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Predictors of sleep quality among university students: the use of advanced machine learning techniques

Alia A. Alghwiri [1] • Fidaa Almomani [2] • Alaa A. Alghwiri [3] • Susan L. Whitney [4]

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Abstract

Purpose To assess the prevalence of sleep disturbances among university students and investigate potential correlated factors and their relative importance in quantifying sleep quality using advanced machine learning techniques.

Methods A total of 1600 university students participated in this cross-sectional study. Sociodemographic information was collected, and the Pittsburgh Sleep Quality Index (PSQI) was administered to assess sleep quality among university students. Study variables were evaluated using logistic regression and advanced machine learning techniques. Study variables that were significant in the logistic regression and had high mean decrease in model accuracy in the machine learning technique were considered important predictors of sleep quality.

Results The mean (SD) age of the sample was 26.65 (6.38) and 57% of them were females. The prevalence of poor sleep quality in our sample was 70%. The most accurate and balanced predictive model was the random forest model with a 74% accuracy and a 95% specificity. Age and number of cups of tea per day were identified as protective factors for a better sleep quality, while electronics usage hours, headache, other systematic diseases, and neck pain were found risk factors for poor sleep quality.

Conclusions Six predictors of poor sleep quality were identified in university students in which 2 of them were protective and 3 were risk factors. The results of this study can be used to promote health and well-being in university students, improve their academic performance, and assist in developing appropriate interventions.

Keywords Sleep quality · University students · Logistic regression · Machine learning techniques

Introduction

Sleep is a basic need for humans that plays an essential role in the functioning of body systems [1]. Quality of sleep (QoS) affects physical, mental, and psychological aspects of human health [2]. Physically, QoS has been found to be associated with pain intensity [3], grip strength [4], balance and risk of falling [5], and obesity [6]. Mental health including a person's cognitive ability, well-being, and mood changes is associated with QoS [7]. Depression and anxiety symptoms are among the most frequently reported psychological disorders that were associated with poor sleep quality [8]. Therefore, individuals' overall quality of life is affected by QoS [9].

Poor sleep quality is a common issue in the modern society and has negative consequences on people's health [10]. Sleep disorders have been reported in individuals with Alzheimer's disease [11], rheumatoid arthritis [12], chronic obstructive pulmonary disease [13], Parkinson's disease [14], and multiple sclerosis [15]. Several explanations have been proposed for the sleep disturbances in each disease such as the involvement of brain structure, the nature of the disease, or other factors associated with the course of the disease. However, other populations with no specific health disorders were also found at risk of having poor sleep such as adolescents [7] and university students [16].

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✉ Alia A. Alghwiri
alia.alghwiri@gmail.com

1 Department of physical therapy, School of Rehabilitation Sciences, The University of Jordan, Queen Rania Street, Amman 11942, Jordan

2 Department of rehabilitation sciences, School of Applied Medical Sciences, Jordan University of Science and Technology, Irbid, Jordan

3 Office of the Provost, University of Pittsburgh, Pittsburgh, PA, USA

4 Department of physical therapy, School of Health and Rehabilitation Sciences, University of Pittsburgh, Pittsburgh, PA, USA

It has been shown that poor sleep quality among university students is a global problem. Several studies identified the prevalence of sleep disturbances among university students in various developing and developed countries. In Lebanon, clinical insomnia was present in 11% of university students with 37% classified as poor sleepers [17]. Clinical anxiety was also examined and found to affect 29% of university students. Among those with clinical insomnia and poor sleep, clinical anxiety was more prevalent. Additionally, more than half of those participants with anxiety also experienced excessive daytime sleepiness [17]. Another study reported that 18.8% of nursing students had insomnia which might contribute to their academic performance [16]. Similarly, in a cross-sectional study of a group of university students, 59% reported poor sleep quality with medical students experiencing the worst sleep [9].

Several factors may contribute to sleep disturbances including physical and psychosocial impairments. Body discomfort, physical disability, schizophrenia, and the side effect of medications are all potential factors that may affect QoS [18]. In adolescents, QoS was positively affected by good sleep hygiene and physical activity which usually lead to an earlier bedtime than their peers. Evening light, the use of electronic devices such as mobile phones, computers, and video gaming are potential factors that delay bedtime and subsequently contribute to poor sleep [19, 20]. Other factors that may negatively affect QoS include caffeine consumption, tobacco use, and a poor home environment such as evening light and room temperature [19].

