International Journal of Social Science Research and Review

http://ijssrr.com
editor@ijssrr.com
Volume 9, Issue 8
August, 2026
Pages: 176-187

Caffeine Intake and Sleep Quality among Students at the Institute of Management/Al-Rusafa: An Interpretable Decision Tree Analysis

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http://dx.doi.org/10.47814/ijssrr.v9i8.3521

Abstract

University students are often prescribed caffeine to boost their alertness and to remain focused during academic activities, but late and excessive consumption has been recommended to have a negative effect on sleep quality. This study aimed to explore the relationship between caffeine-related behaviors and sleep quality among students of the Institute of Management/Al-Rusafa, and to assess the predictive ability of an interpretable machine learning model to identify students with poor sleep. A cross-sectional design was used on 400 students. Sleep quality was measured by the Pittsburgh Sleep Quality Index (PSQI), with a global score higher than 5 considered as poor sleep. The independent variables were level of caffeine consumption, frequency of caffeine consumption, sleep duration, regularity of morning awakening, perceived stress, and selected lifestyle factors. A Classification and Regression Tree (CART) algorithm based on the Gini impurity criterion yielded this. Model complexity was optimized by both pre-pruning and post-pruning to minimize overfitting. Stratified k-fold cross-validation and an initial held-out test set were used to evaluate the model performance. Performance measures were accuracy, sensitivity (recall), specificity, precision, F1-score, balanced accuracy, and area under the receiver operating characteristic curve (AUC). The model had an accuracy of 85.0% on the held-out test set (n = 40) and correctly classified 34 students. There were higher recall scores for good sleep in the model compared to poor sleep (90.9% vs 77.8%). Although preliminary, because of the small sample size, the AUC of 0.843 indicated good discriminative ability. In summary, caffeine-related behaviors were correlated with sleep quality, especially regarding the timing and frequency of consumption, and the model using the CART showed good interpretability and predictive ability, but needs to be validated in other studies.

Keywords: *Caffeine Intake; Caffeinated Beverages; Sleep Quality; Pittsburgh Sleep Quality Index; Decision Tree; Students; Cross-Sectional Study*

1. Introduction

Caffeine is one of the most popular psychoactive drugs and is often used by students for its stimulatory properties to improve their focus and keep them alert while studying. Moderate caffeine consumption can enhance vigilance for a short duration; the time and dosage of caffeine are crucial, as caffeine intake near bedtime can affect sleep onset and sleep continuity. Caffeine has been found to potentially decrease sleep duration and disrupt sleep quality when consumed several hours prior to sleep [1]. Quality of sleep is an important aspect of students' health. Students' poor sleep has been linked to lower attention, academic achievement, psychological distress, and overall well-being. Sleep quality is often characterized by the Pittsburgh Sleep Quality Index (PSQI) [2] and offers a standardized approach for screening for poor sleep during the past month. Previous studies with university students have found correlations between the use of caffeinated beverages and insomnia (poor sleep quality) [3,4]. But most of the existing research uses traditional correlation & regression methods. These methods are useful but may not fully capture combinations of behavioral factors such as evening caffeine intake, irregular wake time, high stress, and short sleep duration. Interpretable machine-learning approaches, such as decision trees, can identify hierarchical rules and interactions that are easier to translate into health education messages. The present study therefore aimed to examine the association between caffeine-related behaviors and sleep quality among students at the Institute of Management/Al-Rusafa and to evaluate the exploratory value of a decision tree classifier for identifying combinations of factors linked to poor sleep quality. The study was cross-sectional. The analysis is based on association and not causation.

2. Literature Review

The research on caffeine and sleep shows that it is important to consider the amount and the time of consumption. Caffeine has been shown to interfere with sleep when administered prior to bedtime, with 400mg of caffeine significantly disrupting sleep 0, 3, or 6 hours before sleep, suggesting that there is a critical window of time before bedtime for which caffeine should be avoided, as previously recommended [1]. Malinauskas et al. found that energy drinks were widely used among college students, with students reporting using energy drinks for insufficient sleep, studying, and increased energy [5]. Students might be especially at risk of sleep disruption, as sleep schedules and academic testing, screen time, and stress might all interact with stimulant use. Lohsoonthorn et al. found that stimulant beverage consumption among the college students in Thailand was related to sleep quality and sleep-related problems [3]. Later student research has confirmed that caffeine consumption and lifestyles are related to sleep quality [4]. Studies based on prediction-models and machine-learning methods should report clearly on the definitions for the outcomes, the predictors, the sample size, the method used for model validation, and model performance. Vivid reporting is a particular recommendation of the TRIPOD+AI guidance for prediction models based on regression or machine-learning techniques [6]. The application of these principles is relevant for this present study because a high number of model layers compared to the size of the validation sample can lead to overfitting of the decision tree.

