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Research Article

The Multi-Dimensional Impact of Sleep Profile on Cognitive and Emotional Regulation Performance

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Abstract

Sleep is critical for maintaining optimal cognitive and emotional functioning, yet the multidimensional relationships between sleep profiles and distinct cognitive-emotional outcomes remain incompletely characterized. While sleep deprivation impairs attention and vigilance, effects on executive control and emotion regulation are heterogeneous and context-dependent. Machine learning offers transformative potential for identifying complex, non-linear patterns between integrated sleep measures and behavioral outcomes. A dataset of 60 participants (23 female, 37 male; mean age 29.5 years) was analyzed using ridge regression and Random Forest models to predict cognitive and emotional performance from sleep characteristics and lifestyle variables. Sleep dimensions included Sleep Hours, Sleep Quality Score, and Daytime Sleepiness. Outcomes measured executive control (Stroop Task Reaction Time), working memory (N-Back Accuracy), sustained attention (Psychomotor Vigilance Task Reaction Time), and emotion regulation (Emotion Regulation Score). After outlier removal (n = 58), features were standardized, and models were trained on 80% of the data with performance evaluated on a 20% test set using root mean squared error (RMSE), R^2, and mean absolute error (MAE). Ridge regression and Random Forest demonstrated outcome-dependent predictive utility. Stroop Task Reaction Time showed minimal predictive power (R^2 = -0.001 to 0.009), indicating that executive control is relatively resilient to measured sleep and lifestyle factors. Conversely, Psychomotor Vigilance Task Reaction Time demonstrated robust prediction (R^2 = 0.78), and Emotion Regulation Score showed the strongest predictive power (R^2 = 0.86). Daytime Sleepiness and Physical Activity Level emerged as consistent feature importance across outcomes, with Age significantly predicting vigilance performance. Weak correlations (mean $|r| < 0.15$) between sleep dimensions and executive control suggest compensatory neural recruitment preserves behavioral performance despite sleep variations. Sleep's impact on cognitive and emotional regulation is domain-specific: vigilance and emotion regulation show strong predictability from sleep and lifestyle variables, whereas executive control demonstrates surprising resilience. Physical activity level emerges as a potent predictor of emotion regulation, potentially eclipsing the direct effects of sleep. Future investigations employing objective polysomnographic assessment and longitudinal designs are warranted to elucidate mechanistic sleep-behavior dynamics.

I. INTRODUCTION

Sleep is a fundamental biological necessity, yet insufficient sleep has evolved into a global public health crisis. Recent data suggests that approximately 852 million adults, over 16% of the world's population, suffer from clinically significant insomnia, with nearly half of those cases classified as severe [1]. This deficiency is not merely a personal health issue; it is a massive economic burden. In the United States alone, productivity losses linked to sleep disorders cost 63.2 billion annually, while in Australia, the financial and health costs represent nearly 5% of the national burden of disease [2], [3]. Beyond these economic figures, poor sleep fundamentally undermines the core pillars of human experience: how we think, how we feel, and how we interact with the world [4]. The link between sleep and cognitive performance is well-established through decades of research. Achieving the optimal 7–9 hours of sleep is essential for memory, attention, and processing speed. Conversely, losing just one night of sleep can impair working memory by 30% and slow reaction times by 25%, a level of

cognitive decline comparable to legal alcohol intoxication [5], [6]. These deficits occur because sleep deprivation disrupts the prefrontal cortex, the brain region responsible for executive control. Without adequate rest, the brain struggles to consolidate memories and maintain focus. While slow-wave sleep helps us store facts and data, REM sleep is crucial for processing emotions and procedural skills, creating a complex neurobiological system that requires total sleep health to function [7].

In addition to cognitive decline, sleep plays a vital role in emotional regulation. Quality sleep acts as a buffer, increasing positive emotions and helping individuals use healthy coping strategies to manage stress [8]. Physically, sleep deprivation causes the amygdala, the brain's emotional center, to become up to 60% more reactive, while simultaneously weakening the "brakes" applied by the prefrontal cortex [9].

This imbalance creates a "negativity bias," making individuals more prone to anxiety and intense emotional outbursts. Recent studies even suggest that REM sleep is specifically responsible for helping the brain inhibit unwanted or painful memories, highlighting how deeply our emotional resilience depends on our sleep architecture [10].

