Original Research Article

Associations between Sleep Duration and Physiological Performance on Adults

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ABSTRACT

Sleep is widely recognized as an important factor in physical health and recovery, yet the amount of sleep needed to support optimal physiological performance remains unclear. This study examined whether nightly sleep duration predicts exercise-related performance measures using a large wearable-based archival dataset consisting of over 10,000 adult participants. Single variable statistical tests, including Pearson correlations, were used alongside multivariable modeling through a neural network to evaluate relationships between sleep duration and performance indicators such as resting heart rate, workout duration, burned calories, steps taken, workout intensity, and mood after exercise. Across all analyses, no statistically significant or robust predictive relationships were identified between sleep duration and performance outcomes. These null findings suggest that wearable datasets may mask true sleep-performance relationships due to factors such as device variability, participant heterogeneity, self-reported measures, and unmeasured confounding variables. Despite the absence of significant associations, this study highlights important methodological challenges and provides direction for future research using more standardized sleep tracking and controlled sleep study designs.

Keywords: Sleep; Exercise; Athletic Performance; Fitness Trackers; Well-Being

INTRODUCTION

Sleep is a fundamental process that supports physiological restoration, cognitive functioning, and athletic recovery. Adequate sleep facilitates muscle repair, hormonal regulation, cardiovascular recovery, and memory consolidation, all of which are essential for optimal physical performance. For athletes and physically active individuals, sleep is particularly critical, as performance depends on sustained endurance, strength, coordination, and recovery capacity. Accordingly, sleep metrics are increasingly incorporated into data-driven training and recovery strategies by coaches and trainers. Despite its importance, the demands of modern daily schedules have contributed to widespread sleep restriction, raising concerns regarding sleep deprivation and its impact on athletic and physical performance.

Existing research broadly agrees that insufficient sleep is associated with a decrease in physiological performance, increased fatigue, delayed recovery, and elevated injury risk, whereas sufficient sleep is frequently linked to improvements in both performance and recovery outcomes. However, variation remains regarding the optimal amount and quality of sleep required to maximize performance, with findings differing by population, sport, and methodological approach. Much of the current literature relies on controlled studies or small, homogeneous samples of elite athletes, limiting the applicability of these findings to more diverse, real-world populations.

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Comparative studies examining athletes and non-athletes further highlight the importance of sleep duration in performance outcomes. Charest and Grandner (1) analyzed sleep patterns and performance metrics in a sample of 300 athletes and 300 non-athletes, using actigraphy to assess sleep efficiency and its impact on physiological and sport-specific outcomes. Their findings demonstrated that higher sleep efficiency was associated with improved physiological performance, including lower resting heart rate and enhanced aerobic capacity, as well as improvements in sport-specific outcomes such as maximal power output and skill accuracy. These results suggest that sleep duration plays a critical role in both recovery and performance, providing evidence for an optimal sleep range that supports athletic functioning (1).

Research focusing on injury risk and competitive outcomes further reinforces these conclusions. A study of 42 Division I women's basketball players (2) evaluated the effects of sleep duration and quality on game performance and injury incidence over a full competitive season. Results indicated that reduced sleep duration and poorer sleep duration were associated with increased injury incidence and declines in game performance, including higher turnover rates and reduced scoring efficiency. Predictive modeling approaches in this study showed that sleep deficits significantly increased the likelihood of injury and underperformance, underscoring the importance of adequate sleep for maintaining athlete availability and competitive success (2).

Broader reviews of sleep interventions in athletic populations similarly demonstrate consistent performance effects. A meta-analysis of experimental studies (3), including athletes from multiple sports and age groups, found that sleep restriction led to significant reductions in speed, strength, accuracy, and endurance, while increasing ratings of perceived exertion during physical tasks. Conversely, sleep extension protocols in these studies improved physiological performance, recovery efficiency, and subjective effort, suggesting that increased sleep duration may confer both physical and perceptual benefits (3).

