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Influence of Training Load on Recovery, Wellness, and Performance in Elite Soccer Athletes

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***Purpose*:** Athlete monitoring has emerged as a common method to track athlete status and adjust training for optimal performance. Despite the influx of monitoring-related resources at the collegiate level, actual training load modifications are largely anecdotal. This prospective cohort study investigated relationships between previous day training load, objective nightly recovery, and next-day subjective wellness and max speed (MS) in elite soccer athletes across a collegiate season. ***Methods*:** Twenty-six collegiate female soccer athletes were tracked across the duration of their season (2024–2025) for training load (wearable global positioning systems monitors), objective nightly recovery (wearable recovery rings), next-day subjective wellness (morning wellness survey), and MS performance. ***Results*:** Previous day training load measures of distance and high-speed running were significant predictors of variables related to nightly objective sleep recovery, next day subjective readiness, and next day speed performance. High-speed running models consistently performed better than total distance for predicting changes in recovery, wellness, and MS. ***Conclusions*:** Numerous associations between previous day training load and objective and subjective measures increase accessibility of female athlete monitoring methods for applied practitioners. Although the magnitudes of coefficients vary, the consistency of significant findings across monitoring methods provides utility for continuous and comprehensive athlete monitoring, demonstrating the importance of subjective readiness measures beyond traditional performance metrics, while also addressing the paucity of literature in elite female athletes.

***Keywords*:** female, monitoring, speed, women's football

Tracking external training load is a common method used in elite sport, intended to monitor training adaptations, identify fatigue, and periodize training demands for optimal performance.[1] Global positioning systems (GPS) and accelerometry technologies equip athletes with wearable devices to capture metrics related to volume, intensity, and density.[2] However, exclusive quantification of physical demands lacks the necessary context of internal response, information which is essential for strategic decision-making surrounding readiness and injury risk. Internal metrics have previously been considered determinants of an athlete's functional response, dictating the degree of training adaptation.[3] Notably, sex differences persist in athlete recovery and wellness capacities, whether measured objectively[4] or subjectively,[5] which may contribute to disparate outcomes observed between male and female athletes in sport performance,[6] training availability,[7] and injury likelihood.[8] A sex-specific understanding of training load's influence on objective recovery, subjective wellness, and physical performance is necessary to develop female athlete monitoring protocols that optimize training, improve performance, and reduce injury rates.

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Sufficient recovery from training is necessary for physical adaptations and eventual improvement in sport performance.[9] Monitoring athlete recovery alongside external loads provides a comprehensive understanding of athlete status, which can then be utilized for individualized load prescriptions. Beyond training load, many factors contribute to individual athlete recovery capacity such as fitness,[10] body composition,[11] and training age,[12] making training responses highly individualized even within a single sport. Increased accessibility to wearable devices in recent years has allowed for the monitoring of objective recovery metrics, such as sleep measures related to heart rate, skin temperature, and efficiency. The influence of sleep on athletic performance is well documented.[13] Specific to female athletes, reduced sleep quality and quantity have shown negative impacts on cognitive performance such as reaction time and processing speed,[14] as well as neuromuscular performance.[15] Female athletes are at greater risks for worse sleep quality and daytime sleepiness compared to their male counterparts when measured subjectively,[16] while data using wearable rings show improved sleep metrics for female athletes.[17] Differences between objective and subjective sleep measures may in part be due to variability of the menstrual cycle, particularly related to individual menstrual symptoms[18] which have been shown to influence training load perception.[19]

Subjective wellness monitoring is a low-cost method used to track athlete perceptions in physical and psychological well-being,[20] typically including daily surveys of self-rated perceived fatigue, mood, stress, and soreness. In a recreationally active female sample, subjective wellness measures have been responsive to changes in endurance training volume, while objective sleep variables demonstrated a stronger relationship with training adaptation.[21] This largely aligns with previous literature which demonstrates subjective metrics as more sensitive to changes in acute and chronic training loads, compared to objective measures in a mixed-sex systematic review.[20] Similar findings were observed with English Premier League athletes, showing that while goalkeepers observed distinctly different on-field demands, training load measures were associated with all wellness measures, regardless of position-type.[22] Recent data have also identified associations between variability in subjective measures and sport-specific performance aspects in elite female volleyball athletes,[23] indicating the value of such measures in optimizing athletic performance. Furthermore, the inclusion of wellness measures has been suggested as an integral piece to performance enhancement across numerous sports and age levels.[24]