To the best of our knowledge, there are no studies that utilize advanced machine learning techniques to identify the most important predictors of poor sleep quality in university students. The use of such advanced algorithms may provide us with the most accurate and important factors that may improve or worsen QoS in university students. Therefore, the goals of this study were as follows: (1) to estimate the prevalence of sleep disturbances among university students and (2) to investigate potential correlated factors and their relative importance in quantifying sleep quality.

Materials and methods

Sample and procedures

This was a cross-sectional study that recruited students from 3 private and 3 public universities in Jordan. Students aged 18 years and above were eligible for participation in the study. Exclusion criteria were pregnancy, malignancy, and confirmed diagnosis of sleep or psychological diseases.

Ethical approval was obtained from the Institutional Review Board of Jordan University of Science and Technology. Interested and eligible students signed a written informed consent after informing them about the purpose and procedure of the study. Subsequently, the following information was obtained from study participants: sociodemographic factors (age, gender, marital status, and where they live—town or city), health-related information in the last month (weight, height, caffeine intake, neck pain, headache, prescribed medications, and other systematic diseases), and the daily use of electronics in the last month (smart phone, video gaming, computer, and Internet). Finally, each student was asked to complete the Pittsburgh Sleep Quality Index (PSQI) to assess QoS in the last month [21]. Researchers distributed 2000 copies of the survey questionnaires.

Pittsburgh Sleep Quality Index (PSQI)

The PSQI is a self-reported questionnaire that was developed to measure QoS and difficulty in sleep over a 1-month period [21]. It consists of 19 questions that are rated on a scale of 0–3 with 0 indicating no sleep difficulty and 3 indicating severe sleep difficulties. The PSQI has seven component scores that are summed to form a single global score ranging from of 0–21. A global score of higher than 5 indicates poor sleep quality for all age groups. Therefore, in our study we divided participants into 2 groups (poor sleepers and good sleepers) based on their PSQI global score. The PSQI has good psychometric properties [22] and has been translated and validated into the Arabic language [23].

Statistical analysis

In this study, the PSQI global score was considered the statistical modeling outcome, and the rest of the study variables were the model predictors. The PSQI global score was categorized into 2 categories: good sleepers ≤ 5 and poor sleepers > 5. Logistic regression and advanced machine learning classifiers were used to analyze the data. The level of significance (alpha) 0.05 was used for the analyses, and all the analyses were done using R software (R version 3.4.1, RStudio) for Apple Mac.

Logistic regression

All study predictors were primarily evaluated using the classical statistical approach (logistic regression). Logistic regression is a parametric approach for classification statistical analyses and was used in this study to evaluate the association between study predictors and outcome variable and identify the odds ratio and the significant predictors. Odds ratio represents a useful way in quantifying the impact of the significant predictors on the outcome variable. Logistic regression was applied to all the variables that were collected in the study survey to evaluate QoS and only those that were significant were left in the model. All the following logistic regression assumptions were checked and satisfied: The dependent variable is binary (good or poor) in this study, the observations are independent of each other, there are no multicollinearity among the predictors (all the predictors variance inflation factor values were less than 2), and there is a linear relationship between the logit of the outcome (logit $(p) = \log (p/(1-p))$, where p is the probabilities of the outcome) and each predictor variable [24]. The logistic regression model was coded as 1 for poor sleep quality (measure of interest) and 0 for good sleep quality.

Machine learning models

All study variables were compared using 5 machine learning algorithms: the decision tree, random forest, support vector machine, artificial neural network, and gradient boosting trees. In order to avoid the model overfitting, cross-validation was applied by splitting the data into training (70% (1120 cases)) and testing (30% (480 cases)). The training set was used to build the predictive model, while the testing set was used to check the model accuracy in evaluating new data set that has never participated in the model building stage. Consequently, all the generated results for models evaluations were based on the testing set. A thorough comparison was performed after the model building stage between all the algorithms to select the most accurate and balanced approach using the most common key performance indicators (KPIs) and the receiver operating characteristics curve (ROC). Ultimately, the most accurate predictive model was used to evaluate the association between all the predictors and the PSQI global score to calculate the prevalence of sleep disorders [25]. As we are dealing with a classification problem, the following equation was used to calculate the model accuracy:

$$\frac{(\text{True Positive}) + (\text{True Negative})}{((\text{True Positive}) + (\text{True Negative}) + (\text{False Positive}) + (\text{False Negative}))}$$

Results

A total of 1600 questionnaires were included in the analyses with an estimated response rate of more than 80%. Sociodemographic and other characteristics of the study sample are presented in Table 1. The prevalence of poor sleep quality among university students in Jordan was found to be 70%. Around 16% of the sample reported having other systematic diseases that affected their QoS, and these diseases were mainly diabetes mellitus, hypertension, and musculoskeletal disorders.

