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RESEARCH ARTICLE

Using Wearable Technology to Explore Sleep's Influence on College Women's Basketball Performance

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Abstract

Introduction: This study examined the relationship between sleep patterns and athletic performance among NCAA Division I women's basketball players, emphasizing the importance of sleep in recovery and game readiness. Using wearable technology data, this research aimed to identify how sleep metrics influence game performance and whether integrating sleep data improves performance prediction models.

Method: Data were collected from women basketball athletes over a season using Oura Ring devices to track sleep metrics and game performance (box summary) scores. Mixed-effects linear regression and machine learning models assessed correlations and the predictive value of sleep data on game performance.

Results: Seven athletes provided wearable technology and game performance data over one season of collegiate women's basketball. Sleep disturbances significantly ($p < 0.05$) and negatively correlated with 2-point field goal, field goal percentage, 3-point field goals, total points by athlete, and the overall game time quality score, with greater sleep disturbances linked to poorer outcomes. Sleep duration was inconsistently associated with game performance parameters. Individual athletes demonstrated distinctly different sleep patterns. Models incorporating sleep metrics improved performance predictions compared to player identification alone.

Discussion: The findings from this study highlight the connection between sleep and athletic performance. Wearable technology offers actionable insights, supporting personalized monitoring and targeted interventions to improve sleep and optimize game readiness. Future research should explore interventions to maximize sleep quality. Additional research is needed to explore the impact of extended game seasons and other external influences such as athletic cross-country travel on sleep quality.

Keywords: Sleep, Athletic Performance, Wearable Technology, Women's Basketball, Recovery, Oura Ring.

1. Introduction

The use of wearable devices among college athletes has become increasingly popular in an attempt to harness health related data to enhance training, optimize and/or predict athletic performance, and to assist with injury prevention as well as monitoring rehabilitation when injuries do occur (Seckin et al., 2023). Numerous commercial devices (e.g., Fitbit, Google Watch, Garmin, Oura Ring) are available for use by individual athletes and athletic trainers/coaches. These devices capture multiple health related metrics such as heart rate, steps/day, exercise length and intensity, body temperature, and sleep parameters (Canali et al., 2022).

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Understanding the relationship between sleep and player performance in basketball players is crucial due to the sport's physical and cognitive demands. Sleep supports physical recovery by promoting muscle repair, reducing inflammation, and replenishing energy stores, all essential for the explosive movements and sustained endurance required in basketball (Kryger et al., 2011). Additionally, sleep enhances cognitive functions like reaction time, decision-making, and focus, which are vital for executing strategies and performing under pressure (Fullagar et al., 2015; Watson, 2017). Sleep deprivation can impair these abilities, leading to slower responses, increased errors, and a higher risk of injury due to compromised motor control (Mah et al., 2011). Given the challenges basketball players face, such as late-night games and travel-induced disruptions, prioritizing sleep through strategies like consistent schedules and napping routines can significantly improve performance and recovery (Samuels, 2008). Addressing sleep as a critical component of training ensures that players can meet the physical and mental demands of the game while reducing the risk of injury. The use of wearable technology to capture objective sleep metrics now offers a way to further explore associations between sleep and athletic performance. While wearable technology can provide valuable data, it ultimately relies on user interpretation, which may introduce variability in its application by individuals. Likewise, coaches, trainers, and athletic managers are asking how to best interpret and use the available data (Seckin et al., 2023).

Therefore, the purpose of this study was to explore associations between sleep and athletic performance captured through wearable technology among NCAA Division I women's basketball athletes. As such, this study strived to address the following research questions:

RQ1: Do player sleep characteristics on the night before a game correlate with game performance?

RQ2: If game performance is predominantly determined by player skill (and thus inherently linked to individual players), does incorporating sleep data enhance the accuracy of performance predictions?