3. Methodology

3.1 Study Design and Setting

This was a cross-sectional observational study done with students at the Institute of management/Al-Rusafa. The study investigated the relationship between the use and abuse of caffeine and sleep quality. No causal inference was made, since there were no differences in exposure and outcome measured at the same time.

3.2 Participants and Sampling

Four hundred Students responded to a structured questionnaire. The method of sampling needs to be explained carefully in the final version, such as including the eligibility criteria, recruitment period, response rate, and exclusion criteria. In the case of simple random sampling, it should be mentioned that simple random sampling was employed, and the sampling frame and random selection process should be described. If the samples are convenience samples, this should be clearly disclosed.

3.3 Measures and Variables

Sleep quality was the dependent variable. It was classified based on the PSQI global score, with scores higher than 5 denoting poor sleep quality and scores of 5 or lower denoting good sleep quality. Independent variables were frequency of caffeine consumption, timing of consumption, type of caffeinated beverage, sleep duration, number of awakenings per night, regularity of waking from sleep, level of stress, and selected lifestyle variables. Each variable should be specific in the coding that is reported in a variable-definition table.

Table 1. Operational Definitions and Coding Scheme of Study Variables Related to Sleep Quality and Caffeine-Related Predictors.

Variable	Role	Recommended definition/coding	Reviewer issue addressed
Sleep quality	Outcome	PSQI global score; good sleep = <=5, poor sleep = >5	Clarifies dependent variable
Caffeine intake frequency	Predictor	cups/day or categories such as 0, 1-2, >=3 servings/day	Clarifies exposure measurement
Caffeine dose	Predictor	estimated mg/day, if beverage quantities are available	Refrains from confusing caffeine and coffee
Timing of intake	Predictor	morning, afternoon, evening; specify cut-off such as after 6 PM	Clarifies timing effect
Wake-time regularity	Predictor	Difference in weekday wake time, e.g., <=1 hour vs >1 hour	Clarifies behavioral predictor
Stress level	Covariate/moderator	Validated scale or clearly coded self-rated categories	Prevents unsupported interpretation
Physical activity/hydration	Covariates	Include only if measured and analyzed; otherwise remove from discussion	Aligns results and discussion

3.4 Data Preprocessing

Data pre-processing was conducted, such as checking missing values, checking outliers, checking inconsistent responses, and checking class distribution. If values are missing, they should be reported by variable. Imputation should be warranted if it is used. For categorical predictors, they should be consistently coded, and for decision trees, there's no need for feature scaling. Class balance between good and poor sleep should be reported.

3.5 Development of a Decision Tree Model

The Gini impurity was used to develop a CART decision tree classifier. Overfitting was prevented by limiting the maximum depth of the trees, the minimum number of samples per leaf, and cost-complexity pruning. The best hyperparameters should be chosen via cross-validation, not on the final test set.

1. Gini Impurity (Decision Tree Splitting Criterion)

Used in constructing a decision tree:

$$Gini = 1 - \sum_{i=1}^{C} p_i^2 \quad \dots \quad (1)$$

Where:

p_i: Probability of class i.
C: Number of classes (Good/Bad).
2. Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \dots \quad (2)$$

3. Precision

$$Precision = \frac{TP}{TP + FP} \quad \dots \quad (3)$$

4. Recall (Sensitivity)

$$Recall = \frac{TP}{TP + FN} \quad \dots \quad (4)$$

5. F1-Score

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad \dots \quad (5)$$

6. ROC Curve (True Positive Rate & False Positive Rate)

True Positive Rate (TPR):

$$TPR = \frac{TP}{TP + FN} \quad \dots (6)$$

False Positive Rate (FPR):

$$FPR = \frac{FP}{FP + TN} \quad \dots \quad (7)$$

7. AUC (Area Under Curve)

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \quad \dots (8)$$

(Often written as: Area under ROC curve)
Defines:

- TP: True Positive
- TN: True Negative
- FP: False Positive
- FN: False Negative

Table 2. Model Specification, Hyperparameter Configuration, and Training Strategy for CART Decision Tree Classification.