Intervention-based research comparing multiple sleep optimization strategies further emphasizes the importance of sleep duration. Studies evaluating napping, light manipulation, cold-water exposure, and sleep extension across adolescents and adults (4) consistently identified sleep extension as the most effective intervention for enhancing strength and endurance. These findings suggest that sleep duration may be a particularly influential factor in athletic performance, warranting analysis independent of other sleep-quality interventions (4).

Despite these advances, a critical gap remains in modeling sleep–performance relationships using large, heterogeneous, wearable-based datasets. While wearable devices enable scalable, real-world measurement of sleep and activity, they introduce substantial variability in participant behavior, activity type, and data quality, complicating traditional analytical approaches. As a result, the relationship between sleep duration and multiple performance metrics in ecologically valid settings remains insufficiently understood.

To address this gap, the objective of the present study is to examine the relationship between sleep duration and a range of wearable-derived physical performance metrics within a large, real-world dataset, thereby extending prior laboratory-based findings and contributing to a more generalizable understanding of sleep–performance dynamics.

METHODS AND MATERIALS

Dataset and Participants

The present analyses were conducted on an archival dataset initially collected from https://www.kaggle.com/datasets/adilshamim8/workout-and-fitness-tracker-data on May 19th, 2025. This included over ten thousand participants, who were not necessarily athletes, but all of whom engaged in some kind of physical exercise. In this experiment, the participants were asked to track different variables associated with fitness using a variety of different fitness tracker devices and apps in order to measure their athletic performance. In order to measure the relationship between sleep and athletic performance, the variable Sleep Hours was used as the independent variable, as it pertained to several other dependent variables participants recorded, such as: Resting Heart Rate, Workout Duration, Calories Burned, Steps Taken, Mood After Workout, Workout Intensity, and Workout Type.

Variables and Measures

To measure the relationship between sleep and athletic performance, the variable Sleep Hours was used as the independent variable, in relation to several dependent variables: Resting Heart Rate, Workout Duration, Calories Burned, Steps Taken, Mood After Workout, Workout Intensity, and Workout. Hypotheses were established for each primary variable relationship based on theoretical expectations from the sleep and performance literature. Given that lower resting heart rate indicates improved recovery and reduced cardiovascular stress, it was hypothesized that increased sleep duration would correspond to reduced resting heart rate, reflecting better physiological recovery and readiness for training. Extended sleep was also expected to result in longer and more productive workouts due to improved energy availability and reduced fatigue. Similarly, increased sleep was hypothesized to lead to greater calories burned during exercise sessions, reflecting higher athletic output and energy expenditure. Finally, it was anticipated that increased sleep would improve post-workout mood, potentially enhancing motivation for high-intensity activity.

Categorical variables included Mood After Workout, Workout Intensity, and Workout Type. To enable correlation analyses, these variables were converted to numerical scales. For example, Workout Intensity, previously categorized as Low, Medium, and High, was recorded as 1, 2, and 3. Workout Type was examined using subsets of sleep hour distributions, plotting vertical boxplots for each type.

Statistical Analyses

Analyses were conducted using Python in Google Colab, with Pandas for data manipulation. Correlation tests were performed to assess relationships between variables, and strong correlation evidence was evaluated using R values and p-values. Normality of continuous variables was assessed using the Anderson-Darling test, which indicated that the data approximated a normal distribution. Pearson correlation was applied to continuous, normally distributed variables (e.g., Resting Heart Rate and Calories Burned). Outliers were examined via histograms and boxplots.

Neural Network Modeling

To analyze multivariate relationships, a neural network was constructed to evaluate how multiple variables jointly predict Sleep Hours. Batch normalization was applied to stabilize variable distributions and enhance model performance. Logistic regression was used for categorical outcomes to assess predictors of specific results. The neural network was trained using 70% of the data, with 30% used for validation.