2. Methods

This study requested consent from athletes to use retrospectively available data from women's basketball athletes at a Division I Power Four university in the Southeast. All data used in this analysis were de-identified prior to being analyzed by the statistician to ensure participant confidentiality, as approved by the Institutional Review Board at Clemson University, (#2023-0809-01). The game performance data were obtained from NCAA box scores and covered an entire basketball season. This dataset included comprehensive game statistics for each match played throughout the season. Routinely collected summary (box) scores of game performance were collected during the season by coaching staff using standardized abbreviations and observations for the sport (VidSwap, n.d.).

Sleep data was captured using the Oura Ring device, a commercially available wearable technology monitor that can be continuously worn on a finger to provide health related metrics such as heart rate, heart rate variability, body temperature, activity tracking, and sleep parameters (Oura, n.d.). Sleep metrics such as total duration (length) of sleep, number of minutes of light, deep or rapid eye movement (REM) sleep cycles, restlessness and minutes spent awake are captured. Prior research demonstrates the validity of the Oura Ring to distinguish individual sleep stages with high accuracy (Altini and Kinnunen, 2021). Sleep data was utilized for the night immediately prior to a game. Each night's sleep data, per participant, were aggregated into single values for each parameter. Sleep data were collected on a near-daily basis throughout the entire basketball season. Oura Ring's Application Programming Interface (API) was not disclosed. As such, the metrics used to calculate and categorize sleep stages (light vs. deep for example) were not available. The device output provided the number of minutes for sleep in each predetermined category.

For analyses investigating the relationship between sleep and game performance, sleep data from the night preceding each game were extracted for each player and matched to the corresponding game performance metrics. In contrast, for analyses examining the association between player and sleep pattern, all available sleep data were used.

2.1 Data Processing

To ensure comparability, each parameter in the dataset was normalized to a range between -1 and 1. From the normalized data, we created a composite feature termed "game1," which represents the average of three performance metrics: Field Goal Percentage (FG-PCT), Assists (A), and Turnovers (TO). This composite feature aims to encapsulate player performance based on key aspects typically emphasized by coaches. The range of the "game1" feature extends from -1 to 0.5, resulting in an amplitude of 1.5.

For the game performance-focused analyses, the dataset initially contained 184 entries. After excluding entries with missing values, 173 data points remained for further analysis. For the sleep versus player analysis dataset, which initially comprised 2,154 entries, 1,896 data samples remained following the removal of samples with missing values.

2.1.1 Sleep Versus Game Performance

In the analysis of sleep versus game statistics, the primary goal was to determine any direct relationships between sleep parameters and game performance, while accounting for the varying baseline skill levels of different players. Initially, we examined scatter plots for all pairs of sleep and game performance metrics to identify any apparent non-linear relationships. Upon confirming the absence of such non-linear patterns, we determined that mixed-effects linear regression was suitable for assessing the correlations between these variables.

We constructed a separate mixed-effects linear regression model for each pair of sleep and game performance parameters. To control for individual differences in game skills, in each model, sleep was included as a fixed effect while the player was treated as a random effect, thus accounting for inherent variability across subjects. This approach resulted in a total of 620 models (20 game parameters × 31 sleep parameters). The slope coefficients and their associated p-values for each model were computed and recorded to assess the significance of the relationships. We implemented the mixed-effect models via Python statsmodels library (Seabold & Perktold, 2010, version 0.4.1) with the formulation Y ~ X, where Y represents the outcome and X a sleep feature. Player ID was specified as the grouping variable to account for within-subject correlations. The model selection was guided by theoretical rationale, and parameter estimation was carried out using the Nelder-Mead optimization method, with no hyperparameter tuning.

2.1.2 Player Versus Sleep Patterns

This analysis investigated the association between individual players and their distinct sleep patterns. The rationale for including this analysis is as follows. Game performance is generally correlated with player skill, and thus, is specific to each player. When studying the relationship between sleep and game performance, player skill acts as a confounding variable. We thus needed to include the player as a random variable in the mixed-effects model mentioned above. In other words, the effect of sleep on performance is our signal, while variations in player skill represent noise. We anticipate that the signal-to-noise ratio for this relationship may be low. Thus, this analysis aims to provide an understanding of the strength of the association between player identity and sleep patterns, which will subsequently inform the interpretation of the relationship between sleep and game performance.

