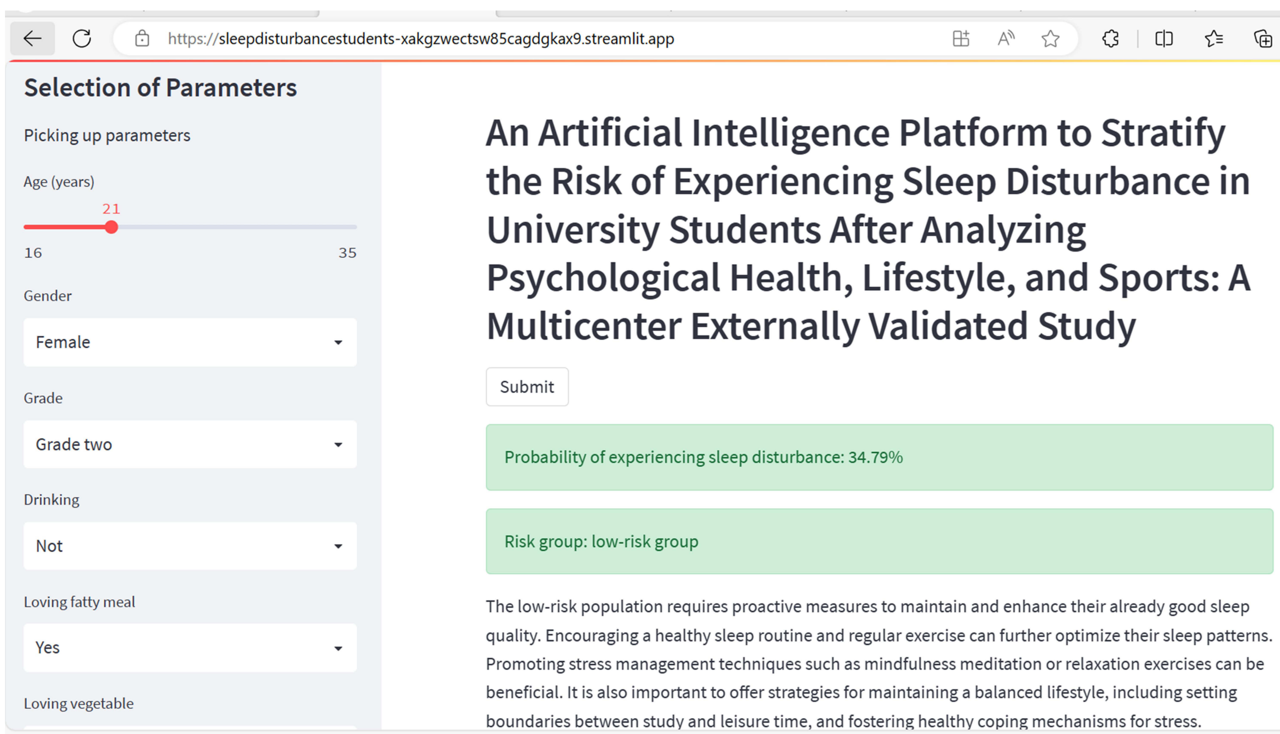

Figure 6 The web-based artificial intelligence model. The user interface was meticulously designed to facilitate the input of relevant patient data and provide efficient access to predicted probabilities. It featured intuitive panels for selecting model parameters, performing probability calculations, and accessing comprehensive information about the underlying model.

human experts was unsatisfactory, with an AUC value ranging from 0.630 to 0.660. This indicates that the human experts were not able to accurately predict the risk of sleep disturbance in university students. On the other hand, the AI model demonstrated superior prediction performance, with an AUC value of 0.779. This suggests that the AI model was more effective in accurately predicting the risk of sleep disturbance compared to human experts. The higher AUC value of the AI model indicates its ability to make more precise and reliable predictions for university students.

Discussion

Principal Findings

The findings of this study highlight the high prevalence of sleep disturbance among university students and the importance of developing effective models for assessing their risk. By leveraging AI techniques, particularly the eXGBM model, this study successfully predicts sleep disturbance risk in university students with superior performance compared to other models. The AI platform developed in this study provides a valuable resource for identifying students at high risk for sleep disturbance and potentially guiding interventions to improve sleep outcomes. The identification of key features, such as stress score, severity of depression, vegetable consumption, age, and sedentary time, further enhances our understanding of the factors contributing to sleep disturbance in this population. The availability of an internet-based AI platform allows for easy access and individualized risk calculation, contributing to the development of personalized interventions and improving sleep health among university students.