Ultimately, sport performance is the paramount outcome in elite athletics. In elite men's soccer, max speed (MS) has been identified as one of the strongest predictors for end of season standing,[25] and significantly higher in female soccer athletes drafted to play professionally compared to nondrafted players.[26] Straight sprinting has been shown as the most frequently executed action in goal-scoring scenarios,[27] clearly communicating the direct impact MS has on game outcome. Investigating the relationships between external loads, recovery, wellness, and speed performance in elite female soccer athletes may provide information for coaches to periodize windows of increased recovery and intensified training as priorities change across the season. Differences in internal load metrics have been established across the menstrual cycle and between sexes, thus elucidating specific relationships between objective recovery metrics and subjective wellness measures supports widespread utility for low to no monetary cost. The purpose of this study was to investigate the influence of previous day training load on objective nightly recovery, next-day subjective wellness, and next-day speed performance in elite female soccer athletes. It is hypothesized that increased previous day training loads will reduce sleep recovery capacity and next day MS but not significantly affect subjective readiness. This study aims to identify meaningful variables of interest for sport practitioners interested in developing athlete monitoring systems to manage recovery, wellness, and performance in elite collegiate female soccer athletes.

Methods

Subjects

Sample size was determined based off existing data in similar populations[28,29] and historical collaboration between the soccer program and the research team. The total sample included 26 total athletes; age and GPS demographics for the sample and by position group are provided in Table 1. Inclusion criteria included being at least 18 years of age and medical clearance for participation in August upon the beginning of the 2024 season. Athletes who were noncompliant with the monitoring methods were not included in the final analysis.

Design

Using a prospective cohort study design, 26 National Collegiate Athletic Association Division I women's soccer athletes were monitored across a single competitive season (2024–2025). Athletes were recruited through an in-person recruitment presentation of the research team which was approved and facilitated by University Athletics staff working with the team. Enrolled athletes were then fitted during preseason testing (end of July) for a wearable recovery ring provided (Oura Health Oy) to collect objective nightly recovery metrics and educated on continued compliance with the daily wellness survey already implemented by sport staff. Training load data were collected from wearable GPS devices (PlayerData) managed by the team sport scientist. The season lasted for 132 total days, including 107 separate days of training or competition. The present study was determined to be exempt by the University of North Carolina at Chapel Hill Institutional Review Board (IRB #: 23-2673). All subjects provided in-person written informed consent allowing access to their athletics data before any data were collected or reviewed by the research team.

Training Load

Athletes were equipped with wearable GPS units (PlayerData) for every practice and competition. Metrics collected for each session included total distance (in meters), high-speed running distance (HSR; meters covered between 17 and 22 km/h), and MS (in kilometers per hour). Data were collected and managed by the team sport scientist, a member of the research team.

Objective Recovery

Upon preseason arrival, athletes were given wearable recovery rings (Heritage Ring, Oura Health Oy). Once fitted, each athlete was assigned a device and charger and asked to wear the ring at minimum during their nightly sleep for the entire duration of their competitive season. A negative temperature coefficient temperature sensor reported sleep temperature as deviation from normal average of previous 2 weeks (°C deviation from the mean). Along with sleep temperature, other metrics recorded during sleep included the lowest nightly resting heart rate (RHR; beats per minute), root mean square of successive differences heart rate variability (HRV; milliseconds), duration (seconds), and efficiency (percentage of time spent asleep vs awake; percentages). Aggregate measures of daily objective readiness (including: RHR, HRV, Δtemp, recovery index, sleep amount, sleep balance, sleep regularity, previous day activity, and activity balance values rated out of 100) and objective sleep score (including sleep variables: total duration, efficiency, restfulness, rapid eye movement stage

Table 1 Participant Descriptive Characteristics for Total Sample and by Position Group