We developed a classification model using sleep parameters as inputs to predict player ID. We implemented the classifier model using the sklearn library's (Pedregosa et al, 2011, version 1.4.0) MLPClassifier and the network comprised a single hidden layer with 48 nodes.To evaluate the model's performance, we used a training-validation data split of 85% and 15%, respectively. Model selection and hyperparameter tuning was conducted on a dedicated validation set by minimizing the validation loss. Monte Carlo Model Evaluation was performed over 100 iterations to quantify the average validation accuracy and its standard deviation.

2.1.3 Predicting Game Performance: The Significance of Sleep Data

Finally, this study explored whether incorporating sleep data improves the prediction of game performance compared to using player ID alone. We constructed two multiple regression models to predict the game performance parameter "game1". We constructed interpretable multiple regression models using Python scikit-learn's LinearRegression. This model was chosen for its ease in defining degrees of freedom for the F-test, and no hyperparameter tuning was performed. Model A incorporated both sleep and player parameters as predictors, while Model B included only the player ID as predictor. In Model A, the sleep parameters included were 'breath_average,' 'average_breath_variation,' 'hr_lowest,' 'hr_average,' and 'rem'; these parameters were selected based on a feature importance analysis.

To compare the performance of these models, we calculated the Root Mean Square Error (RMSE), Residual Sum of Squares (RSS), and the degrees of freedom for each model. The F score was then computed to evaluate the relative fit of Model A against Model B. Since our objective was to compute the F score for model comparison, we used the entire dataset for model fitting without a training-validation data split. We used the sklearn library (Pedregosa et al, 2011, version 1.4.0) for this analysis.

3. Results

Seven female athletes participated in the study allowing retrospective review of their Oura Ring and game performance data across an entire basketball season.

3.1 Sleep Versus Game Performance

Several sleep parameters (such as sleep disturbance and duration of sleep) show significant correlations with game performance, as highlighted in Table 1. The directions of these correlations for each pair are detailed in Table 2. Example scatter plots illustrate visually prominent intra-player correlations between sleep parameters and game performance metrics (see Figure 1). Among the various sleep parameters, 'score_disturbances' is notable for exhibiting the highest number of significant correlations with various game parameters. Score disturbances refers to the number of sleep interruptions that occurred during the night immediately preceding a game day. Sleep disturbances were inversely correlated ($p < 0.05$) with Field Goals (FG), 2-Point Field Goal Attempts (FGA), Field Goal Percentage (FG-PCT),3-Point Field Goals (3FG), Points by Athlete (PTS) and the overall game time quality scores (Qual Score). The variable "Sleep Duration" was significantly correlated ($p < 0.05$) with 3 Point Percentage (3 PCT) in a positive direction (longer sleep associated with higher 3 PCT), but inversely correlated with Free Throws (FT), Free Throw Percentage (FT-PCT) and Assists (A). Other sleep variables such as light sleep, deep sleep, rapid eye movement (REM), and sleep onset were included in the models but were not significantly associated with more than one game variable.

Table 1. *P-values of the Linear Regression Slope Between Pairs of Game versus Sleep Metrics*