RESULTS

Descriptive Analyses

Of the ~10,000 participants, there was an average of 1667.67 participants in each of the six workout types (*SD* = 34.33), showing fairly equal representation of workout types within the dataset.

The descriptive analysis test on Sleep Hours by Workout Type was conducted via visual inspection of its box and whisker plot (Figure 1), revealing relatively equal distributions between all workout types in the dataset. This affirmed that sleep hours were not heavily weighted by any particular workout type, thus allowing additional analyses to be conducted without considering workout type as a direct factor manipulating sleep hours.

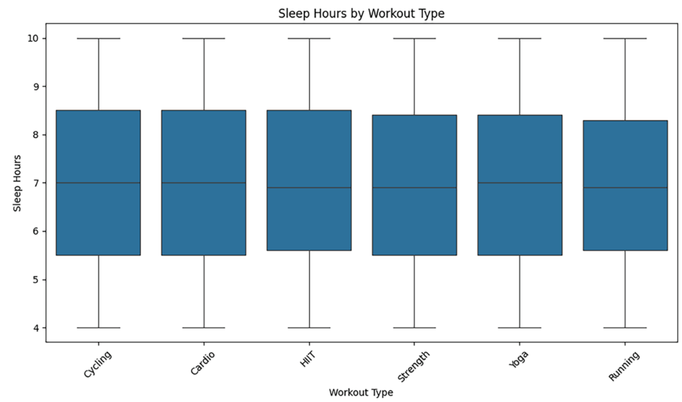

Figure 1. Sleep Duration by Workout Type. *Box-and-whisker plots showing nightly sleep hours across six workout types (Cycling, HIIT, Running, Strength, Yoga, Cardio). Boxes indicate interquartile ranges (IQR), horizontal lines show medians, whiskers extend to 1.5× IQR, and points represent outliers. Similar distributions across workout types (median ≈ 7 hrs) indicate sleep duration was not influenced by exercise modality, confirming that sleep hours were evenly distributed across workout categories and allowing for subsequent analyses without workout type as a confounding factor. n ≈ 1,668 per group.*

Correlation Analyses (Whole Sample)

For the categorical variables tested, the amount of participants in each variable was evenly distributed across each group for both Workout Intensity (Figure 2a) and Mood After Workout (Figure 2b). In addition, for both Workout Intensity and Mood After Workout, there were relatively equal amounts of participants of each workout type for Workout Intensity/Mood After Workout Level.

Pearson correlations were conducted in order to find correlations between the primary variable (Sleep Hours) and all potential correlated variables, including the variables converted from categorical to numerical variables (Table 1). Using the normalized variables

