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Predictive Relationship Between Sleep Quality and Short-Term Memory in Young Adults: A Comparative Machine Learning-Based Analysis in an Indonesian Cohort

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ABSTRACT

Background: Sleep quality is increasingly recognized as a key determinant of cognitive functions, particularly memory. However, the multidimensional structure of sleep and its differential effects on memory domains remain unclear. ***Objective:*** This study aimed to examine the association between components of the Pittsburgh Sleep Quality Index (PSQI) and various types of memory performance in young adults. ***Methods:*** A total of 316 young adults completed PSQI and participated in three memory tasks: the Object Scenery Task (visual-spatial memory), Reading Span Task (verbal/episodic memory), and Digit Backward Span Task (working memory). Principal Component Analysis (PCA) was used to reduce collinearity among PSQI components. Multiple linear regression and machine learning models were applied to examine predictive relationships. ***Results:*** Subjective Sleep Quality and Sleep Disturbance were found to be the strongest predictors of memory performance, particularly in the reading span and object scenery task ($p<0.001$). The Reading Span Task showed the highest number of significant associations with PSQI components. Machine learning models further supported this, with the lowest prediction errors (MAE, MSE, MAPE) observed in verbal memory scores. PCA confirmed the multidimensional sleep structure, allowing five distinct components to be retained for regression analysis. ***Conclusion:*** Different dimensions of sleep affect distinct memory systems, with verbal memory most consistently influenced by sleep quality. These findings highlight the importance of comprehensively assessing sleep and integrating both objective and subjective measures in future sleep-memory research.

Keywords: sleep quality; memory; young adults; machine learning.

1 BACKGROUND

Sleep quality is a crucial health determinant of overall health and well-being, playing a pivotal role in both physiological restoration and neurocognitive functioning. Multiple factors influence sleep quality, including the duration, continuity, and depth of sleep, as well as the absence of disturbances across the sleep cycle [1]. High-quality sleep is essential in maintaining good immune function, metabolic homeostasis, emotional regulation, and optimal cognitive performance [2]. Conversely, poor sleep quality has been linked to a range of adverse health outcomes, such as increased risks of cardiovascular disease, metabolic disorders, obesity, depression, and anxiety [3]. Given these associations, the assessment and optimization of sleep quality are recognized to be critical in both clinical and public health domains [4] [5].

Among the cognitive domains influenced by sleep, short-term memory is particularly susceptible to disruption of sleep architecture. Short-term memory may be defined as the capacity to store and manipulate information temporarily. It is essential for daily functioning and higher-order cognitive processes. Extensive research has established that sleep supports memory consolidation, particularly during slow-wave sleep (SWS) and rapid eye movement (REM) sleep [5] [6]. Sleep continuity and structure may influence neural mechanisms underlying memory encoding and retrieval processes, with poor sleep quality frequently associated with measurable deficits in short-term memory performance [1]. Thus, exploring this relationship would be highly relevant in clinical neuropsychology and applied cognitive neuroscience.

Young adults (ages 18-30) represent a population with unique vulnerabilities to sleep disturbances. This demographic often experiences irregular sleep schedules due to academic, occupational, and social obligations, coupled with increased exposure to screen time and erratic circadian regulation [7]. Lifestyle behaviors such as excessive caffeine or alcohol intake and elevated psychological stress further exacerbate sleep problems in this age group [8]. Despite their cognitive resilience, poor sleep quality in young adults is increasingly recognized as a risk factor for impaired memory, attentional difficulties, and emerging mental health concerns. Understanding how sleep quality impacts short-term memory in this age group is critical for developing targeted behavioral and clinical interventions.

While prior studies have observed the association between sleep and memory, there remains a notable gap in the literature concerning predictive modeling of this relationship using machine learning methods, particularly in Southeast Asian populations such as Indonesia. Most existing studies have relied on classic statistical techniques and have been conducted in Western contexts. Moreover, few have employed multimodal cognitive testing alongside validated sleep quality assessments, nor have they incorporated advanced predictive frameworks to model this complex relationship.