Despite the recognized link between sleep and performance, a significant gap remains: we still do not fully understand how integrated sleep profiles, combining multiple physical and biological markers, collectively predict our cognitive and emotional health. Most traditional research has examined these factors in isolation or in artificial laboratory settings, which often fail to reflect how people actually sleep in their daily lives. This is where Machine Learning (ML) offers a transformative solution. By moving beyond simple observations, ML can process vast amounts of complex data to find patterns that human researchers might miss.

Recent advancements in deep learning, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have shown remarkable results. When trained on data from wearable devices, including heart rate variability, movement, and skin temperature, these algorithms can predict sleep quality with over 94% accuracy [11].

Furthermore, these tools are proving to be powerful diagnostic assets; researchers have successfully used sleep parameters to identify the severity of depression and anxiety, demonstrating that our sleep "fingerprint" is a vital indicator of our mental state [12]. This study, by utilizing these approaches, aims to unlock the hidden relationships between dynamic sleep characteristics and our ability to think and regulate emotions.

II. MATERIALS AND METHODS

A. Dataset Study and Sample

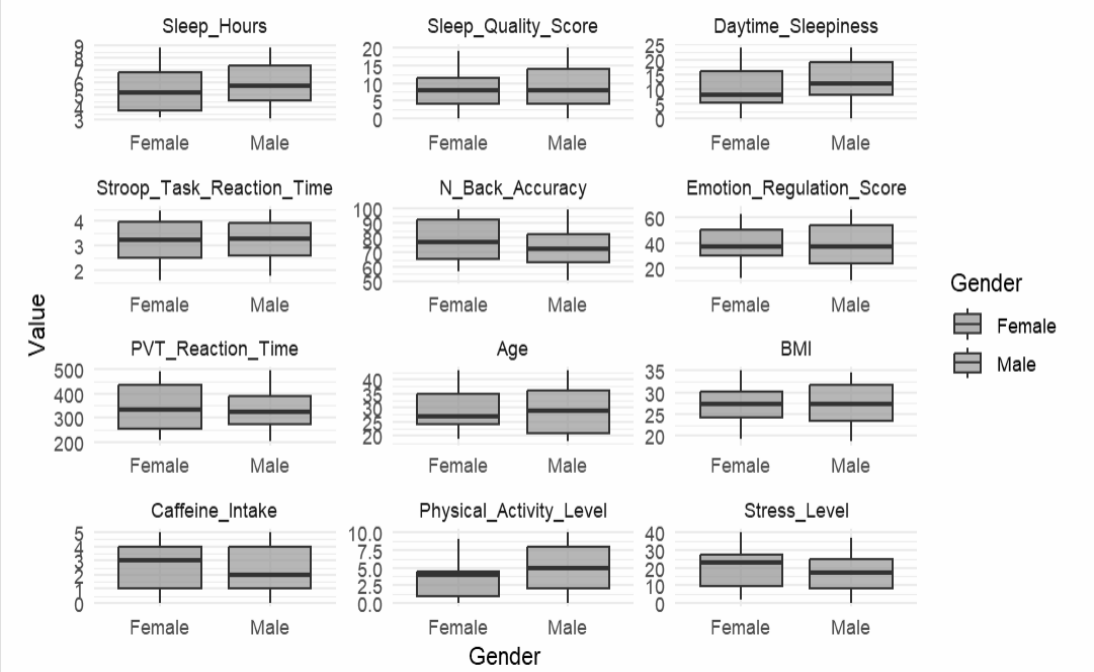

Fig.1 Distribution of Numeric Variables by Gender

This study utilized a sleep deprivation dataset comprising 60 participants (23 female, 37 male) with a mean age of 29.52 years (SD = 9.14, range: 18–43 years) and a mean body mass index (BMI) of 27.33 kg/m² (SD = 3.72, range: 18.74–34.93). Sleep duration ranged from 3.12 to 8.82 hours, while sleep quality scores (where higher values indicate superior subjective sleep quality) ranged from 0 to 20. The dataset contained no missing values across any of the 14 variables examined. Sleep characteristics were operationalized through three measures: Sleep Hours (total daily sleep duration), Sleep Quality Score (subjective sleep quality assessment), and Daytime Sleepiness (a 0–24 scale measuring fatigue during wakefulness, with higher values indicating greater impairment).