Prediction of Sleep Disturbance Among University Students

Previously, we established a nomogram to assess the sleep quality for university students.[9] In the nomogram, chronic disease, smoking, naps at noon, drinking, loving eating vegetable, age, grade, anxiety status, and stress status were used as features. Internal validation showed that the AUC value of the nomogram was only 0.715, and external validation was not achieved. In addition, the method to develop nomogram was based on traditional statistical analysis in the study. More recently, a machine learning-based study was aimed to develop models for predicting sleep quality for university students during the COVID-19 pandemic and closed-loop management.[10] The study found that the pandemic had a detrimental effect on the sleep quality of college students. Eleven variables, including age, gender, residence, specialty, respiratory history, coffee consumption, stay up, internet usage, sudden changes, fears of infection, and closed-loop management, were identified as factors related to sleep quality in this study.[10] This study used logistic regression and three machine learning techniques to develop models, and among the four developed models, the artificial neural network model demonstrated the best performance in predicting sleep problems.[10] Nonetheless, the AUC value of the artificial neural network model was 0.713, indicating the accuracy of the model still needs improvements. In addition, another limitation of this model is that it is based on research conducted during the period of the COVID-19 pandemic.[10] But the situation has significantly changed, with the pandemic being largely under control and various policies, such as closed-loop management, being lifted. Therefore, the applicability of this model in non-pandemic times needs further investigation and research. In the present study, multiple machine learning techniques were utilized to ensure a thorough evaluation of prediction performance. The selected optimal model, eXGBM, demonstrates superior performance compared to other models, with high AUC value, accuracy, precision, F1 score, and favorable calibration ability. Lastly, the study provides practical utility by developing an internet-based AI platform accessible to users. This platform allows individuals to calculate their individualized risk of sleep disturbance and provides valuable guidance for interventions to improve sleep outcomes among university students. Overall, the present study contributes to the existing literature by providing an effective AI model and platform for assessing and addressing sleep disturbance among university students, thereby improving their overall well-being and academic success.

Studies have shown that stress, depression, and anxiety were closely associated with quality of sleep among university students.[22–25] In addition, sleep disturbance may predict the development and persistence of depression,[26] indicating mental state and sleep quality mutually influence each other. In the present study, we also found that healthy eating habits and lifestyle were beneficial to promote good sleep quality. In detail, the study found that abstaining from alcohol, avoiding fatty meals, and having a preference for consuming vegetables were beneficial in promoting good sleep quality. It was also determined that alcohol consumption had a negative impact on the sleep quality of university students.[22–25] In addition, a nomogram was previously developed to assess sleep quality in university students,[9] wherein drinking was identified as a significant risk factor, while a preference for consuming vegetables was considered a protective factor. A systematic review also revealed that high intake of vegetables and fruits was inversely associated with sleep disturbance.[27] Furthermore, the present study found that stress was one of the most important features contributing to sleep disturbance. A study provided clear insights into the stress-induced factors affecting college students, and these factors include anxiety score, worry about the inability to understand concepts taught online, involvement of parents, college hours, and concerns about other workload and deadlines.[28] It highlighted the significant impact of these factors on the well-being and academic performance of young students studying in universities.[28]