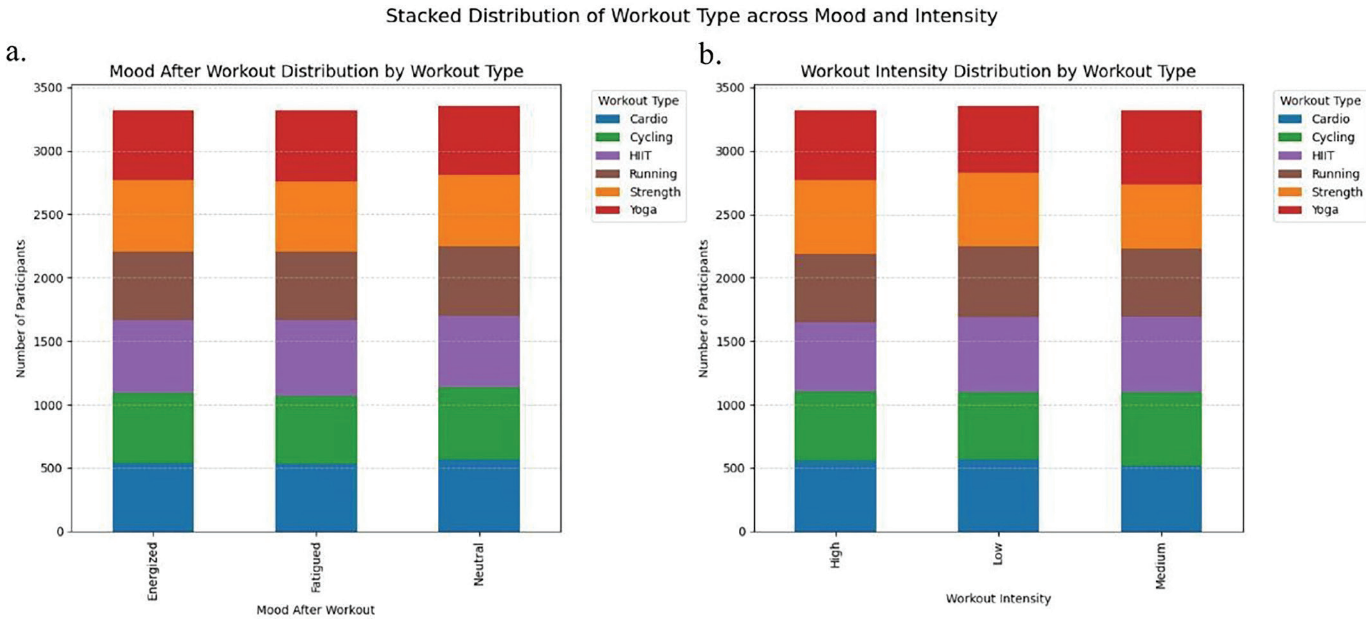

***Figure 2.* Distribution of Participants by Mood After Workout and Workout Intensity Subgrouped by Workout Type.** *Stacked bar charts showing the distribution of participants across categorical variables. (a) Distribution of participants by mood after workout levels (categorical ratings converted to numerical scale) across six workout types (Cycling, HIIT, Running, Strength, Yoga, Cardio). (b) Distribution of participants by workout intensity levels (Low = 1, Medium = 2, High = 3) across the same six workout types. Bars represent participant counts within each subgroup. Relatively equal distributions of participants across mood and intensity levels within each workout type confirm balanced representation of these variables, validating their inclusion in correlation analyses. Total n ≈ 10,000 across all workout types.*

Table 1. Pearson Correlations Between Sleep Hours and Behavioral/Physiological Variables. *Correlation coefficients (r) with corresponding p-values examining the relationship between nightly sleep hours and key physiological and behavioral variables measured during workouts, including resting heart rate, workout duration, calories burned, steps taken, workout intensity (converted from categorical: Low = 1, Medium = 2, High = 3), and mood after workout (converted from categorical ratings to numerical scale). No statistically significant correlations ($|r| > 0.50$, $p < 0.05$) were observed between sleep hours and any measured variable. Variables measured more reliably by wearable devices (e.g., heart rate) tended to have lower p-values compared to self-reported or device-estimated measures (e.g., calories burned), suggesting that measurement variability contributed to statistical uncertainty. These null findings indicate that sleep duration alone may not reliably predict athletic performance outcomes in a heterogeneous, real-world population. n ≈ 10,000 participants.*

Variable	*r*	*p*
Resting Heart Rate (bpm)	–.012	.212
Workout Duration (mins)	–.006	.554
Calories Burned	.000	.997
Steps Taken	.013	.209
Workout Intensity	.000	.998
Mood After Workout	–.009	.347
VO_2 Max	NaN	—
Body Fat (%)	NaN	—

from the Pearson tests, the correlations between all the dependent variables and Sleep Hours was plotted on a linear graph (Figure 3). Across the dataset, there were no statistically significant correlations amongst variables ($|r| < .50$, $p > .05$) were observed. Overall, the results found that Sleep Hours were not linearly correlated with any one physiological or behavioral factor.