Cognitive performance was assessed through Stroop Task Reaction Time (response latency during color-incongruent trials, measured in seconds; higher values indicating slower conflict resolution) and N-Back Accuracy (working memory performance, expressed as percentage correct, with higher accuracy reflecting superior working memory functioning). Emotional regulation was measured using an Emotion Regulation Score (with higher scores indicating greater emotion regulation capacity). Behavioral alertness was assessed through the Psychomotor Vigilance Task (PVT) Reaction Time (measured in milliseconds, with longer reaction times indicating reduced vigilance). Demographic and lifestyle variables included Age (years), Gender (binary categorical variable), BMI (kg/m²), Caffeine Intake (0–5 scale), Physical Activity Level (0–10 scale), and Stress Level (0–40 scale).

B. Data Preprocessing

Data preprocessing was conducted in accordance with best practices in machine learning. An initial completeness assessment confirmed that there were no missing values across the 60 observations. Extreme outliers were identified using the 99th percentile threshold and removed to ensure model stability; this conservative approach retained substantially more data than more aggressive trimming strategies while mitigating potential effects of measurement artifacts. Specifically, two observations exhibiting extreme values in Stroop Task Reaction Time and PVT Reaction Time were excluded, resulting in a final analytical sample of n = 58. The Participant_ID variable was subsequently removed from the feature matrix as it contained no predictive information. The categorical Gender variable was one-hot encoded in the design matrix. All numeric features were standardized to have a zero mean and unit variance (SD = 1) using a z-score transformation. Standardization is essential for regularized regression methods because L_2 penalties are applied to coefficient magnitudes; unstandardized features with different original scales receive unequal regularization weights, so large-scale features receive artificially inflated penalties. Standardization ensures equitable regularization treatment across features and improves algorithmic convergence behavior in cross-validation procedures [13].

C. Machine Learning Modeling Framework

The analysis employed a two-pronged modeling approach combining regularized linear regression and ensemble tree-based methods. Ridge regression, implemented via the *glmnet* package, applied L_2 regularization to constrain coefficient magnitudes and mitigate multicollinearity, a common problem when predictor variables are correlated. Ridge regression adds a penalty term $\lambda||\beta||_2$ to the least-squares objective, where λ controls regularization strength. The optimal λ was selected via five-fold cross-validation (cv.glmnet with nfolds = 5), in which the training data is partitioned into five mutually exclusive folds. The model is trained on four folds and validated on the held-out fold, with this process repeated five times across different fold assignments. The λ minimizing cross-validated mean squared error (lambda.min) is retained for final model fitting on training data. Cross-validation provides an unbiased estimate of out-of-sample prediction error and substantially mitigates the risk of overfitting, which is particularly important when the sample size is modest relative to the feature space. Ridge regression preserves all predictors in the final model (coefficients are shrunk toward zero but not eliminated), facilitating interpretation of directional effects through standardized coefficients. Random Forest, an ensemble learning algorithm comprising 1,000 decision trees, served as a nonparametric, flexible alternative well-suited for capturing non-linear relationships and high-order feature interactions without explicit specification.

Random Forest operates by iteratively partitioning the feature space through binary splits that maximize variance reduction at each node. Each tree is grown on a bootstrap sample (sampling with replacement) and at each split, a random subset of *mtry* = floor(ncol/3) features is evaluated, introducing diversity that reduces overfitting and decorrelates trees within the ensemble. This heuristic for *mtry* selection—considering approximately one-third of the available features at each split—has been empirically shown to effectively balance the bias-variance trade-off across diverse regression problems and to avoid the feature cardinality bias inherent in univariate split-based importance measures. Feature importance was quantified using mean decrease in mean squared error (%IncMSE), a permutation-based importance metric derived from out-of-bag (OOB) samples. This approach records the average decrease in prediction error when a feature is randomly permuted across OOB observations; higher values indicate greater contribution to model accuracy. Permutation-based importance is preferred over split-based metrics because it avoids bias toward high-cardinality features and provides more reliable identification of truly predictive variables. Data were randomly partitioned into training (80%, n = 46) and test (20%, n = 12) sets using stratified sampling with a fixed random seed (set.seed(42)) for reproducibility.