Logistic regression results

Certain sociodemographic factors were significantly associated with QoS among university students. However, only electronics usage hours, age, headache, number of cups of tea per day, other systematic diseases, and neck pain significantly predicted QoS using logistic regression (Table 2). The values of odds ratio presented in Table 2 can be used in quantifying the impact and the direction of the significant predictors on QoS. Four predictors were found as risk factors for poor sleep quality: electronics usage hours, headache, other systematic diseases, and neck pain. Age and number of cups of tea per day were identified as protective factors for good sleep quality (Table 2).

Machine learning models results

Multiple machine learning methodologies were leveraged, and a thorough comparison between these methodologies was applied using the most common KPI's for the classification statistical analyses as shown in Table 3 The overall accuracy presented in Table 3 (data is from testing data set) provides an idea about the agreement between the observed and predicted classes in evaluating each class in the model. However, the overall accuracy makes no distinction about the type of error being made. Therefore, both sensitivity (true positive rate) and specificity (true negative rate) provide us with an idea about the model accuracy in evaluating good and poor sleep quality respectively. In order to have an unconditional generalization about each class and taking the prevalence into account, the analog for sensitivity is the positive predicted value and for the specificity is the negative predicted value [26].

Another common way to evaluate the classifiers is the ROC curves as shown in Fig. 1 (the data presented is from the testing data set). The ROC curves show the performance of each classifier based on the true positive and the false positive values. The vertical axis of the ROC curve represents the true positive rate, and the horizontal axis represents the false positive rate. The model performance using the ROC curves can be evaluated based on the area under each classifier curve, i.e., the greater the area under the curve means the classifier

Table 1 Sample characteristics ($n = 1600$)

Characteristic	Mean ± SD ($n = 1600$)	PSQI ≤ 5 (n = 485)	PSQI > 5 ($n = 1115$)
Age (years)	26.65 ± 6.38	27.65 ± 6.647	26.22 ± 6.218
Body mass index (BMI)	23.67 ± 3.85	23.77 ± 3.453	23.78 ± 4.005
BMI for males	24.13 ± 3.06		
BMI for females	23.5 ± 4.34		
Coffee intake (number of cups per day)	2.11 ± 2.06	2.13 ± 1.996	2.19 ± 2.091
Tea intake (number of cups per day)	2.1 ± 1.84	2.24 ± 1.826	2.16 ± 1.848
Electronics usage (hours per day)	5.49 ± 4.29	4.43 ± 3.62	5.95 ± 4.479
Gender, *n* (%)			
Females	904 (57)	269 (55.5)	635 (57)
Male	696 (43)	215 (44.3)	480 (43)
Marital status, *n* (%)			
Single	1026 (64)	278 (57.3)	748 (67.3)
Married	574 (36)	207 (42.7)	365 (32.7)
Area of living, *n* (%)			
Town	720 (45)	227 (46.8)	493 (44.2)
City	880 (5)	258 (53.2)	622 (55.8)
Neck pain, *n* (%)			
Yes	424 (26.5)	65 (13.4)	359 (32.2)
No	1176 (73.5)	420 (86.6)	756 (67.8)
Headache, *n* (%)			
Yes	577 (36)	106 (21.9)	471 (42.2)
No	1023 (64)	379 (78.1)	644 (57.8)
Prescribed medications, *n* (%)			
Yes	154 (10)	48 (9.9)	106 (9.5)
No	1446 (90)	437 (90.1)	1009 (90.5)
Other systematic diseases, *n* (%)			
Yes	263 (16)	47 (9.7)	216 (19.4)
No	1337 (84)	438 (90.3)	899 (80.6)
Pittsburgh Sleep Quality Index (PSQI)			
Subjective sleep quality	0.94 ± 0.767		
Sleep latency	1.61 ± 1.190		
Sleep duration	0.66 ± 0.714		
Sleep efficiency	0.05 ± 0.292		
Sleep disturbances	1.24 ± 0.658		
Sleep medications	0.56 ± 0.880		
Daytime dysfunction	1.18 ± 0.759		
Global score	6.27 ± 3.058		

performs better. In Fig. 1, it is clear that the random forest model is performing better than all other approaches and has a smooth trend between the true positive and false positive fractions. Moreover, Table 3 is also consistent with Fig. 1 and shows that the random forest model has the maximum overall accuracy and the best balance between classes (based on the value of Cohen's Kappa). Kappa value within 0.30 to 0.50 indicates reasonable agreement between classes, and it is 0.26 in this case which is the closest to the ideal Kappa range [26]. Although the support vector machine has the same overall accuracy as the random forest model, the balance between classes is not close to the reasonable agreement range.