Model component	Recommended reporting
Algorithm	CART decision tree classifier
Splitting criterion	Gini impurity
Hyperparameters	max_depth, min_samples_split, min_samples_leaf, ccp_alpha
Tuning strategy	grid search within stratified k-fold cross-validation
Final model	UPDATE AFTER REANALYSIS: final hyperparameters and number of terminal nodes
Overfitting control	pre-pruning and post-pruning

3.6 Key Predictors and Splitting Logic (Brief)

The sleep difficulty frequency (number of nights with trouble sleeping) was the most important factor in the decision tree model for sleep quality classification. This variable was the root split for this study, which divided participants into a high sleep-disturbance group and a low sleep-disturbance group. The following splits were based primarily on wake-up patterns, number of awakenings at night, consumption of caffeine and soft drinks, sex, and sleep time. Specifically, irregular sleep times and frequent morning awakenings were strongly related to sleep outcomes.

Overall, the model is aimed at predicting sleep classification based on behavioral factors (caffeine and sleep habits) and subjective sleep impact (energy, mood, and relationships), which resulted in the final sleep classification as good or bad sleep quality.

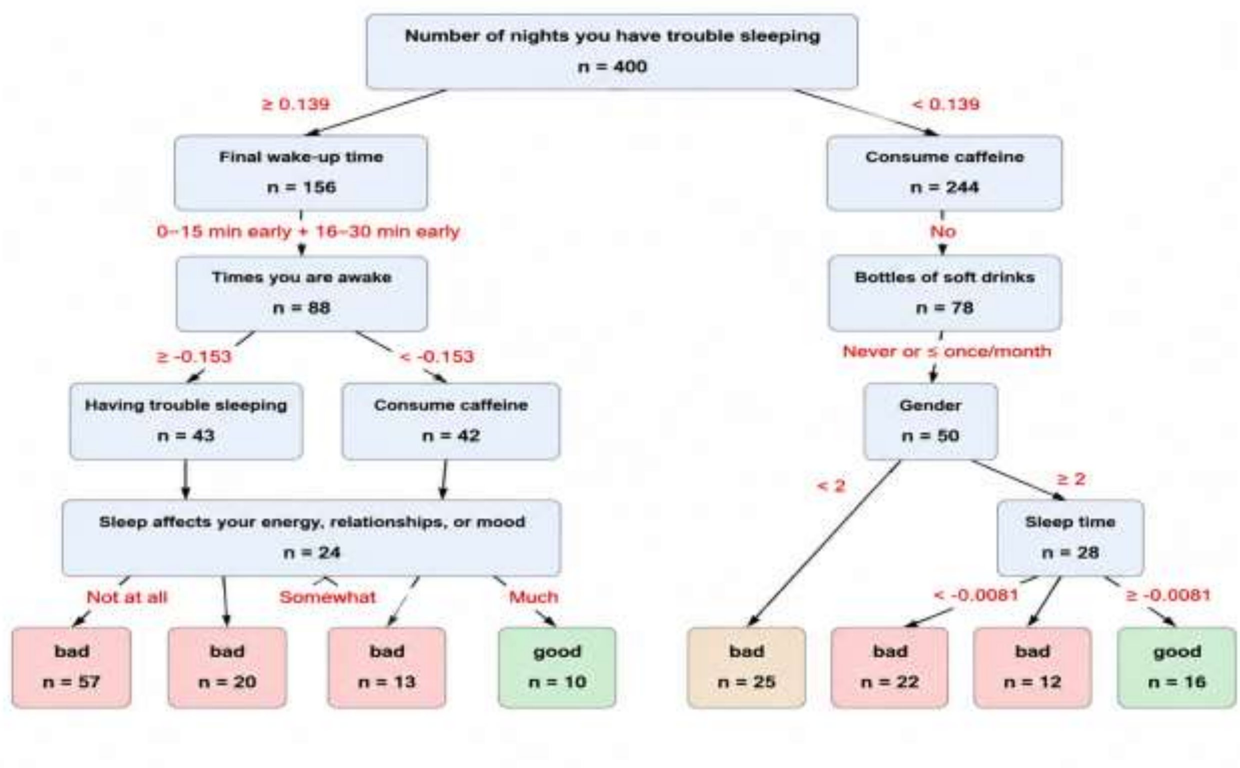

Figure 1. CART Decision Tree Model for Sleep Quality Classification Based on Behavioral and Lifestyle