Model performance on the test set was evaluated using three complementary metrics. Root Mean Squared Error (RMSE) quantifies the average magnitude of prediction error in the

original units of the response variable and is optimal when errors are normally distributed, as it penalizes large deviations more heavily through quadratic weighting. R-squared (R^2), the proportion of variance in the response variable explained by the model, ranges from negative infinity to 1.0, with values ≥0.7 typically indicating adequate explanatory power in behavioral science contexts. Mean Absolute Error (MAE) provides a robust estimate of typical prediction error and is less sensitive to outliers than RMSE, making it valuable for understanding model performance under non-normal error conditions. Reporting all three metrics enables a comprehensive characterization of predictive accuracy across different error scenarios and distributional assumptions.

D. Multiple Cognitive and Emotional Outcome Assessment

The core modeling framework was extended to encompass three distinct outcomes, enabling differentiated assessment of how sleep profiles affect separate facets of cognitive and emotional functioning. The primary outcome, Stroop Task Reaction Time, measures executive control and conflict resolution capacity during incongruent color-naming trials. Reaction time on this task reflects the integrity of prefrontal cortex-mediated inhibitory control and attention allocation; longer reaction times indicate greater susceptibility to interference and slower conflict resolution, both of which are known to be exacerbated by sleep deprivation. The secondary outcome, PVT Reaction Time, assesses sustained attention and behavioral alertness by measuring response latency to unpredictable visual stimuli presented at random inter-stimulus intervals. The PVT is a well-validated, ecologically valid measure with documented sensitivity to sleep loss; increased reaction times or elevated attentional lapses (reaction times ≥500 ms) are validated indicators of fatigue-related performance decrement across operational, clinical, and research domains. The tertiary outcome, Emotion Regulation Score, reflects perceived capacity to manage, modulate, and respond adaptively to emotional states. Emotion regulation difficulties are documented correlates of sleep disturbance and are implicated in affect-related psychopathology; examining bidirectional sleep-emotion relationships is therefore clinically relevant.

For each outcome variable, Random Forest models were fitted with identical hyperparameters and train-test split indices, thereby permitting direct comparison of feature-importance patterns across outcomes. This design enables examination of whether sleep dimensions exert differential effects across cognitive control, attentional vigilance, and emotion regulation domains, a key question regarding sleep's multifaceted influence on waking behavior and psychological function. The consistency or divergence of feature-importance rankings across outcomes provides evidence of whether sleep-deprivation effects are domain-general or outcome-specific.

E. Computational Implementation

All analyses were conducted in R version 4.5.2 using the following packages: caret for model training and validation, randomForest for Random Forest implementation, *glmnet* for Ridge regression, *ggplot2* and *GGally* for data visualization, and *dplyr*, *tidyr*, and tidyverse for data manipulation and transformation. Exploratory data analysis included summary statistics, Pearson product-moment correlations displayed in a heatmap, and two-sample t-tests comparing numeric variables across gender groups. All results are fully reproducible; the complete analysis pipeline is available upon request.