Since the random forest model was found to be the best predictive model for this study, it has been used to evaluate the factors' relative importance using the "mean decrease in accuracy" as shown in Fig. 2. Each grown tree in the random

Table 2 Logistic regression results with significant variables, the estimates for each variable, *P* values, odds ratios, and the confidence intervals

Variable	Model fit parameters	*P* value	Odds ratio	Confidence interval
Intercept	1.578	2.94×10^{-10}	–	2.349 to 10.052
Electronics usage (hours)	0.052	0.049	1.053	0.0005 to 0.1033
Age (years)	− 0.045	0.0001	0.956	− 0.0686 to − 0.0224
Headache (yes)	0.715	2.22×10^{-5}	2.044	0.3883 to 1.0499
Number of tea cups	− 0.086	0.043	0.918	− 0.1689 to − 0.0025
Other diseases (yes)	0.660	0.003	1.935	0.2324 to 1.1068
Neck pain (yes)	0.667	0.00049	1.948	0.2975 to 1.0489

After applying Hosmer and Lemeshow goodness of fit (GOF) test, the following results were found: X-squared = 480, df = 8, *P* value < 2.2E−16

Table 3 Comparison of machine learning models using the most common key performance indicators for the classification statistical analyses

Model	Overall accuracy (%)	Sensitivity (%)	Specificity (%)	Positive predictive value (%)	Negative predicted value (%)	Cohen's Kappa	Area under the curve (ROC)
Logistic regression	71	94	17	73	56	0.14	66.4
Decision tree	67	95	0.04	70	25	0.065	63
Random forest	74	95	28	75	68	0.26	74
Boosted trees	70	93	17	72	50	0.12	68.5
Support vector machine	74	100	14	73	100	0.18	63.8
Artificial neural network	68	89	20	72	44	0.10	62

forest approach has its own out-of-bag sample of data that was not used during the model building. This sample has been used to calculate the importance of specific variable. First, the prediction accuracy on the out-of-bag sample is measured. Then, the values of the variable in the out-of-bag sample are shuffled, keeping all other variables the same. Finally, the decrease in prediction accuracy on the shuffled data is measured [27]. The top eight important factors are mentioned in Fig. 2 ranked from the most to the least importance: electronics usage hours, age, number of cups of coffee per day, headache, BMI, number of cups of tea per day, other systematic diseases, and neck pain.

Supplement 1 shows that there was no high correlation between the predictors that may dilute the importance of key predictors. This also has been proven when the logistic regression assumptions about multicollinearity were checked and found the variance inflation factor less than 2.

Logistic regression and machine learning models

By considering both the significant predictors in the logistic regression model and the most important predictors (> 45% of mean decrease in accuracy) resulting from the machine learning approach, we can clearly see that both approaches agreed on 6 predictors: electronics usage hours, age, headache, number of cups of tea per day, other systematic diseases, and neck pain.

Discussion

The aims of this study were to estimate the prevalence of sleep disturbances among university students and explore the most import predictors of QoS. Seventy percent of university students in Jordan had poor sleep quality as measured by PSQI which is higher than most of the reported prevalence of sleep disorders in university students [9, 16, 17]. Around 19% of nursing students at the University of Perugia had insomnia [16]. A higher percentage of 37% of Lebanese university students reported poor sleep quality [17]. Even a higher percentage (59%) of medical students experienced poor sleep [9]. All previous studies reported lower prevalence of sleep disorders in university students than the prevalence found in our study. However, 70% of medical students in Hong Kong reported a short sleep duration which is a similar percentage compared with Jordanian students [28].

