Association Between Sleep Characteristics and Musculoskeletal Injuries in Elite Paralympic Powerlifters

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ABSTRACT:

This study aims to investigate the relationship between sleep and injuries among Paralympic weightlifters while taking advantage of physiological indicators related to recovery. The study sample consisted of 23 male athletes, and their data was monitored daily for 55 days using the wearable WHOOP 5.0 device, aiming to record sleep duration and quality, as well as to track changes in heart rate variability (HRV) and recovery levels. To analyze the relationship between sleep variables and injuries, the researcher used Spearman's correlation coefficient, and a Random Forest model was built to estimate injury risk based on each athlete's daily data. The study results showed a link between some sleep and recovery indicators and the physiological markers related to the players' condition, which highlights the importance of continuously monitoring these variables. The Random Forest model also showed a good ability to predict injury risk based on a set of daily variables, with recovery indicators, HRV, and sleep appearing among the important factors in the prediction process. These results suggest that daily monitoring of sleep and physiological indicators can provide useful information about recovery status and physical readiness, and that integrating this data into predictive models may help in early identification of high injury risk and support decisions related to training, recovery, and injury prevention for Paralympic weightlifters.

Keywords: Athlete Recovery; Injury Prevention; Wearable Technology; Sports Medicine; Heart Rate Variability.

Introduction

Sleep is one of the most important factors that help athletes maintain their body's efficiency and ability to keep up with training and perform well. Getting enough regular sleep after any physical effort is the best way to recharge the body, especially for athletes. Sleep also helps support recovery processes and maintain the physical and physiological functions necessary for sports performance. Some studies have shown that athletes who suffer from poor sleep quality and short sleep, especially when dealing with high training loads, can experience slower recovery and declines in physical performance and the body's ability to cope with training demands. (Vlahoyiannis et al., 2021; Walsh et al., 2021). Sleep for athletes is not just about the number of hours they get; it's also affected by its quality, consistency, and how well it meets the body's needs after training. This is especially important for Paralympic weightlifters, because training in this sport requires a lot of muscular effort, putting repeated strain on muscles and joints. So, an athlete needs enough time to let their body recover before getting back to training. Some studies have shown that good sleep helps athletes restore their physical abilities, while lack of sleep or irregular sleep can make recovery harder, affect performance, and increase the risk of injuries. (Clemente et al., 2021).

Sleep has started to get more attention in the sports field because it's related to an athlete's ability to recover after training. Evaluating sleep isn't just about counting hours anymore; it's also important to know its quality, consistency, and efficiency during the night. There's also growing interest in monitoring changes in heart rate variability (HRV) as an indicator that gives an idea about the state of the autonomic nervous system and how the body responds to effort and training. Some studies have noticed that lack of sleep or poor sleep quality can be associated with changes in HRV, which may reflect increased stress or incomplete recovery. So, tracking sleep and HRV together can help give a clearer picture of an athlete's condition and their readiness to handle training loads and perform in workouts and competitions. (Chennaoui et al., 2021).

So, regularly monitoring these indicators can help detect early signs of stress and reduce players' physical readiness, which helps coaches and specialists make better decisions about training loads and rest periods. This method can also be useful for players who frequently face high training loads, like weightlifters, because the sport demands repeated high-intensity training. Monitoring sleep and physiological responses can be an essential part of tracking physical condition and reducing the risk of training when recovery is poor. (Walsh et al., 2021).

Information about injuries among Paralympic athletes is still limited compared to athletes without disabilities. Studying this topic is particularly important for athletes with physical disabilities because the nature of the disability can affect movement, performance, and response to physical effort. Some studies have shown that sleep and mental health are aspects that need attention when monitoring the health of Paralympic athletes and the injuries they may face during the sports season, especially for Paralympic weightlifters. Their sport relies on resistance training and muscle strength development, which exposes their bodies to high-intensity, repeated training loads, making proper recovery essential to maintain performance, continue training, and reduce problems caused by physical stress. (Fagher et al., 2023; Walsh et al., 2021). Monitoring sleep and physiological indicators can also help identify changes related to fatigue buildup or reduced recovery, especially when interpreted alongside training load and daily performance instead of relying on a single indicator. This supports making appropriate decisions regarding training load, rest, and recovery. Some studies suggest that tracking sleep and physiological responses is an essential part of monitoring an athlete's condition and reducing factors that might be linked to a higher risk of injury which is particularly important for athletes. (Kemp et al., 2023; Nobari et al., 2023)

With the development of ways to monitor athletes, wearable devices have become a practical means of getting information about a player's condition in their daily life, without needing to be restricted by a specific time or place. These devices provide data that can help track sleep, changes in heart rate, physical activity, and some recovery indicators, which helps in noticing changes that might not be obvious when measurements are taken at farapart times (Düking et al., 2021; Nuuttila et al., 2025). Collecting this data continuously also allows us to look at an athlete's condition as something that changes from day to day, rather than relying on a single measurementWith the development of machine learning methods, it has become possible to handle large amounts of data and study multiple variables at the same time.