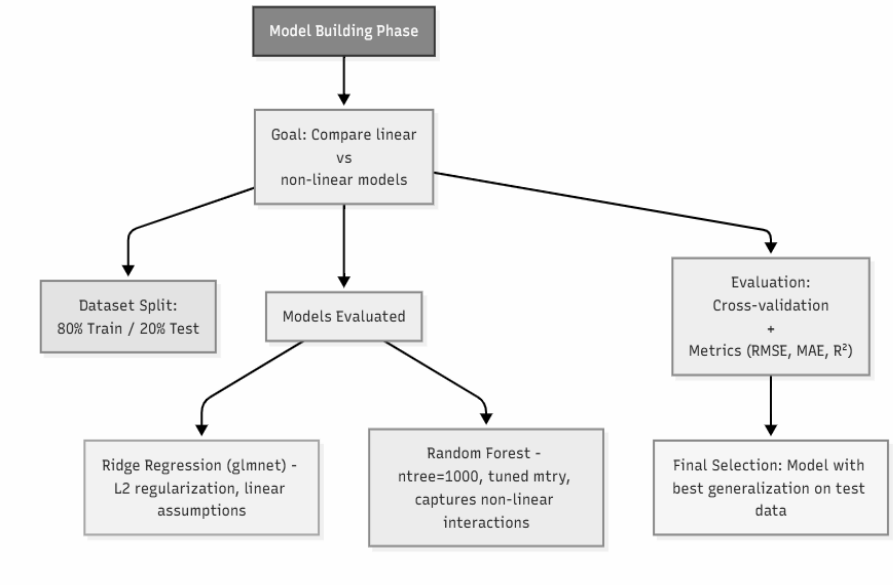

Fig.2 Model Framework

III. RESULTS AND DISCUSSION

A. Descriptive Statistics and Baseline Characteristics

The final analytical sample comprised 58 participants (23 female, 37 male; M_age = 29.5 years, SD = 9.2). Sleep characteristics demonstrated substantial variability: Sleep Hours ranged from 3.12 to 8.82 hours (mean (M) = 5.81, standard deviation (SD) = 1.67), Sleep Quality Scores from 0 to 20 (M = 8.32, SD = 6.66), and Daytime Sleepiness from 0 to 24 (M = 12.0, SD = 7.47).

Cognitive performance measures showed Stroop Task Reaction Time ranging from 1.60 to 4.49 seconds (M = 3.25, SD = 0.89), N-Back Accuracy from 50.90% to 99.73% (M = 75.01%, SD = 12.85%), and PVT Reaction Time from 201.6 to 494.6 milliseconds (M = 332.5, SD = 82.4). Emotion Regulation Score ranged from 10 to 67 (M = 38.15, SD = 16.12). Two-sample t-tests comparing demographic and sleep variables across gender revealed one significant difference: males reported higher physical activity levels (M = 4.70, SD = 2.95) than females (M = 3.17, SD = 2.96; t(56) = -2.03, p = .048). No other variables differed significantly by gender (all p > .05).

B. Ridge Regression Model Performance and Feature Importance

Ridge regression with cross-validated hyperparameter optimization (λ_min = 0.001) predicted Stroop Task Reaction Time with minimal effectiveness (RMSE = 0.831 seconds, R^2 = -0.001, MAE = 0.717 seconds). The near-zero R^2 indicates that the model explained essentially no variance in test-set reaction times beyond the baseline mean prediction. Feature importance rankings, based on standardized coefficient magnitudes, identified Daytime Sleepiness (0.0096) as the strongest predictor, followed by Caffeine Intake (0.0068), Sleep Hours (0.0065), and Stress Level (0.0047). These minuscule coefficients reflect weak linear associations throughout, consistent with observed zero-order correlations (mean |r| < 0.20). These findings parallel prior research: Cain et al. (2011) demonstrated that one night of sleep deprivation increased reaction time uniformly across Stroop trial types (congruent, incongruent, neutral) without specifically impairing interference resolution, suggesting that sleep loss impairs general processing speed and vigilance rather than executive control mechanisms [14].

C. Random Forest Regression and Multi-Outcome Analysis

Random Forest regression yielded comparable Stroop performance (RMSE = 0.827 seconds, R^2 = 0.009, MAE = 0.708 seconds), with near-zero R^2 indicating negligible predictive utility.