	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10	SM11	SM12
Time	0.457	0.765	0.088	0.108	0.516	0.099	0.119	0.265	0.272	0.170	0.416	0.416
FG	0.026	0.679	0.085	0.115	0.336	0.153	0.082	0.995	0.498	0.545	0.406	0.406
FGA	0.047	0.919	0.152	0.339	0.772	0.302	0.232	0.347	0.701	0.589	0.489	0.489
FG-PCT	0.026	0.679	0.085	0.115	0.336	0.153	0.082	0.995	0.498	0.545	0.406	0.406
3FG	0.030	0.255	0.098	0.146	0.172	0.310	0.118	0.177	0.465	0.008	0.953	0.953
3FGA	0.099	0.765	0.323	0.492	0.679	0.531	0.514	0.358	0.771	0.015	0.624	0.624
3PCT	0.217	0.050	0.035	0.015	0.014	0.108	0.013	0.094	0.242	0.019	0.548	0.548
FT	0.493	0.786	0.033	0.035	0.469	0.027	0.040	0.646	0.635	0.956	0.007	0.007
FTA	0.780	0.558	0.092	0.124	0.721	0.087	0.144	0.560	0.530	0.959	0.011	0.011
FT-PCT	0.493	0.786	0.033	0.035	0.469	0.027	0.040	0.646	0.635	0.956	0.007	0.007
OFF	0.204	0.974	0.882	0.446	0.541	0.543	0.347	0.077	0.367	0.366	0.623	0.623
DEF	0.954	0.055	0.179	0.236	0.165	0.474	0.265	1.000	0.235	0.047	0.095	0.095
PF	0.316	0.344	0.073	0.592	0.433	0.270	0.973	0.951	0.718	0.807	0.169	0.169
A	0.082	0.126	0.053	0.016	0.045	0.059	0.017	0.018	0.002	0.639	0.102	0.102
TO	0.198	0.517	0.662	0.712	0.817	0.555	0.616	0.824	0.796	0.064	0.906	0.906
BLK	0.930	0.131	0.961	0.208	0.012	0.842	0.039	0.011	0.025	0.326	0.383	0.383
STL	0.512	0.046	0.075	0.962	0.086	0.294	0.993	0.335	0.398	0.771	0.030	0.030
PTS	0.040	0.468	0.282	0.349	0.382	0.495	0.274	0.667	0.405	0.315	0.853	0.853
QualScore	0.031	0.194	0.936	0.645	0.252	0.955	0.491	0.533	0.456	0.409	0.392	0.392
Game1	0.174	0.771	0.769	0.799	0.961	0.729	0.905	0.263	0.029	0.131	0.202	0.202

Note. Cells where $p<0.05$ are highlighted. Legend of Sleep Metrics (SM) are as follows: score_disturbances (SM1), score_efficiency (SM2), score_total (SM3), duration (SM4), awake (SM5), total (SM6), midpoint_time (SM7), hr_average (SM8), hr_lowest (SM9), lowest_heart_rate_time_offset (SM10), temperature_deviation (SM11), temperature_delta (SM12).

Table 2. *Values of the Linear Regression Slope Between Pairs of Game Versus Sleep Metrics*

	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10	SM11	SM12
Time	-0.056	-0.028	0.089	0.112	0.078	0.110	0.162	-0.134	-0.142	0.072	0.049	0.049
FG	-0.190	-0.044	0.103	0.127	0.133	0.110	0.210	-0.001	0.094	0.037	0.058	0.058
FGA	-0.150	0.010	0.075	0.068	0.035	0.070	0.126	-0.117	-0.050	0.029	0.042	0.042
FG-PCT	-0.190	-0.044	0.103	0.127	0.133	0.110	0.210	-0.001	0.094	0.037	0.058	0.058
3FG	-0.227	-0.146	0.124	0.148	0.232	0.097	0.238	0.211	0.100	0.198	-0.005	-0.005
3FGA	-0.135	-0.030	0.057	0.053	0.054	0.046	0.075	0.110	0.037	0.139	0.033	0.033
3PCT	-0.156	-0.307	0.192	0.299	0.502	0.188	0.456	0.348	0.260	0.214	-0.065	-0.065
FT	0.066	-0.032	-0.142	-0.189	-0.111	-0.188	-0.276	0.061	0.067	0.004	-0.208	-0.208