To address this gap, the present study investigated the relationship between sleep quality, measured by the Pittsburgh Sleep Quality Index (PSQI), and short-term memory performance in Indonesian young adults. Short-term memory was assessed using three complementary tasks: the Digit Span Test (DST), Object Scenery Task (OST), and Reading Span Task (RST). Beyond traditional correlation and regression analysis, we compared a number of different machine learning models by making use of Decision Tree, Random Forest, Support Vector Machine, Artificial Neural Network, and Gradient Boosting Trees. By combining validated psychometric tools and advanced analytics, this research contributes new insights into the role of sleep in cognitive health and lays the groundwork for developing personalized, data-driven interventions to optimize memory performance in youth.

2 METHODS

2.1 Study Design and Participants

This study employed a cross-sectional design to investigate the relationship between sleep quality and short-term memory performance among young adults in Indonesia. A total of 316 participants, between 18 and 30 years, were recruited through purposive sampling from various educational institutions and community settings. The data collection was conducted over a three-month period in 2024.

Participants were eligible for inclusion if they met the following criteria: (1) aged 18-30 years, (2) able to provide informed consent, (3) not currently using any medications known to affect cognitive function or sleep, and (4) without a prior diagnosis of neurological, psychiatric, or sleep disorders. Individuals with self-reported substance abuse or irregular sleep patterns due to medical or occupational reasons were excluded to minimize potential confounding variables. All participants provided written informed consent prior to participation, and the study was approved by the institutional ethical committee.

2.2 Measures

2.2.1 Sleep Quality

Sleep quality was assessed using the Pittsburgh Sleep Quality Index (PSQI), a widely used and validated self-report questionnaire that measures sleep quality over the past month. The PSQI consists of 19 items grouped into seven components: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medications, and daytime dysfunction. Each component is scored on a 0 to 3 scale, yielding a global score ranging from 0 to 21, with higher scores indicating poorer sleep quality. A global score of more than 5 is typically considered indicative of poor sleep quality. PSQI has demonstrated strong psychometric properties across diverse populations, including young adults.

2.2.2 Short-Term Memory

Short-term memory performance was assessed using three complementary cognitive tasks to provide a robust and multidimensional evaluation:

(1) *Digit Backward Span Test (DBST)*
This test, derived from the Wechsler Adult Intelligence Scale (WAIS), required participants to recall sequences of digits in reverse. DBST assessed auditory working memory and attention span. The score was calculated based on the maximum number of digits correctly recalled.

(2) *Object Scenery Task (OST)*
This task evaluated visual short-term memory. Participants were briefly shown a picture of a scene containing various objects and were later asked to recall the objects and their positions. Scoring was based on the number of correctly identified and located items.

(3) *Reading Span Task (RST)*
This task measured verbal working memory capacity. Participants were given a series of unrelated sentences to be read aloud and were then required to recall the final word of each sentence. The total score was derived from the number of correct final-word recalls across all sets.

These three instruments collectively assess different modalities of short-term memory (auditory, visual, and verbal), thereby providing a comprehensive assessment of each participant's memory function.

2.3 Ethical Considerations

This study was conducted in accordance with the principles of the Declaration of Helsinki. Ethical approval for a similar protocol involving the same methodology was previously obtained from Universitas Udayana (Ethical Clearance No. 377/UN14.2.2.VII.14/LT/2022). The present study involved a new, independent population but adhered to the same procedures with no to minimal risk to participants. Given the anonymous data collection, non-clinical population, and non-invasive cognitive assessments, the study qualifies for exemption from full ethical review.

Prior to joining the studies, all respondents were given a detailed explanation of the study's objectives, procedures, potential risks, and benefits. Written informed consent was obtained from each participant. Participation was voluntary, and participants had the right to withdraw at any time without penalty. All participants' data was anonymized and securely stored. Only authorized research team members had access to the data for analysis purposes. The study posed minimal risk, involved non-invasive, self-reported, and standard cognitive assessment tools.

2.4 Statistical Analysis

In this study, the overall short-term memory score was designated as the dependent variable, while the Pittsburgh Sleep Quality Index (PSQI) components served as the predictor variables. Pearson correlation analysis and multicollinearity testing were conducted to assess the reliability and structure of the dataset before applying machine learning algorithms.