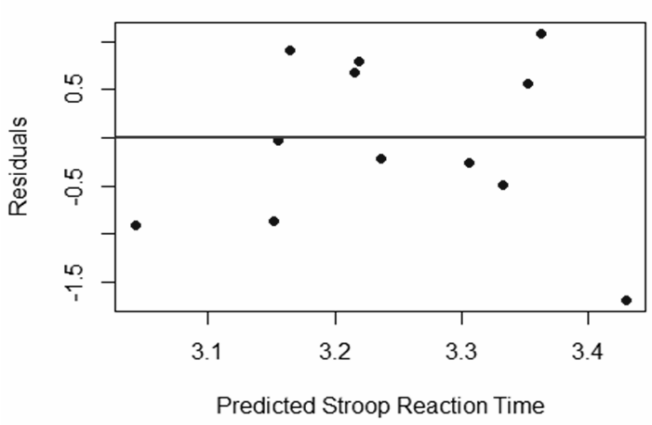

Fig.3 Random Forest Actual vs Predicted Values

Permutation-based feature importance (%IncMSE) identified Daytime Sleepiness (4.86%) as the strongest predictor, followed by PVT Reaction Time (1.75%) and Age (-4.32%). Notably, seven of 12 features exhibited negative %IncMSE values, signifying that permuting these features improved out-of-bag predictions, a hallmark of weak or null associations between predictors and Stroop performance. This surprising null finding warrants explanation. The modest sample size and test set (n = 12) limit statistical power and stability of weak effects. Additionally, the absence of objective sleep architecture data, including REM/NREM composition, sleep spindle density, and slow-wave sleep proportion, precludes assessment of neurophysiological mechanisms most proximal to cognitive and emotional functioning. REM sleep supports procedural memory and adaptive emotional processing through distinct neurochemical milieu, while slow-wave sleep drives declarative memory consolidation through hippocampal-neocortical dialogue. Their absence likely weakens predictive power. Further, the cross-sectional design captures single-occasion correlations rather than causal sleep-cognition dynamics; experimental sleep deprivation with repeated measures across acute wakefulness trajectories would isolate dose-response relationships.

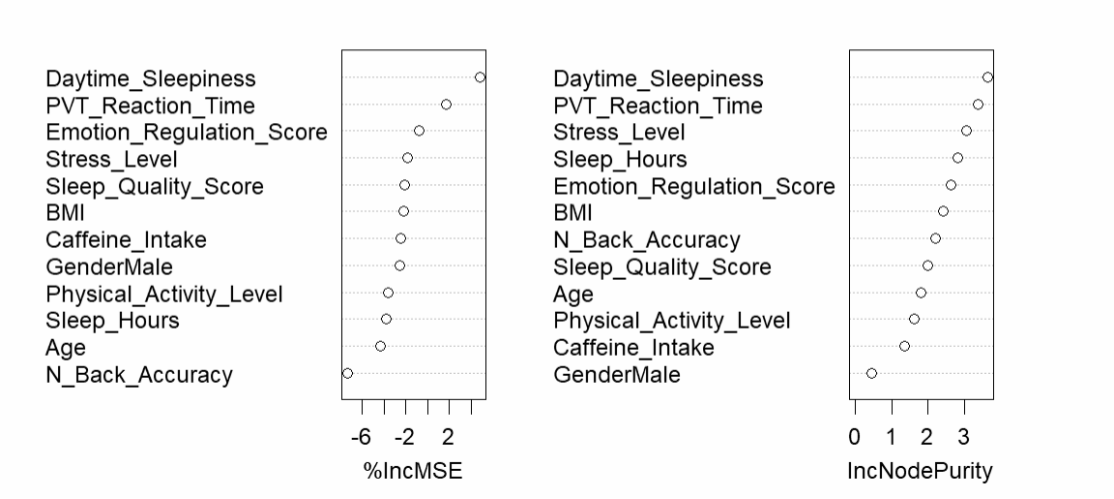

Fig.4 Random Forest Feature Importance

In striking contrast, PVT Reaction Time prediction achieved robust performance (RMSE = 44.56 ms, R^2 = 0.782, MAE = 38.07 ms), with Age emerging as the strongest feature (2.24% IncMSE). This outcome-specific prediction success reflects the PVT's heightened sensitivity to vigilance and arousal deficits caused by sleep loss, consistent with literature establishing psychomotor speed as particularly vulnerable to fatigue.