FTA	0.026	-0.067	-0.109	-0.134	-0.053	-0.141	-0.191	0.075	0.086	0.003	-0.190	-0.190
FT-PCT	0.066	-0.032	-0.142	-0.189	-0.111	-0.188	-0.276	0.061	0.067	0.004	-0.208	-0.208
OFF	-0.091	0.003	0.008	0.052	0.071	0.039	0.096	-0.180	-0.098	-0.046	0.029	0.029
DEF	0.005	-0.216	0.085	0.101	0.202	0.058	0.142	0.000	-0.180	0.125	0.122	0.122
PF	-0.117	0.135	0.145	0.059	-0.145	0.114	-0.006	-0.010	0.068	0.020	0.129	0.129
A	-0.153	0.167	-0.120	-0.199	-0.280	-0.150	-0.293	0.286	0.399	0.029	0.116	0.116
TO	0.106	0.066	0.025	0.028	-0.030	0.043	0.057	-0.026	0.031	0.106	-0.008	-0.008
BLK	-0.007	-0.154	-0.003	0.100	0.331	0.015	0.243	-0.241	-0.239	0.058	-0.060	-0.060
STL	0.049	-0.177	-0.099	-0.004	0.206	-0.076	0.001	0.089	0.080	0.016	0.136	0.136
PTS	-0.171	-0.075	0.063	0.074	0.117	0.051	0.128	0.055	0.113	0.059	-0.013	-0.013
QualScore	-0.190	-0.142	0.005	0.038	0.162	-0.004	0.086	0.083	0.106	0.052	0.061	0.061
Game1	-0.078	0.021	0.012	0.014	-0.004	0.018	0.010	0.094	0.193	0.060	0.059	0.059

Note. Cells where the p-value of the slope <0.05 are highlighted. Legend of Sleep Metrics (SM) are as follows: score_disturbances (SM1), score_efficiency (SM2), score_total (SM3), duration (SM4), awake (SM5), total (SM6), midpoint_time (SM7), hr_average (SM8), hr_lowest (SM9), lowest_heart_rate_time_offset (SM10), temperature_deviation (SM11), temperature_delta (SM12).

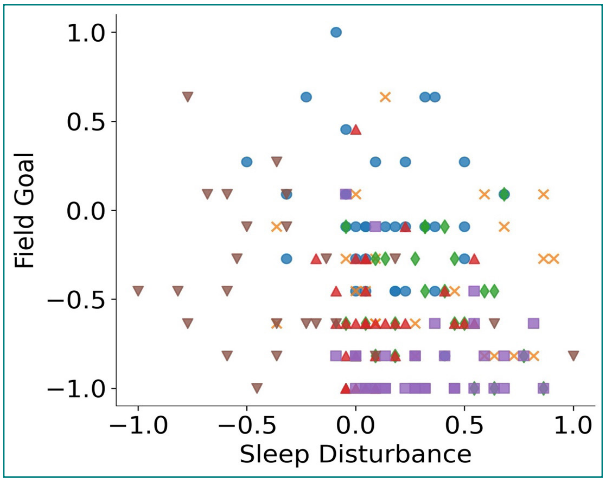

Figure 1. *Sleep Disturbances*

Note: Figure 1 is intended to visually illustrate the presence of intra-player correlation between sleep and game parameters, rather than to provide quantitative data regarding effect sizes.

3.2 Player Versus Sleep Patterns

Based on the neural network model's validation accuracy, the model demonstrates the ability to distinguish between the seven players using data from a single night's sleep with an accuracy of 94.64±0.78%.

3.3 Predicting Game Performance

Model B, which utilizes only player ID as a predictor, achieved a fitting RMSE of approximately 14.9% (0.224 on a scale with a range of 1.5). In contrast, Model A, which incorporates both player ID and sleep information as predictors, attained a slightly better-fitting RMSE of approximately 14.4% (0.216 on the same scale). The F-score for the models was 2.50, and the associated p-value for the F-statistic with degrees of freedom corresponding to our models (df1=5, df2=161) was 0.032. This p-value is significant at the 0.05 threshold, indicating that the inclusion of sleep information as a predictor provides a statistically significant improvement of game performance prediction over using player ID alone. While the RMSE improvement from 14.9% (Model B) to 14.4% (Model A) may appear modest, the associated F score metrics confirm that this difference is statistically significant.