	Age, y	Average distance, m	Average HSR (m ≥17 km/h and ≤22 km/h)	Average MS, km/h
Team (n = 26)	20.1 (1.5)	4118.6 (1044.6)	292.0 (152.0)	22.3 (3.0)
Forwards (n = 6)	19.5 (0.5)	4598.1 (1064.2)	325.6 (168.9)	22.5 (2.2)
Midfielders (n = 8)	19.9 (1.4)	3871.6 (1206.0)	256.2 (179.0)	22.1 (3.6)
Defenders (n = 8)	20.3 (1.9)	4062.9 (581)	315.3 (63.4)	23.2 (0.8)
Goalkeepers (n = 4)	21.0 (1.2)	4005.0 (1150.7)	266.7 (170.9)	20.6 (4.3)

Abbreviations: HSR, high-speed running distance; MS, max speed. Note: Daily GPS measures of distance, HSR, and MS were averaged across every session of the season. The values are presented as mean (SD).

duration, deep stage duration, latency, and timing values rated out of 100) were also included in the analysis. Researchers utilized the cloud-based team platform to download raw data organized by player and day for analysis. The Oura ring has been shown to be a valid measure of nocturnal sleep duration,[30] heart rate measures,[31,32] and distal body temperature across the menstrual cycle.[33]

Subjective Wellness

Athletes were prompted to complete a daily wellness survey through an application (Fitfor90) accessible to the athlete, sport staff, and research team via the cloud-based storage system. Notably, athletes were able to visualize and review their own data on the application and sport staff used responses for training modifications in previous seasons, both which encouraged high athlete compliance. Athletes were asked to rate the metrics of fatigue, stress, mood, soreness, and sleep quality on a 7-point Likert scale (−3 to +3), with negative values indicating worse outcomes (worse stress, more soreness, worse mood, etc) and positive values indicating better outcomes (less fatigue, more restful sleep quality, etc); a common and reliable survey[34] sensitive to changes in external training load.[35] All scores were aggregated into a composite subjective readiness score (percentages).

Statistical Analyses

Previous day training load variables were transformed into seasonal means for each load type (distance, HSR) and each athlete to be used for between-athlete comparisons. Daily observations for each athlete were then subtracted from the athlete's mean to calculate deviation values for within-athlete variables of distance and HSR. Linear mixed effects models were then used to evaluate the within- and between-athlete impact of previous day training load on measures of objective recovery (readiness score, sleep score, sleep temperature, sleep duration, sleep efficiency, RHR, HRV), and subjective wellness (aggregate readiness). The within-athlete deviation scores and between-athlete load mean values were used as L1 and L2 fixed effects, respectively. The day of the season was used as the repeated-measure variable using a first-order autoregressive covariance structure to estimate covariance within-athlete independently. The restricted maximum likelihood estimation method was used. Separate linear mixed effects models were run for distance and HSR as to reduce multicollinearity (bivariate correlation $r = .837$, $P < .001$). Hierarchical multilevel models were used to identify significant training load, objective recovery, and subjective wellness predictors of next day MS while accounting for the repeated-measures nature of the data set. Separate series were applied for distance and HSR, using Akaike Information Criterion (AIC) to estimate model error and determine model selection. All statistical procedures were completed using SPSS (version 31.0.1.0), with an $\alpha = .05$ to determine statistical significance.

Results

Previous Day Training Load

Within-athlete previous day distance deviation and athlete-level total distance mean were both significant predictors for objective readiness ($b = -0.001$, $P < .001$; and $b = -0.001$, $P = .008$, respectively) (Figure 1). For HSR, only within-athlete previous day HSR deviation was a significant predictor of objective readiness ($b = -0.010$, $P < .001$); however, the HSR model was a slightly better fit than distance (distance AIC = 5562; HSR AIC = 5545).

For objective sleep score, within-athlete deviation scores of distance ($b = -0.002$, $P < .001$) and HSR ($b = -0.012$, $P < .001$) were significant predictors. Neither of the athlete-level means significantly predictive objective sleep score (distance $P = .089$, HSR $P = .279$), and HSR provided a slightly better model (distance AIC = 6076, HSR AIC = 6045).