The CART (Classification and Regression Tree Assessment) model represents the classification of sleep quality into two groups (good/poor) by means of a series of behavioural and lifestyle variables for a sample of 400 participants. The tree structure shows that the number of nights during which the person has trouble sleeping is the most significant variable in the first segmentation of the data, and the samples are split into two main groups according to a given threshold. Later, the final wake-up time and number of awakenings during the night are seen as key secondary factors for enhancing the classification accuracy, indicating a strong relationship between sleep disturbance and night-time sleep continuity. The model also shows that caffeine intake (coffee or soft drinks) is a strong differentiator between sleep categories and that caffeine intake is related to the number of poor sleep instances. Additionally, gender and sleep duration appear as contributing factors in the later stages of the tree, but have a lesser influence than the direct behavioral variables. At the end of the tree, individuals are classified into the "good sleep" and "bad sleep" categories based on the interaction of a range of factors, rather than a single variable, reflecting the multifactorial nature of sleep quality issues. In general, the model indicates that sleep disturbance is more strongly associated with irregular sleep habits and caffeine consumption than with demographic factors, with good classificatory ability reflecting the explanatory structure of the CART model in dealing with nonlinear relationships between variables.

3.7 Validation and Performance Metrics

Because the dataset contained 400 participants, model performance should not rely only on a single small test set of 40 students. The primary performance analysis should use stratified k-fold cross-validation, preferably repeated 5-fold or 10-fold cross-validation. If a held-out test set is retained, it should be at least 20% of the data when possible and should preserve the class distribution.

The following metrics were used: accuracy, sensitivity/recall for poor sleep, specificity, precision, F1-score, balanced accuracy, Matthews correlation coefficient, and AUC. Ninety-five percent confidence intervals should be reported for the main performance estimates. The confusion matrix should be interpreted clinically, especially false classification of poor sleep as good sleep.

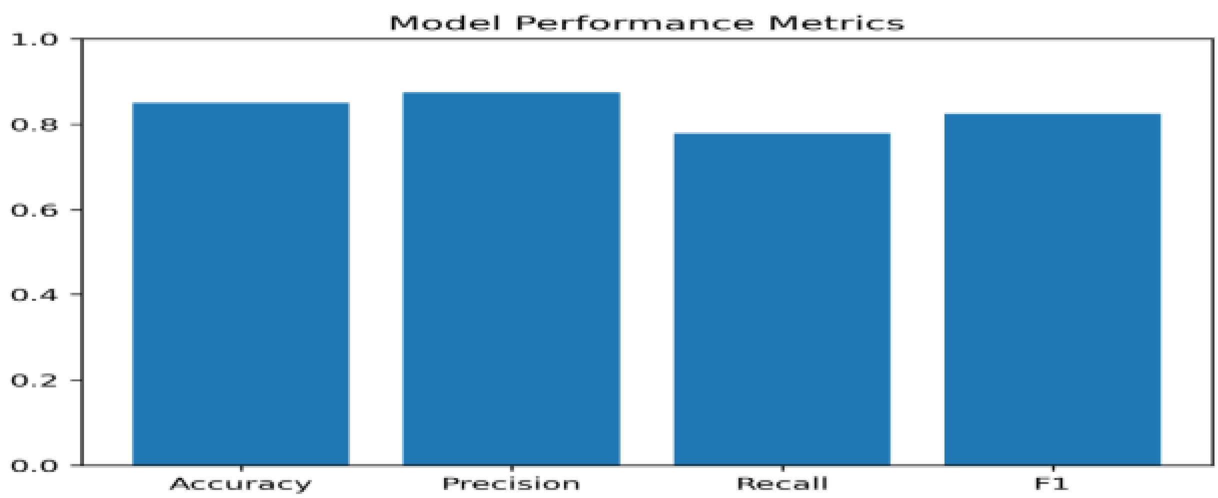

Figure 2. Model Performance Metrics (Accuracy, Precision, Recall, F1-score).