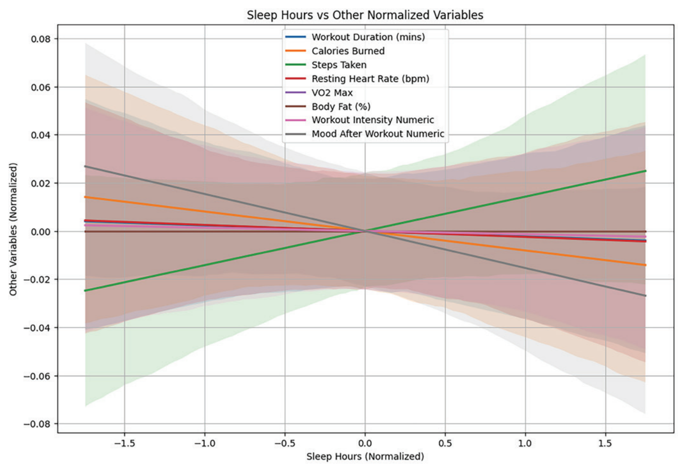

Figure 3.* *Correlation Plot of Normalized Variables Across Sleep Hours. *Linear scatter plots displaying Pearson correlations between sleep hours (x-axis) and normalized physiological and behavioral variables (e.g. resting heart rate, workout duration, calories burned, steps taken, workout intensity, and mood after workout). All variables were normalized using batch normalization to enable direct comparison. Each plot shows individual data points with fitted regression lines. No statistically significant correlations ($|r| < 0.50$, $p > 0.05$) were observed between sleep hours and any single physiological or behavioral variable, indicating that sleep duration was not linearly associated with any one performance metric in this population. n ≈ 10,000 participants.*

Neural Network Modeling

Given the limited results gained by the single variable correlations, a neural network was implemented to determine if results could be gained from a multi-variable approach - if Sleep Hours were a result of a combination of predictors. The network included three hidden layers of 128, 64, and 32 units along with ReLU activations, batch normalization, along with an adaptive learning rate starting at 0.0005. Overall, the model demonstrated rapid learning on the training within the first several epochs which carried over well onto the validation test set. Learning on the training set was further demonstrated over the remaining epochs, while the loss on the validation set showed some plateauing and eventual increase suggesting partial overfitting of the model to the training set (Figure 4) (Table 2). The neural network struggled to predict sleep across the full sample (avg error ≈2 hours), but performing modeling within workout-type subgroups reduced error (~0.8 hr MAE) and produced modest strength between the two variables ($R^2 \approx 0.27–0.35$). This pattern implies that sleep predictors vary by exercise context and that a single neural model cannot fully encompass these relationships among such a wide population in the case of these 10000+ participants.

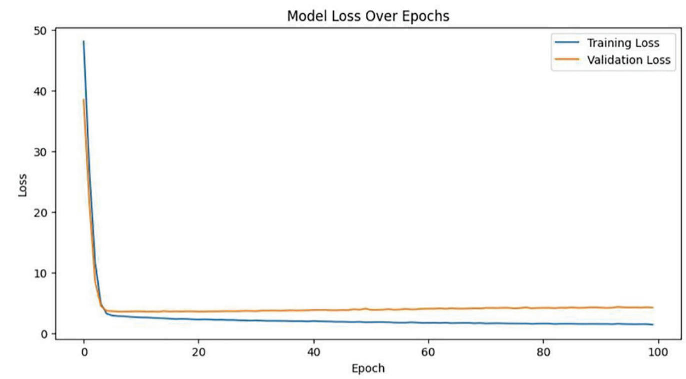

Figure 4.* *Training and Validation Loss Curves for Neural Network Predicting Sleep Hours. *Loss (mean squared error) plotted against training epochs for a neural network designed to predict sleep hours from multiple physiological and behavioral variables. The model architecture consisted of three hidden layers (128, 64, and 32 units) with ReLU activations and batch normalization, trained using an adaptive learning rate starting at 0.0005. The solid line represents training loss, and the dashed line represents validation loss. Rapid learning occurred within the first several epochs on the training set, with strong initial generalization to the validation set. Continued training showed progressive learning on the training set, while validation loss plateaued and eventually increased, suggesting partial overfitting to the training data. Despite convergence, model performance remained limited (see Table 2), consistent with the absence of strong single-variable correlations.*