When students enter the university, they frequently encounter new situations that they have not experienced before, such as self-regulation of sleep and wake cycles. Additionally, the presence of a roommate, increased independence, and frequently living away from home for the first time are all factors that may affect QoS. It has been shown that parent-set bedtime correlated with lengthier sleep [19]. However, when a student leaves home and becomes responsible for sleeping and waking, this may have a negative effect on sleep. Therefore, implementing sleep health education programs for university

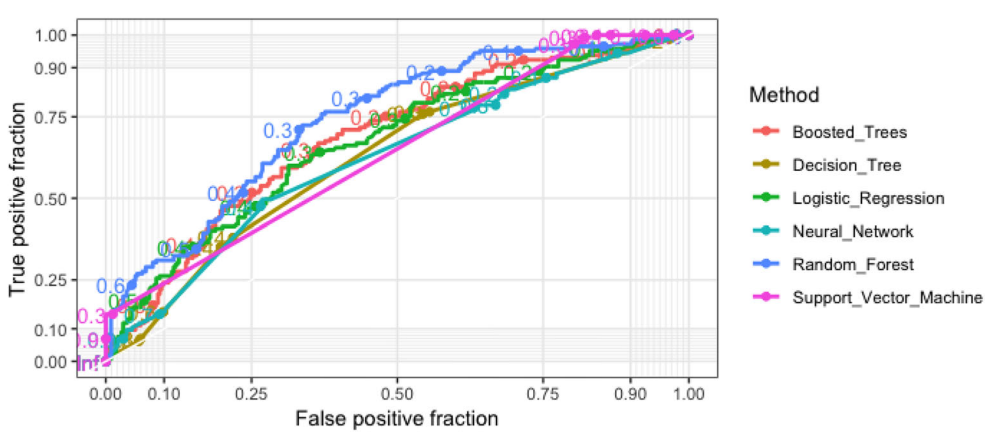

Fig. 1 Receiver operating characteristic (ROC) curves for advanced machine learning models

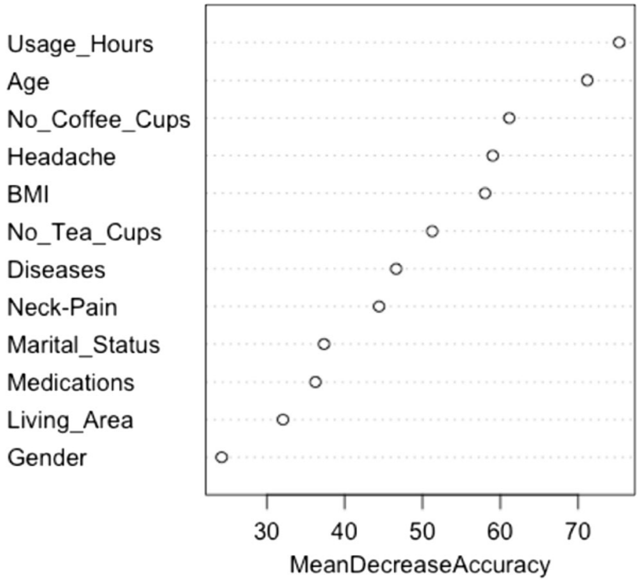

Fig. 2 Factors' relative importance in the prediction of sleep quality based on their "mean decrease in accuracy" using the random forest model

students at the beginning of their academic life might be beneficial for them [29].

To the best of our knowledge, this is the first study that identifies the most important predictors of poor sleep quality in university students using the results of both logistic regression and advanced machine learning techniques. Six factors were found to be the most important predictors of poor sleep quality in university students: electronics usage hours, age, headache, number of cups of tea per day, other systematic diseases, and neck pain. This predictive model was able to predict QoS in university students with 74% accuracy and 95% sensitivity. Note that the sensitivity is high in evaluating poor sleep quality which is the interest of this study. Using the odds ratio values of the most important predictors, we can see that the likelihood of poor sleep quality is twice as likely in students who have either a headache, a neck pain, or other systematic diseases compared with students who do not.

Several studies have reported the relationship between headache and poor sleep quality. In a recent study that recruited individuals with tension headache, they found that headache intensity and duration were correlated with poor sleep quality [30]. Additionally, depressive and emotional symptoms from headache explained 27.5% of the QoS in a group of individuals with chronic tension headache [30]. A 2015 systematic review also confirmed the association between QoS and tension headache [31]. In people with migraine headache, the prevalence of poor sleep quality was 48% compared with probable migrainers who reported a prevalence of 35% sleep disturbances [32].

In our sample, neck pain was found to be a predictor of poor sleep quality in university students. Poor sleep quality was reported in people with mechanical neck pain with worse sleep disturbances in higher pain intensity [33]. Another study confirmed that people with mechanical neck pain had higher disability and sleep disturbances than healthy controls [34]. The interaction between neck pain and poor sleep quality is bidirectional since the posture of the neck during sleeping may affect the QoS [35].