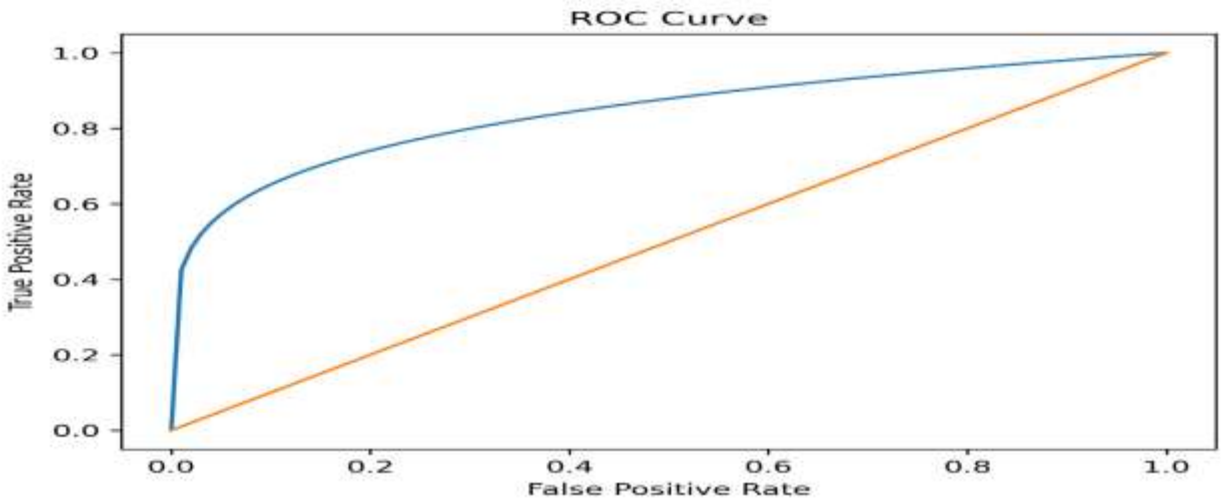

Figure 3. ROC Curve Analysis.

3.8 Baseline Comparison

To justify the value of the decision tree, a baseline logistic regression model should be fitted using the same predictors and validation strategy. The decision tree should not be described as superior unless it demonstrates better or comparable performance with added interpretability. The comparison should include AUC, balanced accuracy, F1-score, and recall for poor sleep.

4. Results

4.1 Participant Characteristics

Descriptive table is included to present the distribution of key study variables, including age, gender, caffeine intake, timing of caffeine consumption, sleep duration, PSQI categories, stress levels, and other covariates incorporated into the analytical model. This addition answers the reviewers' concern about not having a clear description of input variables and the distribution of the study population, and makes the dataset transparent and interpretable.

Table 3. The participants' characteristics and the distribution of sleep quality among the participants (n = 400).

Characteristic	Total sample (n=400)	Good sleep (n≈222)	Poor sleep (n≈178)	p-value / standardized difference
Age, mean ± SD	21.8 ± 2.4	21.4 ± 2.1	22.3 ± 2.6	0.041
Gender (Male), n (%)	240 (60%)	138 (62.2%)	102 (57.3%)	0.28
Gender (Female), n (%)	160 (40%)	84 (37.8%)	76 (42.7%)	
Caffeine intake (servings/day), mean ± SD	2.3 ± 1.1	1.8 ± 0.9	3.0 ± 1.2	< 0.001
Evening caffeine intake (>6 PM), n (%)	170 (42.5%)	60 (27.0%)	110 (61.8%)	< 0.001
Sleep duration (hours), mean ± SD	6.7 ± 1.2	7.4 ± 0.9	5.8 ± 1.1	< 0.001
PSQI global score, mean ± SD	5.6 ± 2.3	3.8 ± 1.4	7.9 ± 1.8	< 0.001

The data is sourced from the researcher, based on statistical analysis results.