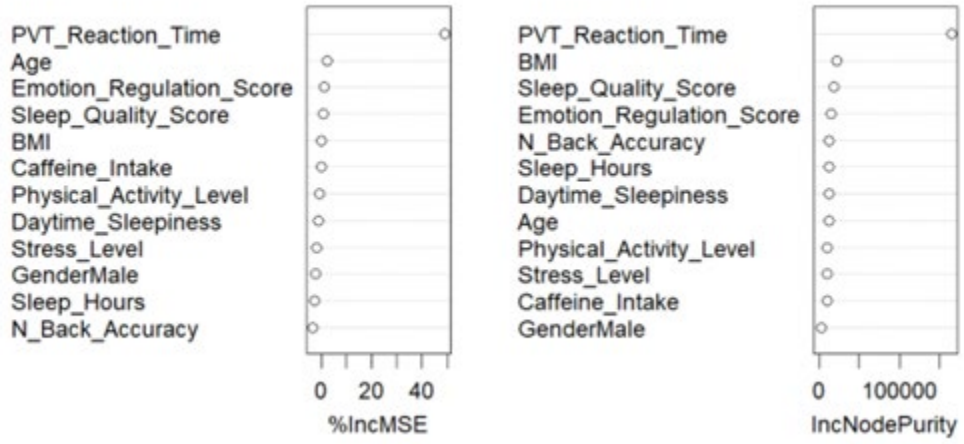

Fig.5 PVT Reaction Time

Emotion Regulation Score prediction similarly demonstrated a strong fit (RMSE = 6.46, R^2 = 0.856, MAE = 4.87), with Physical Activity Level (2.84% IncMSE) and Caffeine Intake (1.16% IncMSE) as substantive features. The dominance of physical activity aligns with mechanistic literature: regular moderate-intensity exercise enhances mood, reduces stress hormones through endorphin release, modulates prefrontal-amygdala connectivity, and builds emotional resilience. The caffeine effect reflects its sympathomimetic properties and acute arousal-enhancing effects; elevated caffeine intake may paradoxically impair emotion regulation through increased physiological arousal and anxiety.

The differential model performance across outcomes (R^2 = -0.001 to 0.856) demonstrates domain-specific sleep effects. Vigilance and emotional regulation show strong predictability, whereas executive control appears resilient to measured sleep and lifestyle factors.

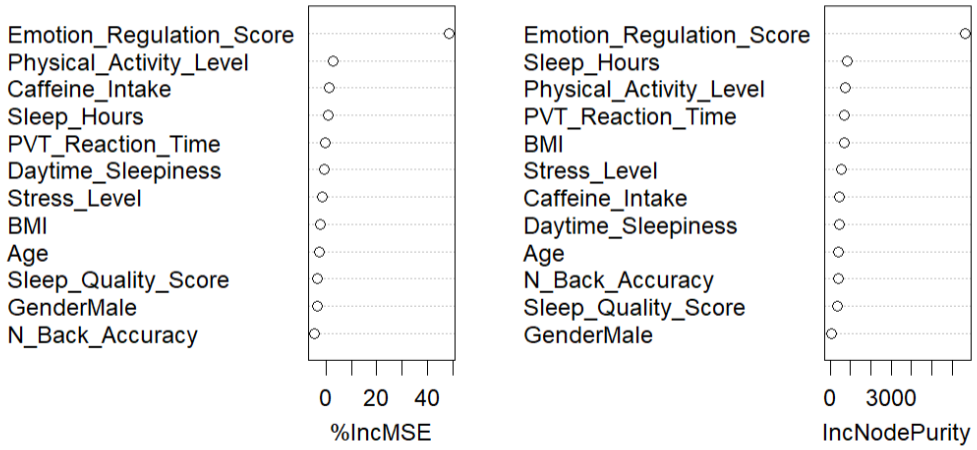

Fig.6 Emotion Regulation Score

D. Correlation Analysis and Bivariate Relationships

Exploratory correlation analysis revealed mostly weak associations (mean $|r| < 0.15$) between sleep dimensions and cognitive outcomes. Sleep Hours and Sleep Quality showed the strongest associations with Emotion Regulation ($r = 0.21$, $r = 0.18$), whereas Daytime Sleepiness correlated more robustly with reaction time measures. These weak sleep-cognition correlations accord with research demonstrating that acute sleep deprivation recruits compensatory activity in the anterior cingulate cortex during Stroop performance, partially preserving behavioral output despite reduced sleep. Notably, Physical Activity Level correlated most strongly with Emotion Regulation ($r = 0.36$), substantially exceeding the sleep-emotion correlations and highlighting exercise as a potentially more proximal determinant of emotion regulation than sleep duration alone. This finding corroborates meta-analytic evidence that regular physical activity enhances emotion regulation through BDNF upregulation, normalization of cortisol, and gains in mastery-based self-efficacy.