Correlation Analyses (By Workout Type)

In order to account for correlations driven by workout type, correlations were analysed in each specific workout subgroup (Cycling, HIIT, yoga, strength, running, cardio) between sleep hours and the dependent variables (Table 3). Overall, the results revealed inconsistent trends

Table 2. Neural Network Performance Metrics for Predicting Sleep Hours (Rounded to 3 Decimal Places). *Comprehensive evaluation metrics for the feedforward neural network model (architecture: three hidden layers of 128, 64, and 32 units with ReLU activations and batch normalization; see Figure 4 for training curves). Metrics include coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE), reported separately for training set (70% of data, $n \approx 7{,}000$) and validation set (30% of data, $n \approx 3{,}000$). Despite rapid initial learning and convergence, the model demonstrated limited predictive performance, with validation metrics indicating weak generalization. The relatively low R^2 and elevated error metrics are consistent with the absence of strong univariate correlations (Table 1), suggesting that the combination of multiple predictors does not substantially improve prediction of sleep duration in this heterogeneous dataset. Partial overfitting is evident from the divergence between training and validation loss curves in later epochs (Figure 4).*

Workout Type	MAE (hrs)	MSE	R^2	Notes
Full Sample	2.074	6.613	1.214	Model trained on all data
HIIT	.772	2.014	.303	Subgroup model
Strength	.797	2.17	.268	Subgroup model
Running	.764	1.959	.347	Subgroup model
Cycling	.801	2.145	.28	Subgroup model
Cardio	.791	1.995	.33	Subgroup model
Yoga	.793	1.995	.308	Subgroup model

Table 3. Pearson Correlations Between Sleep Hours and Selected Variables by Workout Type (Rounded to 3 Decimal Places). *Correlation coefficients (r) with corresponding p-values, stratified by workout type (Cycling, HIIT, Running, Strength, Yoga, Cardio). This table examines relationships between sleep hours and key physiological and behavioral variables (resting heart rate, workout duration, calories burned, steps taken, workout intensity, mood after workout) within each workout subgroup to identify potential workout-specific patterns masked in the full-sample analysis (Table 1). Inconsistent and statistically non-significant correlations ($|r| < 0.50$, $p > 0.05$) were observed across all workout types, indicating that exercise modality did not reveal hidden sleep-performance associations. These null findings within subgroups are consistent with the full-sample results, suggesting that the heterogeneity of participants, device variability, and unmeasured confounding factors (e.g., naps, training consistency, diet) limit the detectability of sleep-performance relationships in real-world wearable datasets. Sample sizes per workout type: $n \approx 1{,}668$. Neural network models trained separately by workout type (subgroup-model approach) produced lower MAE compared to the full-sample model, suggesting modest improvements when accounting for workout-specific patterns, though overall predictive power remained limited (Figure 5).*

Workout Type	Resting HR	Workout Duration	Calories Burned	Steps Taken	Mood After	Intensity
Cycling	–.022	–.037	.011	.024	–.056	–.050
HIIT	–.007	–.004	–.035	–.019	–.014	–.007
Running	–.010	.036	.021	.019	–.008	.012
Strength	.005	–.011	–.009	–.012	.015	.007
Yoga	.013	–.027	.014	–.005	–.009	–.010
Cardio	.008	.012	–.020	–.003	–.016	.005

of association regardless of workout type, all of which were too small to be considered statistically significant ($|r| > 0.50$, $p < 0.05$), thus the style of workout did not have an impact on the variables. Then, the multivariable correlation was used, as the neural network prediction was compared to the actual sleep hours and was plotted on the graph. Each data point was colored by the workout each person did (Figure 5). Overall, it shows that model predictions regress toward the sample mean and that predicted sleep is clustered while actual sleep values are more dispersed; with the colors indicating no clear separation by workout type in the model, supporting the subgroup-model approach (which produced lower MAE). The scatter's spread and outliers are consistent, likely contributing to the model's limited full-sample performance.