All statistical analyses were performed using Python Interpreter (Python version 3.10.12) in the Ubuntu Operating System Environment. The Pearson correlation coefficient was calculated to evaluate the linear relationships between pairs of variables, ensuring that predictors were meaningfully associated with the outcome. The formula of the Pearson correlation coefficient is shown below:

$$r_{Pearson} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Whereas x and y are two variables of interest, and i represents the index of data points.

To assess the risk of multicollinearity among predictor variables, the Variance Inflation Factor (VIF) is calculated for each PSQI component. A high VIF (typically >5 or 10) indicates collinearity and potential redundancy. The VIF was computed using the following formula:

$$VIF_i = \frac{1}{1 - R_i^2}$$

Whereas R_i^2 is the coefficient of determination of the predictor i on all other predictors.

If multicollinearity was detected, high-VIF variables were also removed. To generalize the analysis, we considered using another method, such as Principal Component Analysis (PCA), to reduce redundancy while preserving maximum variance. This preprocessing ensured that input features fed into machine learning models were orthogonal, thus enhancing model stability and interpretability.

2.5 Regression Analysis

A multiple linear regression analysis was conducted to further examine the relationship between sleep quality and short-term memory performance. This approach evaluates the joint effects of several independent variables (PSQI components) on the dependent variable (memory score). Multiple linear regression extends simple linear regression by incorporating more than one predictor, and its general form is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon$$

Where Y is the predicted memory score, X_1, X_2, ..., X_k represent the PSQI components, β_0 is the intercept, β_1, ..., β_k are the regression coefficients, and ε is the error term.

This method provided coefficient estimation, p-values, and standard errors, enabling statistical inference on the influence of each sleep quality dimension on memory outcomes. The regression model also served as a comparative baseline for the machine learning models.

2.6 Machine Learning Model

To enhance predictive performance and capture complex nonlinear relationships, five supervised machine learning algorithms were implemented to model the relationship between sleep quality and short-term memory: Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Gradient Boosting Trees (GBT). All models were developed using Python's Scikit-learn and TensorFlow libraries.

Prior to modeling, the dataset was randomly split into training (80%) and testing (20%) subsets to ensure reliable generalization. Cross-validation was used during the training phase to mitigate the overfitting risk and fine-tune model hyperparameters. The testing subset was exclusively used for final evaluation.

Each model's predictive performance was assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), providing robust measures of average prediction error and sensitivity to large deviations, respectively. These metrics were calculated using the following formulas:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}$$

Whereas x_i is the observed value, $\hat{x}_i$ is the predicted value, and n is the number of test observations.

The model yielding the lowest MAE and RMSE values was considered the most accurate and generalizable for predicting short-term memory performance based on sleep quality parameters.

3 RESULTS

3.1 Descriptive and Preliminary Analysis

The final sample consisted of 316 participants, with a mean age of 21.70 years (SD = 1.52) and a gender distribution of 62.3% female and 37.7% male. The global PSQI scores ranged from 0-18, with an average of 7.57, indicating the prevalence of good sleep quality among participants. Memory performance was assessed using three modalities: The Reading Span Task, Object Scenery Task, and Digit Backward Span Test, each yielding a standardized score for comparative analysis (see Table 1).

TABLE 1: Descriptive statistics of participants, including Pittsburgh Sleep Quality Index (PSQI) component scores and performance on three memory tests. *SD = Standard Deviation*.

Variable	Mean	SD	Minimum	Maximum
Age (years)	21.70	1.52	18	31
Gender				
Male (%)	37.7%	–	–	–
Female (%)	62.3%	–	–	–
Sleep Quality				
Global PSQI	7.57	3.09	0	18
Subjective Sleep Quality	1.37	0.65	0	3
Sleep Latency	1.59	1.01	0	3
Sleep Duration	1.46	0.94	0	3
Efficiency of Sleep Habits	0.62	0.99	0	3
Sleep Disturbance Score	1.14	0.54	0	3
Consumption of Sleeping Pills	0.13	0.41	0	3
Daytime Dysfunction	1.26	0.78	0	3
Short-Term Memory				
Reading Span Score	2.29	2.30	0	5
Digit Backward Span Score	4.60	2.08	0	7
Object Scenery Memory Score	5.65	6.45	0	24

3.2 Correlation and Multicollinearity Analysis

Pearson correlation coefficients among PSQI components are visualized in Figure 1. None of the pairwise correlations exceeded the 0.6 threshold, suggesting limited collinearity among sleep quality components. The strongest association was found between Subjective Sleep Quality and Daytime Dysfunction (r = 0.46), whereas other components demonstrated mild to moderate correlations (less than 0.46).