4. Discussion

This study highlights the significant relationship between sleep quality (i.e. uninterrupted sleep) and athletic performance in women's collegiate basketball. The findings indicate that sleep disturbances consistently correlate with reduced game performance, emphasizing the critical role of sleep quality on improving athletic performance. This finding aligns with prior research such as a prior study completed by Fox et al. (2021) who monitored seven male players, across one season of semi-professional basketball, finding that subjectively reported sleep quality (the night prior to a game) was positively associated with field goals, free-throws accuracy, rebounds, assists, blocks and other player statistics. Of note, this study did not find any significant association between sleep duration (length of sleep) and player performance (Fox et al., 2021). In comparison, a previously reported systematic review on basketball player performance, sleep and recovery concluded that both sleep quality and sleep duration (longer sleep time) are positively linked to on-court performance (Ochoa-Lacar, et al., 2022). Currently, the ability to make direct comparisons to previous research on sleep metrics and basketball player performance are limited as multiple different methods of data collection (devices and/or self-report) have been used as markers of sleep quality.

Our study found inconsistent correlations between sleep duration (length of sleep) and game performance parameters. Only one game parameter, 3 Point Percentage (3 PCT), was positively associated with longer sleep while Free Throws (FT), Free Throw Percentage (FT-PCT) and Assists (A) were found to be negatively associated. This is not consistent with prior research in men's basketball (Mah et al., 2011) exploring the impact of sleep duration on performance. Mah et al. (2011) reported improved athletic performance in sprint time, shooting accuracy with free throws and 3-point field goals associated with longer sleep duration (averaging an increase of 110 minutes of more sleep per night). A separate study in women basketball players found a significant relationship between longer sleep duration and game performance, although they noted that correlations between the length of sleep and performance were highly individualized with variability noted between athletes (Staunton et. al., 2017). The contradictions in our study related to sleep duration and game performance may potentially be explained by the inclusion of sleep duration for only one night immediately prior to a game. Other studies have utilized longer time frames for monitoring sleep which may speak to a cumulative effect of longer sleep times in the days leading up to a game. In the Mau et al. (2011) study, sleep data was captured by actigraphy for 17 days at baseline and 41 days during the sleep extension period. Additionally, our study did not capture additional sleep time resulting from naps. This may have impacted our findings as naps around 60 minutes in duration (range 20-90 minutes) have been linked to improved athletic performance in multiple sports (Canha, et. al., 2023). Additionally, our inconsistent findings between sleep duration and game performance may have been influenced by our small sample size.

Given our study design with seven athletes contributing many observations each, concerns may arise about data independence and pseudo replication if using traditional analyses. To address this, we used a linear mixed-effects model suited for longitudinal data with repeated measures. In such a model, each athlete acts as a "mini-experiment" with a subject-specific random intercept to account for individual differences. This method partitions variance into within- and between-subject components, mitigating biases from correlated measures. Unlike ordinary least squares regression—which assumes independent observations—the mixed-effect framework explicitly models inherent dependencies through random effects. Although conventional correlational analyses typically require more unique subjects per predictor, we use the mixed-effect modeling approach to boost statistical power and robustness. By using multiple observations per athlete, we effectively capture the within-individual relationship between sleep quality and game performance. We also verified key model assumptions, including the normality of residuals and the random effects structure, to ensure the validity of our approach. In summary, the mixed-effect modeling approach overcomes the limitations of small subject numbers which pose a challenge for traditional regression and enhances detection of within-subject effects, supporting the validity of our findings on sleep quality and performance.