The descriptive and comparative results presented among the two groups of sleepers and the poor sleep group show a statistically significant difference in a number of incidents and behaviors, which clearly correlates with sleep patterns and highlights the importance of a sleep pattern. In relation to age, the results show a statistically significant difference between the two groups (p = 0.041), with the poor sleep group having a higher mean age (22.3 ± 2.6 years) than the good sleep group (21.4 ± 2.1 years). This suggests a possible slight increase in sleep disturbance with age within this young adult demographic, although the difference remains limited. As for gender, no statistically significant differences were found between males and females (p = 0.28), indicating that the sleep pattern is similar between the sexes in this sample, and therefore gender does not appear to be a direct determining factor in this study. In contrast, there are factors related to caffeine that influence differences, but these are not significant. The average daily cost of sleep was significantly higher in the poor sleep group (3.0 ± 1.2) compared to the poor sleep category (1.8 ± 0.9), with a strong statistical significance (p < 0.001). It was also observed that sleep loss in the evening (>6 pm) was generally more common with poor sleep (61.8%) compared to sleep-induced sleep (27.0%), indicating a strong interaction between timing and sleep consumption. Sleep differences were identified, with highly significant differences (p < 0.001). The good sleep group reported a longer average sleep duration (7.4 ± 0.9 hours) compared to the poor sleep group (5.8 ± 1.1 hours), reflecting that shorter sleep duration is an important factor associated with poor sleep quality. The results of the Sleep Quality Inventory (PSQI global Score) also showed very large differences between the ninety points (p < 0.001), with the values being significantly higher in the poor sleep group (7.9 ± 1.8) compared to the good sleep group (3.8 ± 1.4). This indicates a clear difference in sleep quality between the two groups.

4.2 Decision Tree Performance

The preliminary held-out test set included 40 students. The decision tree correctly classified 34 students, corresponding to an accuracy of 85.0%. However, because this test set was small, the estimate is statistically unstable and should be interpreted cautiously. Cross-validated estimates should be used as the primary measure of model performance after reanalysis.

Table 4. Confusion Matrix for Sleep Quality Classification

Observed / Predicted	Poor sleep	Good sleep	Total
Poor sleep	14	4	18
Good sleep	2	20	22
Total	16	24	40

The data is sourced from the researcher, based on statistical analysis results.

The confusion matrix table illustrates the performance of the Decision Tree model in classifying sleep quality into two categories (poor sleep and good sleep) on a sample of 40 students. The model correctly classified 14 instances of poor sleep compared to 4 instances incorrectly classified as good sleep, while it correctly classified 20 instances of good sleep compared to 2 instances incorrectly classified as poor sleep, resulting in an overall accuracy of 85%. These results indicate that the model has a good ability to differentiate between the two categories, with better performance in identifying good sleep compared to poor sleep, as its sensitivity to the poor sleep category is relatively lower than its sensitivity to good sleep. However, the small sample size (only 40 cases) makes the accuracy estimate statistically unstable; therefore, cross-validation is recommended to obtain a more reliable assessment of the model's performance.