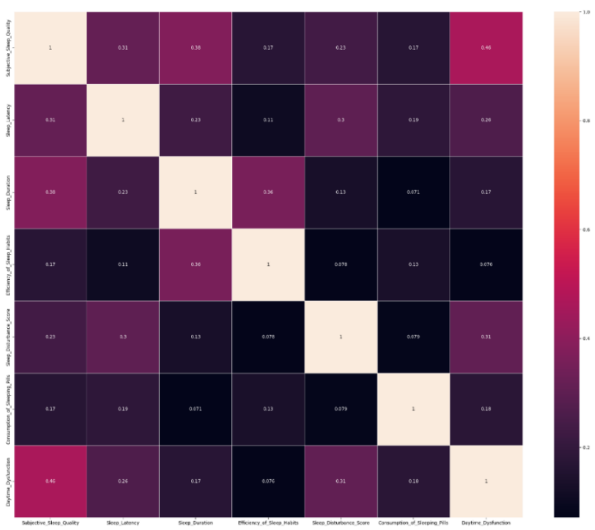

FIGURE 1: Pearson correlation heatmap of the Pittsburgh Sleep Quality Index (PSQI) components. No pairwise correlation exceeded 0.6, indicating acceptable levels of multicollinearity.

Despite relatively low intercorrelations, multicollinearity diagnostics using the Variance Inflation Factor (VIF) indicated that Subjective Sleep Quality (VIF = 7.28) and Sleep Disturbance Score (VIF = 5.06) exceeded the common multicollinearity threshold of 5 (see Table 2). As a result, these two variables were excluded from further regression modeling.

TABLE 2: Variation Inflation Factor (VIF) values for PSQI components used in multicollinearity assessment. Variables with VIF > 5 were removed from the regression analysis.

Variables	VIF
Subjective Sleep Quality	7.278606
Sleep Latency	4.130641
Sleep Duration	4.272429
Efficiency of Sleep Habits	1.630215
Sleep Disturbance Score	5.058941
Consumption of Sleeping Pills	1.169763
Daytime Dysfunction	4.839409

3.3 Dimensionality Reduction via Principal Component Analysis (PCA)

To validate multicollinearity findings and explore component consolidation, PCA was employed through explained variance analysis. The result suggested that five principal components captured the majority of variance within the PSQI dataset, due to the first five principal component variables reaching an 80% threshold to maintain an explainable multivariate. Unlike VIF-based elimination, PCA prioritized variance structure over correlation, ultimately recommending exclusion of the two lowest-loading features. Despite different methodologies, both approaches converged on a reduced predictor set of five variables.

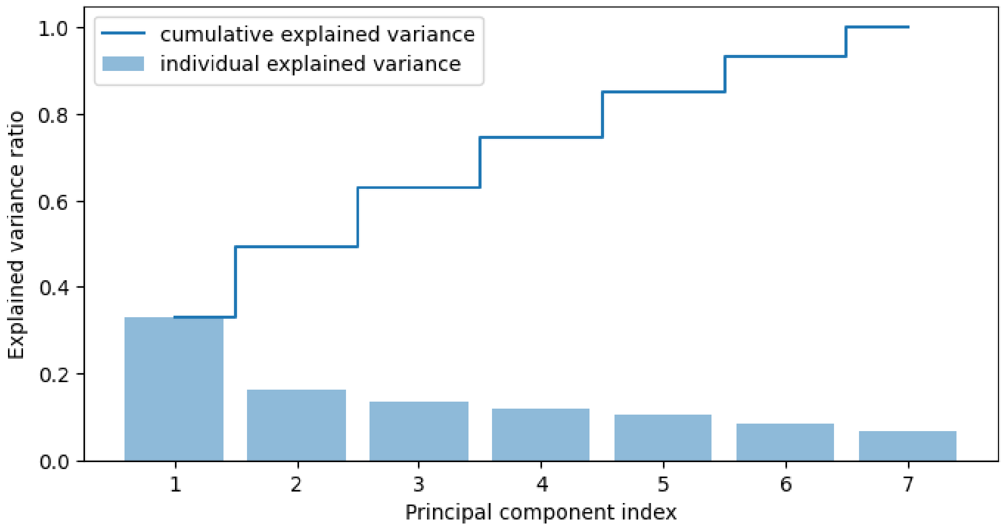

FIGURE 2: Explained variance analysis shows that the number of variables needs to be reduced to show a reliable result.