Our study also found that individuals have very distinctive sleep patterns. This finding has been reported in other studies investigating sleep, such as the Staunton, et al. (2017) study which has been previously described. Costa et al. (2021) also examined the sleep habits of high-level female athletes over two weeks of competition. The participants wore wrist actigraph units which measured their sleep duration and sleep efficiency. The study found individual variations in sleep which led the authors to state "sleep duration may be affected by training and match schedules and workloads" (Costa et al., 2021, p. 2). A separate study identified individual variations in female athletes' sleep patterns and fatigue surrounding game days for soccer matches (Moen et al., 2021). These findings imply that interventions to improve sleep may need to be individually tailored to address specific differences in individual sleep patterns.

Sleep is a critical factor in optimizing athletic performance, recovery, and overall health (e.g., Hamlin et al., 2021; Steidten et al., 2021). Athletes require high-quality and adequate sleep to support the physical and mental demands of training and competition. Sleep plays a vital role in muscle repair, immune function, and the regulation of hormones such as growth hormone, which are essential for recovery and adaptation (Hausswirth & Mujika, 2013). Moreover, insufficient sleep can negatively impact reaction times, decision-making, and motor function, all of which are crucial for athletic performance (Fullagar et al., 2015). Athletes often face unique challenges that can interfere with sleep quality and duration, including early morning training sessions, travel across time zones, and pre-competition anxiety (Juliff et al., 2015). Sleep deprivation or irregular sleep patterns can result in increased perceived exertion and decreased endurance during physical activities (Nedelec et al., 2015). These prior studies showcase the value of monitoring athlete's sleep and intervening to maximize sleep quality, which in turn can improve athletic performance.

Evidenced-based interventions to improve sleep are available and should be evaluated for implementation in athletic programs. These interventions include cognitive behavioral activities such as sleep education to teach mindfulness, relaxation therapies, and behavioral training related to nighttime routines (Saruhanjan, et al., 2021). The integration of wearable technology can provide personalized and actionable insights into sleep patterns and their influence on health. As our study demonstrated, the inclusion of sleep data into game performance prediction models can enhance accuracy, suggesting that sleep metrics offer unique, complementary value beyond traditional performance predictors such as player skill. This finding supports prior studies emphasizing the utility of wearable devices in monitoring and optimizing athlete health and performance (Seshadri et al., 2019; Svensson et al., 2024).

The present study highlights the variability of individual sleep patterns among players, suggesting that personalized approaches to sleep management could maximize recovery and performance outcomes. This observation aligns with Nédélec et al. (2015), who advocated for individualized recovery strategies based on unique physiological and psychological needs.

4.1 Implications

The findings of this study have significant implications for collegiate basketball programs, sports science research, and the broader application of wearable technology in athletic performance. The observed relationship between sleep quality, particularly sleep disturbances, and game performance underscores the need for integrating sleep optimization strategies into athletic training programs. Coaches, athletic trainers, and sports psychologists can use wearable data to design personalized recovery and sleep protocols, helping athletes achieve peak physical and mental readiness for competition (Luczak et al., 2020; Rao, 2021; Stokowski et al., 2020). Wearable devices provide a practical and continuous method for monitoring critical physiological metrics, enabling data-driven decision-making about training intensity, game readiness, and rest schedules, but would benefit from additional validation and guidance on how the data should be used.

Additionally, the ability to distinguish players based on their unique sleep patterns highlights the potential for personalized training and recovery regimens (Luczak et al., 2020). Tailoring strategies to the specific needs of individual athletes could improve sleep and performance outcomes, therefore offering a competitive advantage. While this study focuses on women's collegiate basketball, the insights gained have broader applications across other sports and athletic disciplines. Sleep's influence on physical and cognitive performance is universal, suggesting that other teams and sports could similarly benefit from sleep monitoring and optimization. Overall, our findings reinforce the critical role of sleep in athletic performance, advocating for the integration of wearable technology and personalized interventions in collegiate sports to support athlete well-being and optimize competitive success. By fostering a holistic approach to performance and recovery, these programs can improve not only team performance but also the long-term health and well-being of student-athletes (Stokowski & Rubin, 2024).