Sixteen percent of our sample reported having other systematic diseases that affected their QoS including diabetes mellitus, hypertension, and musculoskeletal disorders. In a recent review for people with diabetes mellitus, it was found that poor sleep quality and impaired sleep duration are prevalent in this population [36]. A different study has reported the association between insomnia and increased blood pressure [37]. Musculoskeletal disorders are common in the general population, and sleep disturbances were reported in several studies that examined QoS in people with musculoskeletal disorders [38].

The use of mobile phones and other electronics is not only bad for QoS but also for the general health [39]. The use of electronics such as mobile phones, computers, and video gaming has been found to delay bedtimes which negatively affect QoS [19]. Poor sleep quality in university students has an impact on students' academic burnout. In a 2015 study, the QoS predicted academic burnout 37% of the time [40]. When students get academic burnout, they usually restrict their participation in class activities, show no interest in learning, and report a feeling of meaninglessness [40].

According to logistic regression results, it is clear that electronics usage hours, headache, other systematic diseases, and neck pain had a negative impact on the QoS in university students suggesting that they are risk factors for poor sleep. Conversely, both age and the number of cups of tea per day had a positive impact on the QoS, suggesting that they are protective factors from poor sleep.

Age and the number of cups of tea per day were found to be protective factors from poor sleep quality, i.e., older students had a better QoS and tea consumption may help in a better QoS. Others have reported that being older was related to a better sleep in persons between 20 and 40 years of age [41]. They reported that with increased age, life style regulation including sleep improved. However, other studies that have examined QoS in the elderly population found controversial results. In a recent study in Saudi Arabia with a wide age range (18–100 years old), they found that older adults had worse sleep quality than middle-aged and younger-aged individuals [42]. There may be differences in QoS based on whether the person is young, middle aged, or those that are elderly.

Regarding tea consumption, a study reported that tea consumption was a risk factor of insomnia [42]. However, others found that daily tea consumption may have an alerting effect during the day but not to the level that interrupt sleeping during the night [43]. In Hindmarch et al. (2000) study, they compared the effect of daily consumption of caffeinated tea and coffee on alertness and QoS. They found that tea has a similar alerting effect to coffee during the day but it does not have a negative effect on QoS [43]. Other studies even recommend herbal tea to improve QoS [44]. The mechanism of the effect of tea on sleep quality is not clear. However, some studies suggested that herbal tea (*Passiflora incarnata*) may have a positive effect on anxiety that is correlated with poor sleep [44, 45]. Other studies investigated the effect of Maoyecha tea on GABAergic neurotransmission and found that it has a sleep promoting effect [46].

This study is not without limitations related to the design of the study. Cross-sectional design has its biases since the data is collected at one time point. Longitudinal studies with more than one time point may have provided us with more data about the QoS in university students. Moreover, it was unknown if the students lived at home or with their parents or how active they were. Therefore, collecting more information about students' living status and activity level would have helped us better interpret the results.

Conclusions

The prevalence of poor sleep quality in Jordanian university students was high (70%). Several factors were found to be the most important predictors for poor sleep quality using both logistic regression and advance machine learning models. Electronics usage hours, age, headache, number of cups of tea per day, other systematic diseases, and neck pain were the most important predictors for QoS. Identifying high-risk groups may assist in early identification, screening, and prevention of psychosocial impairments that may result from sleep disturbances.

Authors' contributions All authors contributed to the conception and design of the study, acquisition of data, or analysis and interpretation of data; drafting the article and revising it critically, and final approval of the manuscript submitted.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethics approval Was obtained from the Institutional Review Board of Jordan University of Science and Technology. Interested and eligible students signed a written informed consent after informing them about the purpose and procedure of the study.