Within-athlete previous day distance deviation and the athlete-level distance mean were significant predictors of objective sleep efficiency ($b = -3.745 \cdot 10^{-4}$, $P = .010$; and $b = -0.001$, $P = .013$, respectively) (Figure 2). Only within-athlete HSR deviation significantly predicted sleep efficiency ($b = -0.005$, $P < .001$),

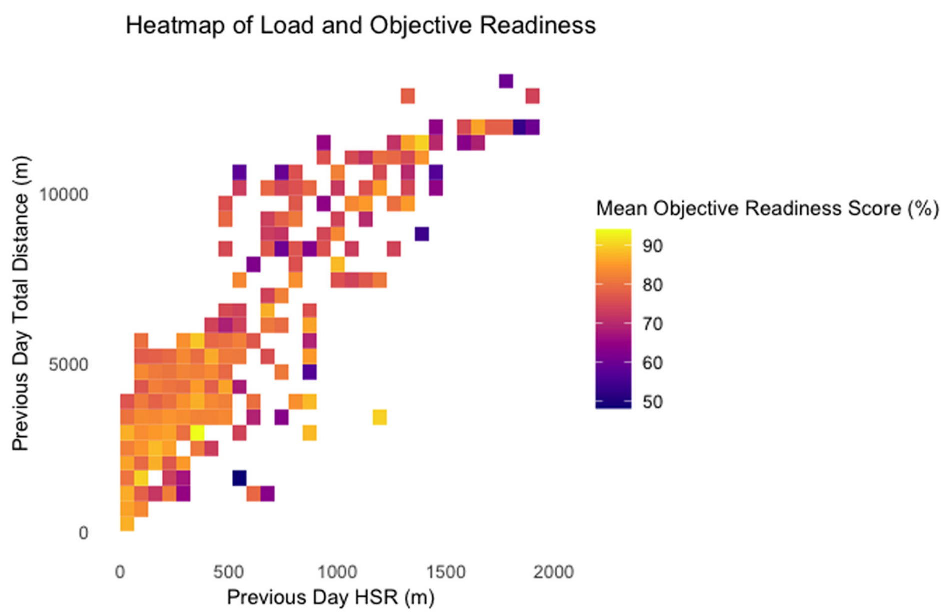

Figure 1 — Heatmap demonstrating previous day total distance (meters) and previous day high-speed running (HSR) distance (meters), with the color intensity representing low (blue; darker shade) to high (yellow; lighter shade) objective readiness (percentages).

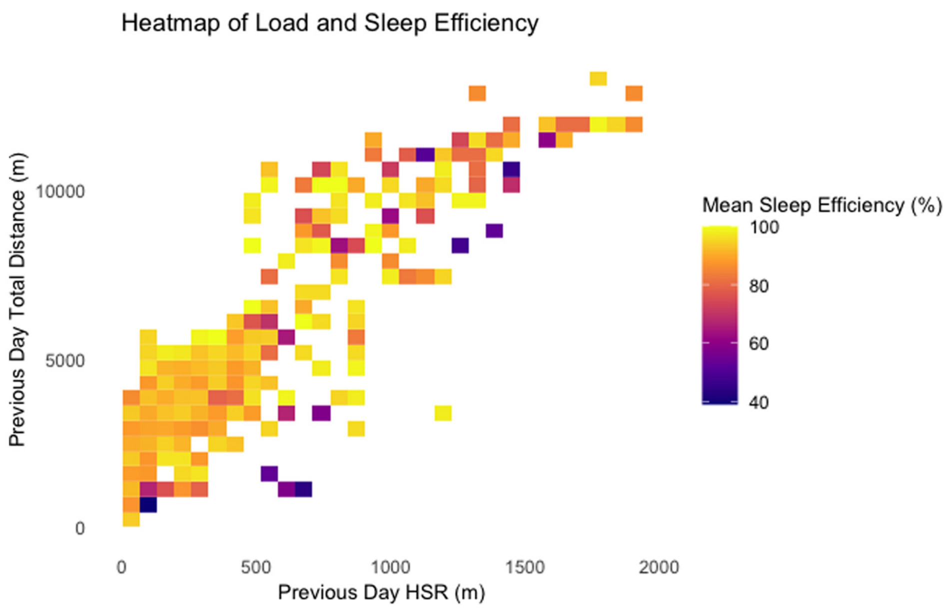

Figure 2 — Heatmap demonstrating previous day total distance (meters) and previous day high-speed running (HSR) distance (meters), with the color intensity representing low (blue; darker shade) to high (yellow; lighter shade) sleep efficiency (percentages).

although the athlete-level HSR mean was trending toward significance ($b = -0.010$, $P = .052$). The HSR model performed marginally better than that of the distance model (distance AIC = 6228, HSR AIC = 6208).