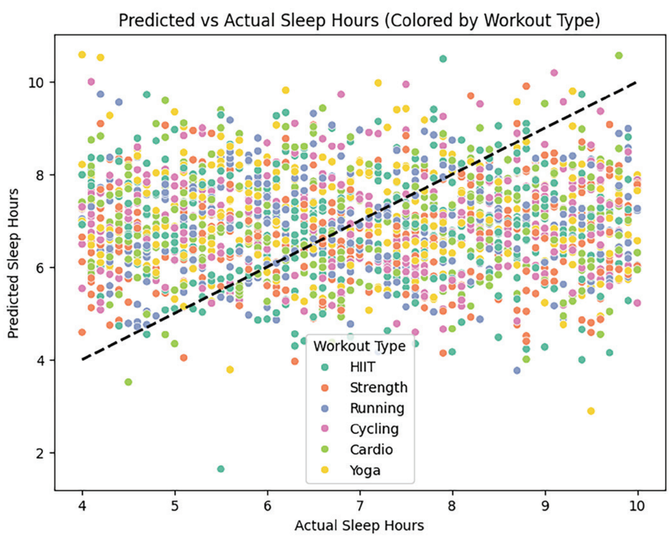

Figure 5. ***Scatterplot of Predicted vs. Actual Sleep Hours Colored by Workout Type.*** *Scatterplot comparing neural network predictions (y-axis) against actual observed sleep hours (x-axis) for all participants in the test set. Each point represents one participant, colored by their workout type (Cycling, HIIT, Running, Strength, Yoga, Cardio). The diagonal reference line (y = x) represents perfect predictions; points closer to this line indicate more accurate predictions. Model predictions regress toward the sample mean (≈7 hours), resulting in clustered predicted values despite more dispersed actual sleep values. The wide scatter and presence of outliers are consistent with the model's limited predictive performance (R^2 and MAE reported in Table 2). No clear separation by workout type is evident, supporting the findings that workout modality does not substantially influence sleep-performance relationships in this dataset. The subgroup-specific models (analyzed separately by workout type in Table 3) produced lower mean absolute error, suggesting that workout-stratified approaches may capture subtle patterns masked in the full-sample model. n = test set (≈3,000 participants, 30% of total dataset).*

DISCUSSION

The overall goal of this experiment was to identify the ideal amount of sleep needed to maximize athletic performance. This study investigated whether sleep duration are associated with measures of athletic performance in a real-world population. It was hypothesized that variables such as Resting Heart Rate would decrease with increasing Sleep Hours, whereas variables such as Workout Duration, Calories Burned, and Mood After Workout would increase. Based on the analyses, no significant correlations were observed between Sleep Hours and the physiological or performance variables examined. Multi-variable correlations and neural network models also failed to identify consistent patterns across subgroups. Overall, Sleep Hours were not significantly associated with the measured athletic performance outcomes, suggesting that these metrics alone may not reliably predict performance in a heterogeneous population.

These null results highlight several considerations regarding the dataset. While the dataset included over 10,000 participants, the data were collected from various fitness-tracking apps and devices, limiting control over measurement accuracy and consistency. Self-reported metrics may also be subject to participant bias, such as under- or overestimation of mood or activity levels. Previous literature reports that fitness trackers are generally most accurate for Heart Rate, moderately accurate for sleep, and least accurate for energy expenditure, with exercise duration varying by type (5). Accordingly, variables measured more reliably by devices (e.g., HR) tended to have lower p-values, suggesting that device-based variance contributed to statistical uncertainty.