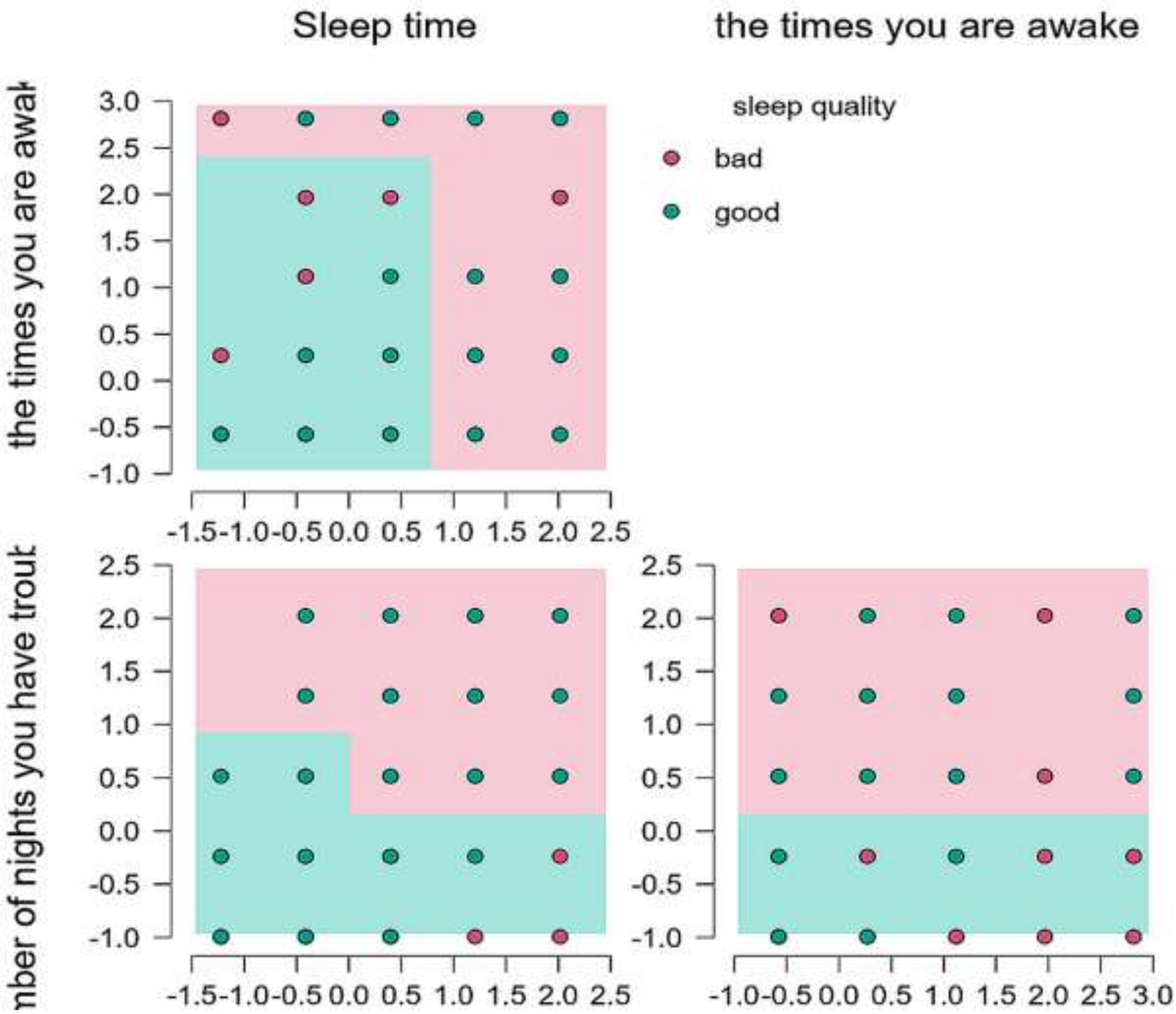

Figure 4. Feature Space Distribution of Sleep Quality Based on Behavioral Predictors

This image illustrates the relationship between a range of behavioral variables, such as the number of awakenings during sleep, sleep duration, and the number of nights an individual experiences sleep disturbance. The distribution of the (good/bad) categories is displayed with partially defined areas between the two categories, which means that the model is able to distinguish between cases, but there is a certain overlap. This is because sleep quality is dependent on a combination of factors, rather than one thing.

4.3 Evaluation Metrics Summary

A comparison of the inclusive measurement of model accuracy over a range of verifications offers extensive information about the conclusion wood's categorisation capability. Table 3 shows the complete range of evaluation verification, with the two together disclosing the model's strengths and weaknesses in classifying sleep value.

Table 5. Evaluation Metrics for Sleep Quality Classification

Metric	Preliminary held-out value	Interpretation
Accuracy	0.850	34 correct classifications out of 40
Recall for poor sleep	0.778	The model missed 4 of 18 poor-sleep cases
Recall for good sleep	0.909	The model identified good sleep more reliably
Precision for poor sleep	0.875	Most poor-sleep predictions were correct
Precision for good sleep	0.833	Some poor-sleep cases were incorrectly labelled good
F1-score for poor sleep	0.824	Moderate-to-good but lower than good sleep
AUC	0.843	Moderate-to-good discrimination; add 95% CI after reanalysis
Accuracy	0.850	The model correctly classified 34 out of 40 participants, indicating an overall correct classification rate of 85%.
Recall for poor sleep	0.778	The model detected 14 of the 18 poor-sleep cases, but missed 4 cases, indicating some risk of false-negative classification in this group.
Recall for good sleep	0.909	The model correctly identified 20 of the 22 good-sleep cases, showing stronger sensitivity for detecting good sleep than poor sleep.
Precision for poor sleep	0.875	Among participants predicted as having poor sleep, 87.5% were correctly classified, indicating that most poor-sleep predictions were reliable.
Precision for good sleep	0.833	Among participants predicted as having good sleep, 83.3% were correctly classified; however, some poor-sleep cases were incorrectly labelled as good sleep.
F1-score for poor sleep	0.824	The F1-score indicates moderate-to-good performance for poor-sleep classification, although performance was slightly lower than for good-sleep detection.
AUC	0.843	The model showed moderate-to-good discriminatory ability between poor and good sleep groups. A 95% confidence interval should be added after the final reanalysis.