Only within-athlete distance deviation and within-athlete HSR deviation values were significant predictors of sleep duration ($b = -0.610$, $P < .001$; and $b = -4.612$, $P < .001$, respectively). The HSR also exhibited a lower AIC compared to total distance (distance AIC = 16,093, HSR AIC = 16,081), demonstrating marginally better performance of the model.

Both within-athlete distance deviation and athlete-level distance mean were significant predictors of RHR ($b = 4.050 \cdot 10^{-4}$, $P < .001$; and $b = 0.002$, $P < .004$, respectively). For HSR, both within-athlete HSR deviation and athlete-level HSR mean were significantly predictive of RHR ($b = 0.003$, $P < .001$, and $b = 0.018$, $P = .006$, respectively). The HSR model demonstrated a marginally lower AIC (distance AIC = 4192, HSR AIC = 4177), indicating slightly better performance.

Within-athlete deviation measures distance and HSR were both significant predictors of HRV ($b = -0.001$, $P < .001$; and $b = -0.007$, $P < .001$, respectively). Neither athlete-level mean variables of distance nor HSR were significant predictors of HRV. HSR demonstrated a lower AIC (AIC = 7056) compared to distance (AIC = 7066), indicating marginally better performance of the HSR model.

Within-athlete deviation scores for distance and HSR were significant predictors of next day subjective wellness ($b = -0.002$, $P < .001$; and $b = -0.015$, $P < .001$, respectively) (Figure 3). However, neither of the athlete-level means for distance or HSR were significant. The HSR model performed marginally better (AIC = 5887) compared to the distance model (AIC = 5924) for subjective readiness.

Predicting Max Speed

Using hierarchical multilevel modeling to identify significant predictors of daily MS, independent variables from each area were chosen. The final model, indicated by the lowest AIC of 3389, included training load variables of within-athlete HSR deviation ($b = -0.010$, $P < .001$) and athlete-level HSR mean ($b = 0.008$, $P = .052$). Objective recovery predictors of HRV (b = 0.022, P = .031) and RHR (b = 0.221, P = .001), as well as the aggregate variable of subjective readiness (b = 0.085, P < .001) were also included in the final model.

Discussion

Characterizing relationships between training load, recovery, wellness, and performance is critical for improving athlete readiness and mitigating injury, thereby enhancing long-term athlete development and resulting sport performance. Identifying the magnitude and strength of relationships between these variables is a necessary step for future implementation of load management procedures, recovery protocols, and performance preparation. Collectively, results of this study demonstrate the interrelated nature of training load on recovery capacity, perceived wellness, and next-day speed performance in collegiate women's soccer. Previous day load measures of distance and HSR influenced elements of objective recovery, subjective wellness, and MS on within- and between-athlete levels. Some variables saw influence of previous day training load at both the within- and between-athlete levels, such as objective readiness which demonstrated decreased scores following days when athletes covered more total and HSR distance than their typical average, with a 1% decrease in readiness for every 100 m covered at HSR speeds the day prior. A significant between-athlete effect was also observed for athletes with higher total distance means showing lower readiness scores across the season, irrespective of day-to-day fluctuations. Notably, average HSR did not significantly influence readiness, suggesting that while acute HSR fluctuations impact readiness to the greatest extent, chronic distance, as compared to chronic HSR, plays a more influential on readiness scores between athletes. Similarly, predictor variables from every data type (previous day training load, objective