3.4 Multiple Linear Regression Analyses

Regression analyses were conducted separately for each memory task outcome using the seven original PSQI components. The Reading Span Task emerged as the most predictive model, with six of seven components significantly associated with memory scores ($p < 0.05$). The Digit Backward Span model identified four significant predictors, while the Object Scenery Task had only two.

The regression analysis revealed distinct patterns of association between sleep quality components and memory performance across different cognitive tasks. In the Object Scenery Task, two variables emerged as significant predictors: Subjective Sleep Quality ($\beta = 2.43,\ p < 0.001$) and Sleep Disturbance Score ($\beta = 3.86,\ p < 0.001$), indicating that poor subjective sleep and frequent sleep disturbances were strongly linked to lower visual memory performance.

For the Reading Span Task, nearly all PSQI components were significantly associated with memory scores, except for Consumption of Sleeping Pills, which did not reach statistical significance. Among the predictors, Subjective Sleep Quality ($\beta = 1.01,\ p < 0.001$) and Sleep Disturbance Score ($\beta = 1.09,\ p < 0.001$) showed the strongest relationships, suggesting that these sleep issues may substantially impact verbal working memory.

In the Digit Backward Span Task, the associations were comparatively weaker. Nonetheless, Sleep Duration ($\beta = 0.60$, $p < 0.001$) and Subjective Sleep Quality ($\beta = 1.08$, $p < 0.001$) were found to significantly predict memory performance, although with a lower overall model fit relative to the Reading Span Task. This suggested that while sleep quality still played a role, its impact may vary depending on the type of memory being tested. Detailed coefficients and confidence intervals for each model are provided in Table 3.

TABLE 3: Multivariate regression results for the Object Scenery, Reading Span, and Digit Span Backward memory tasks using the full PSQI components as predictors. Significant predictors are bolded ($p < 0.05$).

Sleep Component	Coefficient	Standard Error	*t*	*p*-value	95% CI (Lower)	95% CI (Upper)
Object Scenery Method						
Subjective Sleep Quality	2.4307	0.64	3.801	**0**	1.172	3.689
Sleep Latency	0.4022	0.388	1.036	0.301	-0.362	1.166
Sleep Duration	0.3025	0.429	0.705	0.481	-0.541	1.146
Efficiency of Sleep Habits	-0.3818	0.395	-0.967	0.334	-1.159	0.395
Sleep Disturbance Score	3.8632	0.644	6.002	**0**	2.597	5.13
Consumption of Sleeping Pills	0.0498	0.91	0.055	0.956	-1.74	1.84
Daytime Dysfunction	0.8934	0.536	1.667	0.097	-0.161	1.948
Reading Span Task						
Subjective Sleep Quality	1.005	0.169	5.95	**0**	0.673	1.337
Sleep Latency	0.2802	0.102	2.734	**0.007**	0.079	0.482
Sleep Duration	0.3528	0.113	3.115	**0.002**	0.13	0.576
Efficiency of Sleep Habits	-0.3176	0.104	-3.046	**0.003**	-0.523	-0.112
Sleep Disturbance Score	1.0896	0.17	6.41	**0**	0.755	1.424
Consumption of Sleeping Pills	-0.1957	0.24	-0.814	0.416	-0.668	0.277
Daytime Dysfunction	0.2864	0.142	2.023	**0.044**	0.008	0.565
Digit Span Backward Task						
Subjective Sleep Quality	1.0811	0.245	4.418	**0**	0.6	1.563
Sleep Latency	0.3768	0.149	2.537	**0.012**	0.085	0.669
Sleep Duration	0.6027	0.164	3.673	**0**	0.28	0.926
Efficiency of Sleep Habits	-0.2719	0.151	-1.8	0.073	-0.569	0.025
Sleep Disturbance Score	1.0499	0.246	4.263	**0**	0.565	1.535
Consumption of Sleeping Pills	-0.0525	0.348	-0.151	0.88	-0.737	0.632
Daytime Dysfunction	0.1439	0.205	0.702	0.483	-0.26	0.547