References

1. Barnes CM, Drake CL (2015) Prioritizing sleep health: public health policy recommendations. Perspect Psychol Sci 10:733–737
2. Lund HG, Reider BD, Whiting AB, Prichard JR (2010) Sleep patterns and predictors of disturbed sleep in a large population of college students. J Adolesc Health 46:124–132
3. Smith MT, Wickwire EM, Grace EG, Edwards RR, Buenaver LF, Peterson S, Klick B, Haythornthwaite JA (2009) Sleep disorders and their association with laboratory pain sensitivity in temporomandibular joint disorder. Sleep 32:779–790
4. Lee G, Baek S, Park HW, Kang EK (2018) Sleep quality and attention may correlate with hand grip strength: FARM study. Ann Rehabil Med 42:822–832
5. Ma T, Shi G, Zhu Y, Wang Y, Chu X, Jiang X, Liu Z, Cai J, Wang H, Jin L, Wang Z, Wang X (2017) Sleep disturbances and risk of falls in an old Chinese population-Rugao longevity and ageing study. Arch Gerontol Geriatr 73:8–14
6. Jarrin DC, McGrath JJ, Drake CL (2013) Beyond sleep duration: distinct sleep dimensions are associated with obesity in children and adolescents. Int J Obes 37:552–558
7. Thumann BF, Bornhorst C, Michels N, Veidebaum T, Solea A, Reisch L et al (2019) Cross-sectional and longitudinal associations between psychosocial well-being and sleep in European children and adolescents. J Sleep Res 28:e12783
8. Dinis J, Braganca M (2018) Quality of sleep and depression in college students: a systematic review. Sleep Sci 11:290–301
9. Preisegolaviciute E, Leskauskas D, Adomaitiene V (2010) Associations of quality of sleep with lifestyle factors and profile of studies among Lithuanian students. Medicina (Kaunas) 46:482–489
10. Leger D, Partinen M, Hirshkowitz M, Chokroverty S, Hedner J, Investigators ES (2010) Characteristics of insomnia in a primary care setting: EQUINOX survey of 5293 insomniacs from 10 countries. Sleep Med 11:987–998
11. Peter-Derex L, Yammine P, Bastuji H, Croisile B (2015) Sleep and Alzheimer's disease. Sleep Med Rev 19:29–38
12. Sariyildiz MA, Batmaz I, Bozkurt M, Bez Y, Cetincakmak MG, Yazmalar L et al (2014) Sleep quality in rheumatoid arthritis: relationship between the disease severity, depression, functional status and the quality of life. J Clin Med Res 6:44–52
13. Soler X, Gaio E, Powell FL, Ramsdell JW, Loredo JS, Malhotra A, Ries AL (2015) High prevalence of obstructive sleep apnea in patients with moderate to severe chronic obstructive pulmonary disease. Ann Am Thorac Soc 12:1219–1225
14. Alatriste-Booth V, Rodriguez-Violante M, Camacho-Ordonez A, Cervantes-Arriaga A (2015) Prevalence and correlates of sleep disorders in Parkinson's disease: a polysomnographic study. Arq Neuropsiquiatr 73:241–245
15. Strober LB (2015) Fatigue in multiple sclerosis: a look at the role of poor sleep. Front Neurol 6:21
16. Gianfredi V, Nucci D, Tonzani A, Amodeo R, Benvenuti AL, Villarini M, Moretti M (2018) Sleep disorder, Mediterranean Diet and learning performance among nursing students: inSOMNIA, a cross-sectional study. Ann Ig 30:470–481
17. Choueiry N, Salamoun T, Jabbour H, El Osta N, Hajj A, Rabbaa Khabbaz L (2016) Insomnia and relationship with anxiety in university students: a cross-sectional designed study. PLoS One 11: e0149643
18. Chung KF, Cheung MM (2008) Sleep-wake patterns and sleep disturbance among Hong Kong Chinese adolescents. Sleep 31: 185–194
19. Bartel KA, Gradisar M, Williamson P (2015) Protective and risk factors for adolescent sleep: a meta-analytic review. Sleep Med Rev 21:72–85