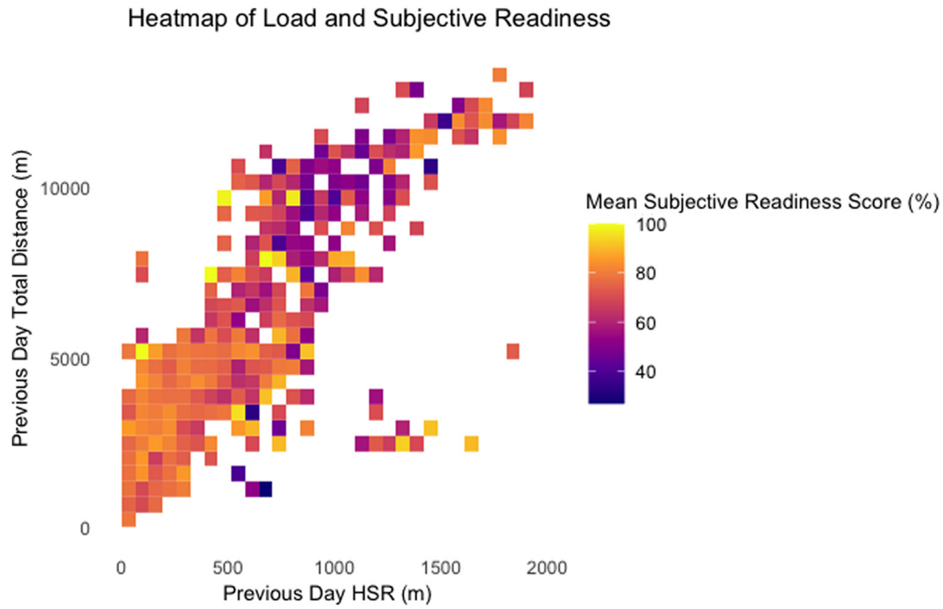

Figure 3 — Heatmap demonstrating previous day total distance (meters) and previous day high-speed running (HSR) distance (meters), with the color intensity representing low (blue; darker shade) to high (yellow; lighter shade) subjective readiness (percentages).

recovery, and subjective wellness) were significant predictors for MS, one of the most important capacities for soccer performance. Collectively, these results demonstrate the interrelated nature of training, adaptation, and performance during a collegiate women's soccer season while also suggesting both objective recovery and subjective wellness monitoring strategies may be effective in describing athlete status in applied sport environments, particularly on an individual scale.

Using wearable technology is a common method of capturing external training load in elite sport for strategic athlete management.[36] While the utility of such methods is not new, the application of this technology has gained considerable interest and popularity over the last decade.[36] The current implementation of fatigue-related athlete monitoring decision making from training load data is largely anecdotal when lacking inclusion of internal response variables. Previous data in national team women's soccer suggest subjective variables, rather than objective sleep metrics, are sensitive to training loads,[2] with individual investigations showing similar findings between distance and subjective soreness at the collegiate level.[37] Results of the present study were disparate in this aspect, demonstrating numerous significant relationships of previous day training load measures on objective recovery variables measured during sleep in collegiate women's soccer athletes. For instance, the present study found a significant, between-athlete effect of lower sleep efficiency in athletes with greater average distance volumes, with a 200 m above average day in HSR distance resulting in a 1% reduction in sleep efficiency. Sleep duration was negatively impacted by both within-athlete distance (1000 m above average distance resulting in a sleep deficit of 610 s, or about 10 min) and within-athlete HSR deviation (100 m of greater HSR volume beyond average predicts a sleep deficit of 461 s, or just under 8 min). Differences in findings of the present study and previous investigations may be due to the type of training load measure used, with HSR consistently demonstrating superior model performance compared to total distance. This is reflected in other prior research which compared HRV between high and low training load weeks; greater change in morning HRV from beginning of the week baseline was observed for the high load weeks in collegiate female soccer athletes who reported greater subjective fatigue.[38] These findings align with those of the present study which also showed reduced HRV values following days of above-average total distance and HSR loads; for every additional 143 m of HSR above the norm, HRV is reduced by 1 millisecond. Similarly, every additional 200 m of HSR distance covered above average predicts a 1% reduction in sleep efficiency. Finally, subjective readiness was also significantly affected at an individual level, demonstrating 2% lower subjective readiness scores following days with above average total distance volumes of 1000 m, and 3% lower scores following days they covered 200 m more than their typical HSR average. The small increments of change in subjective readiness may be due subaggregate differences in the way female athletes perceive stress as compared to the other components of the readiness formula. Previous research has shown an incongruent relationship between perceived stress and rate of perceived exertion[39,40] compared to other subjective measures of soreness, fatigue, and sleep quality in female athletes. These results are opposite of findings observed in male athletes[41] which demonstrated perceived stress as trending in similar direction as other subjective measures (fatigue, soreness, and mood), further underscoring the importance of female-specific evaluations of relationships between training load and subjective wellness outcomes. Investigations such as the present study may also provide a roadmap to distilling data streams to avoid information overload for athletes and improve efficiency of data utilization to inform training methodologies[42] while maintaining a female-specific lens.