3.5 Machine Learning Model Performance

To further explore predictive power, five machine learning algorithms — Support Vector Regression (SVR), Decision Tree, Random Forest, Artificial Neural Network (ANN), and AdaBoost — were trained using the PSQI predictors to estimate memory performance for each task. Model evaluation was based on Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) (see Table 4).

Across all metrics, Reading Span Task models consistently outperformed those of Scenery and Digit tasks. The ANN model achieved the lowest error (MSE = 0.402, MAE = 0.506, MAPE = 50.4%), followed closely by AdaBoost (MSE = 0.393). The consistency of low MAE and MAPE in these models suggests both robustness and reliability in prediction, potentially due to the broader variance and scale of their score range.

The Digit Backward Span and Object Scenery tasks showed greater prediction errors and higher sensitivity to outliers, especially in MAPE values (>53% and >49%, respectively), indicating potential inconsistencies in their relationship with PSQI components. These discrepancies may be attributed to limited score variance and the respective memory tasks' contextual difficulty.

TABLE 4: Machine learning model evaluation across three memory tasks. Metrics include Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

Dataset	Model Name	MSE	MAE	MAPE (%)
Object Scenery Task	SVR	**13.001**	2.678	49.626
	Decision Tree	17.903	3.155	51.036
	Random Forest	14.760	2.936	51.127
	ANN	13.717	2.811	52.681
	AdaBoost	13.717	3.039	52.217
Reading Span Task	SVR	0.490	0.564	48.849
	Decision Tree	0.599	0.572	50.464
	Random Forest	0.514	0.579	50.000
	ANN	0.402	0.506	50.420
	AdaBoost	**0.393**	0.553	50.460
Digit Span Backward Task	SVR	3.204	1.429	54.830
	Decision Tree	4.359	1.740	54.688
	Random Forest	3.652	0.572	53.984
	ANN	2.979	1.414	53.876
	AdaBoost	**2.857**	1.357	54.511

4 DISCUSSION

Across three cognitive tasks, Subjective Sleep Quality and Sleep Disturbance emerged as significant predictors. The strongest associations were observed in the Reading Span Task, where all components except consumption of sleeping pills significantly predicted performance, particularly Subjective Sleep Quality ($\beta = 1.01,\ p < 0.001$) and Sleep Disturbance Score ($\beta = 1.09,\ p < 0.001$). Similarly, in the Object Scenery Task, Subjective Sleep Quality ($\beta = 2.43,\ p < 0.001$) and Sleep Disturbance ($\beta = 3.86,\ p < 0.001$) significantly influenced outcomes. In contrast, the Digit Backward Span Task showed weaker associations, though Subjective Sleep Quality ($\beta = 1.08,\ p < 0.001$) and Sleep Duration ($\beta = 0.60,\ p < 0.001$) remained significant predictors.

The low correlation observed among PSQI components highlights sleep quality's complex and multifaceted nature. Each component of sleep quality has been found to represent distinct physiological and psychological aspects of sleep [9]. For instance, sleep latency is largely influenced by circadian rhythms and melatonin secretion, while sleep duration is determined by overall homeostatic needs [10]. The absence of strong correlations (<0.6) among these components aligns with the understanding that these factors, while interrelated, are not tightly coupled in their effects on sleep health [11].

The multicollinearity detected in some components, as revealed by the variance inflation factor (VIF) analysis, underscores the overlap in how certain PSQI metrics capture shared dimensions of sleep. Specifically, the high VIF values for Subjective Sleep Quality and Sleep Disturbance Score suggest these variables may reflect similar underlying perceptions of sleep experience. This redundancy could dilute the statistical robustness of models relying on these predictors. Dimensionality reduction techniques, such as principal component analysis (PCA), provided a solution by identifying and preserving the most distinct and informative components. By reducing the predictors to five, PCA ensures that models are streamlined and less prone to noise, improving interpretability without compromising predictive power.