4.2 Limitations

While this study provides valuable insights into the relationship between sleep and performance in women's basketball, several limitations must be acknowledged. While Oura Ring has been found to be a valid and reliable tool for tracking sleep data (Svensson et al., 2024), the use of wearable technology in research remains in its infancy. This limitation highlights potential challenges in data accuracy and generalizability, which should be considered when interpreting the findings. It should also be noted that each of the device validation studies referenced within our study contained one or more authors that reported financial and/or employment affiliations with Oura Ring, introducing a potential for bias.

Additionally, the present study was conducted with a small sample size, involving only one team and seven athletes. This limited scope reduces the statistical power of the findings, and the low effect sizes observed could have potentially occurred by chance. Consequently, the results should be interpreted cautiously and may not be representative of broader populations. The correlation between sleep and performance was assessed on an individual player basis, using sleep data for only one-night preceding each game day. This personalized approach limits the generalizability of the findings to other teams or athletes and may not be representative of overall sleep patterns. Additionally, game performance metrics were retrieved from box scores (meaning routinely captured summary results from a competitive game), which may not comprehensively capture all aspects of performance.

The inability to measure overall performance further restricts the scope of the conclusions drawn from the study. The performance data used in this study are derived solely from box score statistics. These metrics, while widely utilized, by themselves do not account for factors such as the defensive strength of opposing teams. Future research should consider integrating more objective measures—such as those provided by wearable devices (e.g., Kinexon), which track accelerations, jump height, and distance covered—to enhance the assessment of in-game performance. Although this study included a small sample size, it is important to note that data was collected over an entire basketball season which provided multiple data points for evaluation.

4.3 Future Directions

While this study enhances our understanding of the relationship between sleep and athletic performance in women's basketball, it also highlights several areas for future exploration. Investigating the longitudinal effects of tailored sleep interventions could provide deeper insights into how specific strategies influence recovery and performance over time. Furthermore, future research should assess the interplay between sleep parameters, such as REM and deep sleep, and cognitive aspects of game performance, such as decision-making and focus.

Given the dual roles of female student-athletes, addressing their unique sleep challenges is critical for improving both academic and athletic outcomes. Incorporating variables such as diet, exercise, and academic stress into future studies would offer a more holistic perspective on the factors influencing sleep quality. Additionally, examining the impact of conference realignments and expanding athletic seasons on sleep patterns could provide actionable insights for scheduling and workload management.

User interpretation of wearable technology data remains a significant challenge. Research is needed to understand how athletes and coaches utilize this data and to develop education strategies that enable actionable outcomes. Interventions targeting specific sleep disturbances in this population also warrant further investigation. Future studies should continue to leverage wearable technology data while addressing its limitations, such as user adherence and privacy concerns, to maximize its impact on athlete health and performance.

5. Conclusion

The findings of this study underscore the significant relationship between sleep quality and game performance in collegiate women's basketball players. Notably, metrics such as sleep disturbance were consistently correlated with reduced performance, emphasizing the critical role of sleep quality in athletic success. These results highlight the value of leveraging wearable technologies (like Oura Ring) to monitor and optimize sleep patterns; thus, enabling targeted interventions aimed at enhancing recovery and game readiness. Furthermore, the integration of sleep data into performance prediction models demonstrated a statistically significant improvement over relying solely on player identification. This outcome suggests that sleep metrics offer meaningful insights that can complement existing performance assessments. Furthermore, the ability to distinguish individual players based on their unique sleep patterns suggests the utility of sleep data as a biometric tool in sports performance management. In conclusion, prioritizing sleep as an integral component of training and recovery strategies has the potential to enhance both individual and team outcomes in collegiate basketball.

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Conflict of Interest

Authors have no conflicts of interest to disclose.

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