20. Wang PY, Chen KL, Yang SY, Lin PH (2019) Relationship of sleep quality, smartphone dependence, and health-related behaviors in female junior college students. PLoS One 14:e0214769
21. Carpenter JS, Andrykowski MA (1998) Psychometric evaluation of the Pittsburgh Sleep Quality Index. J Psychosom Res 45:5–13
22. Backhaus J, Junghanns K, Broocks A, Riemann D, Hohagen F (2002) Test-retest reliability and validity of the Pittsburgh Sleep Quality Index in primary insomnia. J Psychosom Res 53:737–740
23. Suleiman KH, Yates BC, Berger AM, Pozehl B, Meza J (2010) Translating the Pittsburgh Sleep Quality Index into Arabic. West J Nurs Res 32:250–268
24. kassambara A, *Machine Learning Essentials: Practical Guide in R*. 1 ed. 2017: STHDA
25. Kuhn M. *Confusion Matrix*. 2019 [cited 2019; Calculates a cross-tabulation of observed and predicted classes with associated statistics.]. Available from: https://www.rdocumentation.org/packages/caret/versions/6.0-82/topics/confusionMatrix?fbclid=IwAR0csufSFqWgnAVkKgOiPpHtIciJGd8roOctvDEd8Qog7ytZD2MAXo_CSd8
26. Kuhn M, Johnson K (2016) Applied predictive modeling. Springer Nature, New York
27. Louppe G, Wehenkel L, Sutera A Geurts P. Understanding variable importances in forests of randomized trees
28. Huen LL, Chan TW, Yu WM, Wing YK (2007) Do medical students in Hong Kong have enough sleep? Sleep Biol Rhythms 5: 226–230
29. Levenson JC, Miller E, Hafer B, Reidell MF, Buysse DJ, Franzen PL (2016) Pilot study of a sleep health promotion program for college students. Sleep Health 2:167–174
30. Palacios-Cena M, Fernandez-Munoz JJ, Castaldo M, Wang K, Guerrero-Peral A, Arendt-Nielsen L et al (2017) The association of headache frequency with pain interference and the burden of disease is mediated by depression and sleep quality, but not anxiety, in chronic tension type headache. J Headache Pain 18:19
31. Rains JC, Davis RE, Smitherman TA (2015) Tension-type headache and sleep. Curr Neurol Neurosci Rep 15:520
32. Song TJ, Cho SJ, Kim WJ, Yang KI, Yun CH, Chu MK (2018) Poor sleep quality in migraine and probable migraine: a population study. J Headache Pain 19:58
33. Valenza MC, Valenza G, Gonzalez-Jimenez E, De-la-Llave-Rincon AI, Arroyo-Morales M, Fernandez-de-Las-Penas C (2012) Alteration in sleep quality in patients with mechanical insidious neck pain and whiplash-associated neck pain. Am J Phys Med Rehabil 91:584–591
34. Munoz-Munoz S, Munoz-Garcia MT, Alburquerque-Sendin F, Arroyo-Morales M, Fernandez-de-las-Penas C (2012) Myofascial trigger points, pain, disability, and sleep quality in individuals with mechanical neck pain. J Manip Physiol Ther 35:608–613
35. Lee WH, Ko MS (2017) Effect of sleep posture on neck muscle activity. J Phys Ther Sci 29:1021–1024
36. Zhu B, Vincent C, Kapella MC, Quinn L, Collins EG, Ruggiero L, Park C, Fritschi C (2018) Sleep disturbance in people with diabetes: a concept analysis. J Clin Nurs 27:e50–e60
37. Thomas SJ, Calhoun D (2017) Sleep, insomnia, and hypertension: current findings and future directions. J Am Soc Hypertens 11:122–129
38. Lavigne GJ, Nashed A, Manzini C, Carra MC (2011) Does sleep differ among patients with common musculoskeletal pain disorders? Curr Rheumatol Rep 13:535–542
39. Eyvazlou M, Zarei E, Rahimi A, Abazari M (2016) Association between overuse of mobile phones on quality of sleep and general health among occupational health and safety students. Chronobiol Int 33:293–300
40. Arbabisarjou A, Hashemi SM, Sharif MR, Haji Alizadeh K, Yarmohammadzadeh P, Feyzollahi Z (2015) The relationship between sleep quality and social intimacy, and academic burn-out in students of medical sciences. Global J Health Sci 8:231–238
41. Monk TH, Petrie SR, Hayes AJ, Kupfer DJ (1994) Regularity of daily life in relation to personality, age, gender, sleep quality and circadian rhythms. J Sleep Res 3:196–205
42. Ahmed AE, Al-Jahdali H, Fatani A, Al-Rouqi K, Al-Jahdali F, Al-Harbi A et al (2017) The effects of age and gender on the prevalence of insomnia in a sample of the Saudi population. Ethn Health 22: 285–294
43. Hindmarch I, Rigney U, Stanley N, Quinlan P, Rycroft J, Lane J (2000) A naturalistic investigation of the effects of day-long consumption of tea, coffee and water on alertness, sleep onset and sleep quality. Psychopharmacology 149:203–216
44. Ngan A, Conduit R (2011) A double-blind, placebo-controlled investigation of the effects of Passiflora incarnata (passionflower) herbal tea on subjective sleep quality. Phytother Res 25:1153–1159
45. Movafegh A, Alizadeh R, Hajimohamadi F, Esfehani F, Nejatfar M (2008) Preoperative oral Passiflora incarnata reduces anxiety in ambulatory surgery patients: a double-blind, placebo-controlled study. Anesth Analg 106:1728–1732
46. Wu C, Huang Y, Lai X, Lai R, Zhao Z, Zhang M et al (2014) Study on quality components and sleep-promoting effect of GABA Maoyecha tea. J Funct Foods 7:180–190