Another limitation relates to participant heterogeneity. The dataset likely included individuals with highly variable fitness levels and training routines. Unlike elite athletes, casual exercisers do not train with consistent intensity or volume, meaning physiological responses may not be primarily influenced by sleep adaptation. Controlled athlete studies, such as Mah *et al.* (6), demonstrate measurable performance improvements when sleep is experimentally extended. In Mah *et al.*'s study, collegiate basketball players increased nightly time in bed to approximately ten hours under closely monitored conditions, resulting in improved sprint times, shooting accuracy, reaction speed, and subjective energy. The strength of these findings lies in the uniform training schedules and similar athletic baselines of participants, which minimized environmental and behavioral variability, making the sleep–performance association more observable. By comparison, the present dataset reflects a heterogeneous population of casual exercisers, where routines, fitness levels, stress loads, and device brands vary substantially. These differences likely contributed to the null findings.

Despite these limitations, the results remain informative. Sleep metrics alone may not acutely predict athletic performance, and observed associations may be context-dependent, influenced by factors such as training load, caffeine intake, and physiological readiness. Romyn *et al*. (7) demonstrated that total daily sleep, including daytime naps, predicted performance in trained soccer players under controlled sleep restriction conditions. Performance deficits from short nighttime sleep were slightly mitigated by napping, indicating that studies relying solely on nighttime sleep may not capture true sleep–performance relationships. In the present dataset, the lack of nap or sleep efficiency data may have obscured underlying associations.

These findings highlight the importance of consistent and objective measurement of physiological performance and sleep, as well as the need to account for participant heterogeneity in real-world datasets. Confounding variables in the datas*et al*so factored into the null findings. Collecting additional variables such as training volume, cortisol levels, and diet may provide a more complete understanding of performance variability. Incorporating intervention-based designs that manipulate sleep duration or quality could clarify potential causal relationships. Using more advanced multivariate or machine learning approaches with standardized inputs may also improve prediction of athletic outcomes.

In summary, Sleep Hours were not significantly associated with the physiological variables measured in this real-world population. These findings underscore the challenges of studying sleep outside controlled environments, particularly when considering variability in measurement devices, participant behavior, and unmeasured factors such as naps, training consistency, and physiological readiness. Although no significant associations were detected, these results provide valuable insight for future research on sleep and athletic performance, emphasizing the need for standardized measurement, controlled study designs, and inclusion of additional contextual variables.

CONCLUSION

This study examined the relationship between sleep duration and physiological performance metrics in a large, real-world dataset of over 10,000 adults using wearable fitness tracking devices. Contrary to hypotheses based on controlled studies, no statistically significant associations were identified between nightly sleep hours and key performance indicators (e.g. resting heart rate, workout duration, calories burned, steps taken, workout intensity, etc.) These null findings persisted across both single-variable correlation analyses and multi-variable neural network modes, and remained consistent when analyses were conducted by workout type.

The absence of detectable sleep-performance relationships in this heterogeneous dataset highlights critical methodological challenges in applying controlled research findings to real-world populations. Device variability in terms of measurement accuracy, participant differences in fitness levels and training consistency, reliance on self-reported metrics, and unmeasured confounding variables (e.g. daytime naps, caffeine intake, stress, and diet) likely obscured true correlations between sleep and performance. These findings underscore that sleep metrics alone may not be able to predict athletic performance in diverse populations without consideration of broader contextual factors.

Despite yielding null results, this research contributes meaningfully to the sleep-performance literature by demonstrating the limitations of different wearable datasets while identifying key factors that must be addressed in future investigations. Specifically, future studies should prioritize standardized sleep protocols, collect comprehensive contextual variables such as total daily sleep and training load, employ intervention-based designs to establish causality, and utilize similar populations with controlled training regimens. By addressing these methodological gaps, subsequent research can advance understanding of how sleep duration optimally supports physiological performance across diverse fitness contexts.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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