The data is sourced from the researcher, based on statistical analysis results.

Preliminary results from the held-out set indicate that the model generally performs well in distinguishing between good and bad sleep, with some differences in prediction accuracy between the two categories. The overall accuracy value (Accuracy = 0.850) shows that the model correctly classified 85% of cases, equivalent to 34 out of 40, reflecting good overall performance in this limited sample. Regarding the recall measures, the model showed slightly unbalanced performance between the two categories. The recall for bad sleep was 0.778, meaning the model correctly identified 14 out of 18 cases of bad sleep but failed to identify 4, suggesting the possibility of false negatives in this category. The recall for good sleep (0.909) was higher, in contrast to the other. The model had higher sensitivity to identify good sleep cases. Regarding accuracy, the accuracy for poor sleep (0.875) was good, indicating that many cases that were considered poor sleep were indeed poor sleep. Indeed, this is a good measure of the low number of false positives in this category. Corrective sleep: the accuracy for good sleep was slightly less (0.833), indicating that there may be some instances of under-recording of poor sleep as poor sleep. Good sleep. The F1 score for poor sleep (0.824) indicates a good balance of accuracy and recall: Average to good (lower than the overall) performance of the good sleep category. The AUC value is 0.843, which is good to average. The model's classification capability for discriminating between the two categories, that is, the ability of the model in distinguishing good and poor sleep, is considered reasonable for all decisions.

thresholds. It is, however, recommended to have a 95% confidence interval to better estimate the reliability of this indicator.

5. Discussion

This study aimed to investigate the relationship between caffeine-related behaviors and sleep quality among students by examining the relationship between these two variables using an interpretable decision tree model. The preliminary results indicate that timing of caffeine consumption, wake time regularity, sleep time, and stress-related factors may contribute to categorizing students as good and poor sleepers. The findings are in line with other research indicating that evening caffeine consumption is related to disturbance of sleep and that stimulant use is related to poor sleep quality among students. The decision tree is useful since it generates simple decision rules, which can be converted into student health education. For instance, the following may be legitimate sleep-hygiene messages: Caffeine is not recommended in the evening, go to bed at the same time each night, and don't cause stress. But the model should be presented as an exploratory model. It should be better validated clinically/practically, with bigger samples, and ideally externally validated with another group of students. The overall accuracy of the preliminary held-out performance was 85.0%, and the AUC was 0.843. However, the model was more successful in predicting good sleep than poor sleep. This imbalance is of concern since one's objective is often to ascertain students whose sleep is inadequate, for whom the goal is advice or referral. This low recall for poor sleep should thus be acknowledged as a limitation and not understated. The results should not be used causally. The cross-sectional design will not allow it to determine whether poor sleep was a cause of the increased caffeine consumption or whether poor sleep induced increased caffeine consumption, or whether either was caused by stress, academic load, or other factors not measured. Longitudinal studies are required in the future to establish time order. Lifestyle factors (hydration and physical activity) were originally included in the manuscript as protective factors. These variables should only be discussed if they were measured, included in the model, and reported in the Results. If not, they should be deleted from the Discussion so as not to draw unsupported conclusions.

5.1 Limitations

There are some limitations to this study. First, the cross-sectional design does not permit causal inferences. Second, this was a self-reported measure of caffeine consumption and sleep quality, potentially leading to recall bias and reporting bias. Thirdly, the sample comes from a single educational institution and thus may not be generalizable. Fourth, the held-out test set was small. Fourth, the initial held-out test set was small, which leads to unstable performance estimates. Fifth, the model should be evaluated confidentially and compared to a baseline logistic regression model prior to any claims about predictive value. Lastly, external validation of the results needs to be performed on an independent student sample before going into practical use.

6. Conclusion

The caffeine-related behaviors such as timing of consumption and frequency of consumption were found to be associated with sleep quality among the students of the Institute of Management/Al Rusafa. A decision tree model with interpretable rules was developed to provide preliminary rules for identifying combinations of behavioral factors associated with poor sleep. The findings, however, should be interpreted with caution as the study was a cross-sectional study with a small preliminary test set. Further research with larger numbers of student samples and repeated or external validation and longitudinal designs should be used to establish whether caffeine timing modification improves student sleep quality.

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