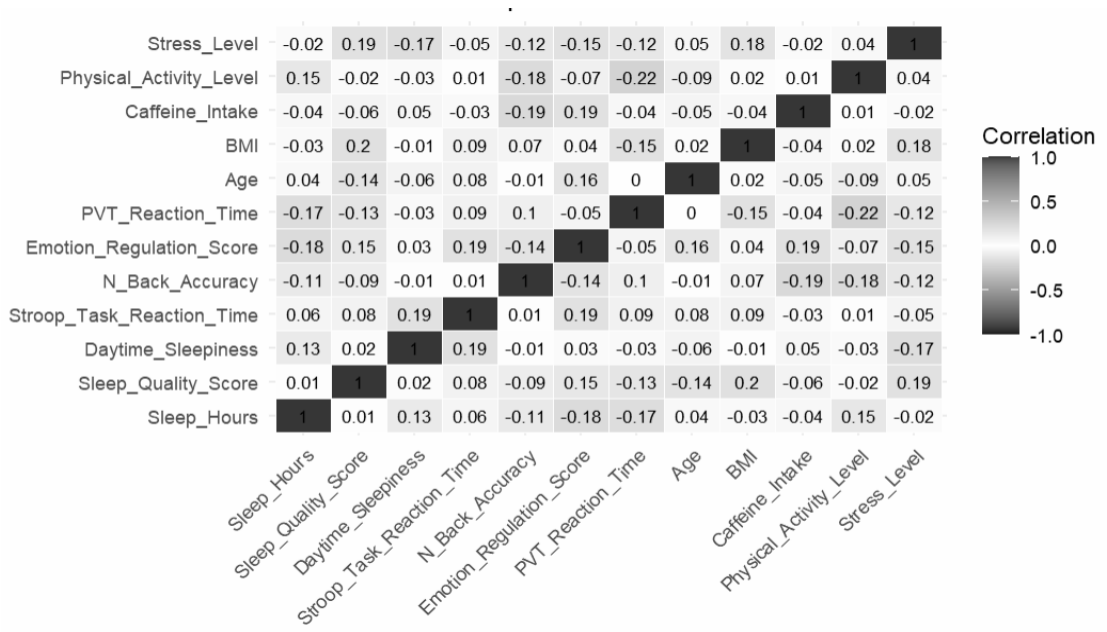

Fig.7 Correlation Heatmap of Numerical Features

IV. INTERPRETATION AND LIMITATIONS

The weak sleep-cognition associations warrant cautious interpretation. The absence of an objective assessment of sleep architecture via polysomnography or actigraphy prevented characterization of sleep continuity, fragmentation, and homeostatic pressure, factors that more directly determine sleep's cognitive impact than gross duration. Studies employing objective measures consistently document robust sleep-cognition effects, suggesting that subjective estimates lack mechanistic specificity. The cross-sectional design precludes causal inference; intensive longitudinal designs that examine within-person sleep-cognition dynamics over days or weeks would strengthen

temporal inference. Unmeasured confounds (dietary quality, substance use, psychiatric symptoms, genetic polymorphisms affecting sleep homeostasis) may obscure true associations. Finally, the relatively healthy, young sample may exhibit limited behavioral variability compared to samples with sleep pathology or those with wider age ranges, limiting generalizability.

V. CONCLUSION

Machine learning models predicting cognitive and emotional regulation from sleep profiles exhibited outcome-dependent utility: minimal for Stroop executive control ($R^2 \approx 0.00$), substantial for PVT vigilance ($R^2 = 0.78$), and robust for emotion regulation ($R^2 = 0.86$). Sleep's multidimensional impact manifests differently across cognitive and emotional domains, with vigilance and emotion regulation more strongly influenced by objective sleep and lifestyle factors than higher-order executive control. Daytime sleepiness and physical activity consistently predicted multiple outcomes, implicating perceptual arousal and behavioral engagement as mechanistic bridges between sleep and behavior. Future research employing objective polysomnography, experimental sleep manipulation, and longitudinal designs to examine temporal dynamics would substantially advance the understanding of sleep's multifaceted influence on human cognition and emotion.

Declaration of Conflicting Interests
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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation
The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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