The regression results provided valuable insights into the relationship between sleep components and memory performance. The Reading Span Task, which was focused on verbal and episodic memory, showed the strongest correlations with most PSQI components. These findings aligned with well-established physiological theories, as slow-wave sleep (SWS) and rapid-eye-movement (REM) sleep phases are known to play critical roles in consolidating verbal and symbolic memories [12]. The lack of significant correlation for the Consumption of Sleeping Pills variable may be attributed to the disruptive effects of these medications on sleep architecture, particularly on SWS and REM phases, which are essential for memory processing [13].

The Digit Backward Span and Object Scenery tasks demonstrated fewer significant correlations. The Digit Backward Span Tasks, reliant on working memory, showed limited associations with components like Daytime Dysfunction, possibly due to their greater dependence on attentional and executive processes rather than long-term memory consolidation [14][15]. The Object Scenery Task revealed strong correlations with Subjective Sleep Quality and Sleep Disturbance Score, emphasizing the importance of overall sleep continuity in supporting visual-spatial memory, which may be more sensitive to sleep interruptions [16].

Machine learning models further validated these findings by demonstrating superior performance in predicting memory scores from the Reading Span Task. Across all evaluation metrics — Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) — the Reading Span models consistently produced the least error, suggesting that verbal memory tasks provide more stable and interpretable data. This superior performance may be due to the stronger physiological link between sleep quality and verbal memory consolidation, as well as a broader range of scores, which allowed machine learning models to capture more nuanced patterns [13][17].

The reduction of error by normalizing score ranges through MAPE emphasized the robustness of Reading Span memory predictions. Verbal memory tasks were possibly less influenced by individual variability than visual-spatial tasks, which can depend heavily on innate abilities or personal experiences [18]. These findings are consistent with dual-process theories of memory, which distinguish between hippocampal-dependent processes (e.g., verbal memory) and non-hippocampal systems (e.g., visual-spatial memory), both of which are affected by sleep differently [19].

The results highlighted the multidimensional nature of sleep-cognition relationships. Intervention targeting subjective perceptions of sleep quality and reducing sleep disturbances may be more effective than solely increasing sleep duration. These findings are particularly relevant for young adult populations, including students, with high sleep disruption and cognitive demand [20]. Furthermore, the results suggest that specific cognitive tests, like the Reading Span Tasks, may be more sensitive for screening sleep-related cognitive impairment.

This study has several limitations. First, its cross-sectional design limits causal interpretations. Second, all sleep data were self-reported via PSQI, which may be subject to bias. Although the study used PCA to reduce multicollinearity and control model complexity, residual confounding may remain. Additionally, the sample consisted solely of young adults, potentially limiting generalizability to other age groups or clinical populations.

Future studies should consider longitudinal or experimental designs to determine causality. Expanding the sample to include a more diverse population regarding age, background, and sleep disorders would enhance generalizability. The inclusion of objective sleep measures, such as actigraphy or polysomnography, could also increase reliability. Moreover, exploring interaction effects between specific PSQI components and cognitive domains could inform targeted cognitive or behavioral interventions.

5 CONCLUSIONS

This study demonstrated that sleep quality, particularly subjective sleep perception and sleep disturbance, plays a significant role in memory performance among young adults. The strongest associations were observed in verbal memory tasks, especially the Reading Span Task, where most Pittsburgh Sleep Quality Index (PSQI) components significantly predicted performance. In contrast, working memory (Digit Span) and visual-spatial memory (Object Scenery) showed more limited or selective associations.

The findings suggested that not all aspects of sleep contribute equally to cognitive functioning. Subjective sleep quality and disturbances appeared to be the most consistent predictors across memory domains, while other components, like sleep duration or latency, have more task-specific effects. Moreover, the use of dimensionality reduction techniques and machine learning models enhanced the interpretability and predictive accuracy of sleep-cognition relationships.

These insights emphasized the need for targeted interventions that address the most impactful dimensions of sleep, rather than focusing solely on quantity. Improving sleep continuity and addressing subjective perceptions of sleep quality may be particularly beneficial for cognitive health in young adults. Future research should further expand on the findings using objective sleep measures and broader population samples to elucidate the complex interactions between sleep and cognition.

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