Speed is a critical priority for soccer athletes, with prior research demonstrating MS as a determinant of team success in elite soccer.[25] Load management is a process which tracks load data in order to delicately balance athlete development with player performance.[36] To effectively optimize performance, sport practitioners would benefit from an understanding of influential variables on individual performance measures, such as MS, ahead of time, as to make necessary adjustments in real time. Using a similarly structured daily wellness survey in professional male soccer players, a one standard deviation reduction in aggregate well-being resulted in a 0.9-km/h reduction in MS.[43] The present study found previous day within-athlete HSR deviation to be the largest predictor of MS in collegiate women's soccer, demonstrating that for every 100 m of HSR distance covered above an athlete's average, a reduction of 1 km/h was observed in their next day MS. Other variables in the final model included sleep HRV and RHR, and subjective readiness, with athlete-specific HSR average also retained in the model, though not statistically significant ($P = .052$). These results demonstrate the importance of monitoring subjective and objective variables of athlete status for a better understanding of individual sport performance. Furthermore, adjustments in training loads and implementation of recovery protocols can be used to monitor athlete status and predict MS as priorities change across the season. For example, impaired wellness and reduced MS may be observed during the preseason period when accumulating load is of higher importance, compared to the postseason tournament when ensuring players are capable of their highest MS on match day is the priority. Although multiple training load, recovery, and wellness predictors were deemed significant, the small size of significant coefficients suggests the need for future research into other contributing factors to elite female soccer athlete speed performance.

The present study provides important considerations and next steps for sport practitioners interested in developing comprehensive monitoring methods specific to elite collegiate female soccer athletes, though, it is not without limitations. Female physiology, such as the menstrual cycle, menstrual dysfunction, and hormonal contraceptive use may influence elements of recovery and wellness; however, this was beyond the scope of the current study. Additionally, software measured variables for the GPS units were prioritized for translatability to practitioners, although this may have limitations as compared to analyses using raw data. Furthermore, the present study only included a single collegiate women's soccer team and may lack generalizability to other sports or different teams, even at the same level of competition. Future research could seek to combine multiple women's soccer teams at the same divisional classification to expand the sample while also maintaining a high caliber of athlete. As well as include chronic methods of capturing menstrual cycle and/or hormonal contraceptive implications.

Practical Applications

Collectively, this study demonstrated the influence of previous day training loads on nightly recovery and subjective wellness, in addition to identifying specific training load, recovery, and wellness variables as predictors of MS on individual and between-athlete scales. Understanding such relationships can inform load periodization across the changing priorities of a soccer season. Impaired wellness, recovery, and speed may be observed with greater training loads in preseason when the training priority is developing fitness via high load accumulation; however, as the team transitions into the latter portion of conference and championship tournament play, coaches have the contextual understanding of how much to reduce loads to ensure players are capable of their highest speeds for match day. Finally, the numerous relationships observed for within-athlete fluctuations of subjective and objective measures underpins the importance of individualized athlete monitoring and suggests implementing a survey-based monitoring system may be an effective, low-burden method to track athlete status for lower-resourced teams.

Conclusions

The present study demonstrates significant within- and between-athlete influences of previous day training loads on nightly recovery and next-day wellness in collegiate female soccer players. Although coefficients were small in magnitude, these significant relationships may still provide key targets for monitoring athlete status related to external training loads, particularly for implementation of individualized recovery and performance strategies. This study demonstrated fluctuations in both objective and subjective variables contribute to speed performance, in addition to previous day training load. These findings provide useful information for tracking athlete status to better understand relationships between physical demands, recovery, well-being, and performance, while also strengthening the literature on elite female athletes.

Acknowledgments

Data Availability Statement: Data of the present study may be made available upon reasonable request from the corresponding author. **Funding**: Financial support was provided by the University of Oklahoma Libraries' Open Access Fund. **Ethics Approval Statement**: The present study was determined as exempt by the University of North Carolina at Chapel Hill Institutional Review Board (IRB #: 23-2673), and all subjects provided written informed consent prior to any data collection or review by the research team.

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