Individualized Intervention for Sleep Disturbance

Sleep disturbance is a prevalent issue among college students and requires targeted intervention strategies to address the specific needs of this population. Several studies have explored various interventions to improve sleep quality and mitigate the negative consequences of sleep disturbance among university students. One effective intervention is the delivery of mindfulness meditation through the modality of "Calm", which has been shown to reduce stress and improve mindfulness and self-compassion in stressed college students.[29] This intervention highlights the potential of mindfulness-based approaches in managing sleep disturbance among students. Another beneficial intervention is increasing sleep self-awareness and general knowledge through education for students.[30] Many students lack sufficient knowledge about sleep hygiene and the importance of good sleep habits. By increasing education and awareness, students can learn about the components of good sleep hygiene, such as using the bed only for sleeping, avoiding stimulating activities before bed, and managing thoughts and worries before sleep.[3] Education can empower students to make informed decisions and adopt healthier sleep practices. Online sleep education interventions have also shown promise in improving sleep behaviors, sleep quality, and depression scores among college students.[31] These brief and personalized interventions provide an effective and inexpensive remedy for sleep deprivation and poor sleep habits among students. Notably, a review of interventions for sleep disturbance among college students identified several categories, including sleep hygiene, cognitive-behavioral therapy (CBT), relaxation, mindfulness, hypnotherapy, and other psychotherapeutic interventions.[32] CBT interventions have demonstrated the most significant effects in improving sleep variables. Combining CBT with relaxation techniques, mindfulness, and hypnotherapy can be beneficial in addressing psychological factors affecting sleep. Other psychotherapeutic interventions have also shown medium effects.

According to the stratification of participants in the AI mode in the present study, for high-risk individuals with poor sleep quality, targeted intervention strategies should be implemented. This includes providing education on sleep hygiene and promoting consistent sleep schedules, creating a conducive sleep environment, avoiding stimulants close to bedtime, and incorporating relaxation techniques before sleep. CBT for insomnia can also be employed to address psychological factors and modify negative sleep thoughts, implement behavioral techniques, and enhance relaxation skills. In contrast, the low-risk population requires proactive measures to maintain and enhance their already good sleep quality. Encouraging a healthy sleep routine, regular exercise, stress management techniques such as mindfulness meditation or relaxation exercises, and strategies for maintaining a balanced lifestyle are beneficial for this group. The artificial intelligence model developed in this study using the eXGBM technique exhibited promising results and could provide accurate predictions of sleep disturbance risk among university students. However, it is important to consider that clinical expertise and individual context should also be taken into account when developing therapeutic strategies based on the AI model's recommendations.

Overall, this study highlights the potential of AI technology in predicting and addressing sleep disturbance among university students. By leveraging machine learning algorithms and data analysis, AI models offer more accurate and consistent predictions, enhancing the efficiency and reliability of sleep disturbance risk assessment. This has significant implications for the development of personalized interventions and treatment strategies to improve sleep outcomes in the university student population. Targeted university management and social support are also crucial in addressing sleep issues faced by college students, and implementing early interventions using predictive models can potentially improve their sleep conditions.

Limitations

Despite its valuable contributions, this study has several limitations that should be acknowledged. Firstly, the study sample consisted of university students from a specific geographic region, which may limit the generalizability of the findings to other populations or cultural contexts. Future research should aim to include more diverse samples to enhance the external validity of the AI model. Secondly, the data used in this study relied on self-report measures, which are subject to recall bias and may not always accurately reflect the participants' actual behaviors and experiences. Objective measures, such as actigraphy or polysomnography, could provide more reliable data for future studies. Another limitation is the reliance on cross-sectional data, which limits our ability to establish causal relationships between the identified risk factors and sleep disturbance. Longitudinal studies are needed to better understand the temporal associations between these factors and sleep outcomes. Moreover, the AI model developed in this study was founded on a set of pre-defined features. However, there could be other crucial factors, such as time spent using digital media like smartphones, time spent on academic tasks, time spent working, and whether participants live with family or alone, that were not taken into account in the analysis. Exploring these features and integrating more comprehensive data has the potential to improve the predictive accuracy of the model. Lastly, the AI platform developed in this study is an internet-based platform, which may not be accessible to all university students, especially those who do not have reliable internet access or technological resources. It is important to consider the potential limitations and biases associated with the use of online platforms and ensure that alternative methods are available for those who may not be able to access or utilize the AI platform. Despite these limitations, this study provides valuable insights into the prediction of sleep disturbance risk in university students using AI techniques. Future research should address these limitations and further refine the AI model to enhance its accuracy and applicability in diverse populations.

Conclusions

This study demonstrates the prevalence of sleep disturbance among university students and presents an AI model that effectively identifies students at high risk for sleep disturbance. The developed AI platform may serve as a valuable resource for guiding interventions and improving sleep outcomes in the university student population.

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Disclosure

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