This helps in predicting sports injuries before they occur, because sometimes an injury doesn't happen due to a single factor, but could result from the interaction of several factors, like training load, how much rest and recovery the athlete gets relative to their training load, their physiological condition, as well as past injuries. So, these methods can help better understand the relationships between these factors and identify patterns that might be linked to a higher risk of injury.

Previous studies have shown that machine learning models can be used to identify athletes most at risk of injury and determine the most important variables associated with injury risk (Van Eetvelde et al., 2021). But there is still a need to utilize these capabilities in studying Paralympic athletes, especially weightlifters with physical disabilities. Studies on sleep, injuries, and physiological indicators in Paralympic athletes are still limited, and combining sleep data, HRV, physical load, and injury occurrence in a single model hasn't been studied enough in this group.

This study becomes even more important for Paralympic weightlifters due to the nature of their frequent and high-intensity training, which may come with daily changes in recovery and physical readiness. This highlights the need to make use of the data provided by wearable devices and link it to injury and recovery indicators, while using analytical models capable of handling the complex relationships between these variables. The Random Forest model is considered one of the suitable methods that can be tested in this study, as research has shown that ensemble tree models can be used to predict injury risk and deal with multiple influencing factors simultaneously, though it's important to verify their performance and interpret their results before using them in sports decision-making (Van Eetvelde et al., 2021; Rommers et al., 2020).

Materials and Methods

Study Design

A follow-up study was conducted to find out the effect of sleep quality on sports injuries among 23 para powerlifting athletes. Data was collected for 55 days before the start of the competitive season, while they continued their usual training program without any changes to the nature of the training or the number of training sessions.

During this period, the athletes wore wristbands throughout the study without needing to remove them, which helped gather continuous daily data on sleep and some physiological indicators, as well as track changes in the players' condition during the study period under their regular training conditions.

Participants

The study sample consisted of 38 male athletes from the Jordanian Paralympic weightlifting team. Participants were selected according to the study criteria. All the athletes who took part completed the full 55-day monitoring period and provided complete records of their sleep and physiological indicators. Athletes with incomplete follow-up data were excluded.

The players' ages ranged from 24 to 44 years and they represented two disability categories, including spinal cord injuries and polio-related disabilities. It was also noted that seventeen players had previous injuries, while six players had no history of prior injuries. The participants' demographic, anthropometric, and clinical characteristics are presented in the table.

Table 1. Demographic, anthropometric, and clinical characteristics of the participants

Ethical Approval

Participant	Sex	Age (years)	Disability classification	Training experience	Body mass (kg)	Height (cm)	BMI (kg/m²)	Previous injury	Number of previous injuries
P1	Male	36	Spina bifida	>10 years	91	143	44.5	Yes	1
P2	Male	38	Poliomyelitis	>10 years	70	142	34.7	Yes	5
P3	Male	44	Poliomyelitis	>10 years	133	181	40.6	Yes	2
P4	Male	41	Poliomyelitis	>10 years	48	128	29.3	Yes	3
P5	Male	24	Spina bifida	<10 years	52	145	24.7	No	0
P6	Male	27	Poliomyelitis	<10 years	65	150	28.9	Yes	1
P7	Male	29	Spina bifida	>10 years	72	160	28.1	No	0
P8	Male	35	Poliomyelitis	>10 years	80	170	27.7	Yes	2
P9	Male	32	Spina bifida	>10 years	68	155	28.3	Yes	1
P10	Male	40	Poliomyelitis	>10 years	90	175	29.4	Yes	3
P11	Male	26	Spina bifida	<10 years	60	150	26.7	No	0
P12	Male	28	Poliomyelitis	>10 years	75	165	27.5	Yes	2
P13	Male	34	Spina bifida	>10 years	85	172	28.7	Yes	1
P14	Male	31	Poliomyelitis	>10 years	95	180	29.3	Yes	4
P15	Male	25	Spina bifida	<10 years	58	148	26.5	No	0
P16	Male	37	Poliomyelitis	>10 years	100	178	31.6	Yes	2
P17	Male	30	Spina bifida	>10 years	70	160	27.3	Yes	1
P18	Male	33	Poliomyelitis	>10 years	88	174	29.1	Yes	3
P19	Male	39	Spina bifida	>10 years	92	176	29.7	Yes	2
P20	Male	28	Poliomyelitis	<10 years	66	152	28.6	No	0
P21	Male	35	Spina bifida	>10 years	78	168	27.6	Yes	1
P22	Male	42	Poliomyelitis	>10 years	110	182	33.2	Yes	4
P23	Male	29	Spina bifida	<10 years	64	155	26.6	No	0

The final sample consisted of 23 elite male Paralympic powerlifters (mean age = 33.5 ± 5.8 years) Athletes represented two disability classifications (spina bifida, n = 11; poliomyelitis-related impairment, n = 12) Seventeen athletes reported a previous history of musculoskeletal injury (mean number of injuries = 2.1 ± 1.3), while six athletes had no prior injury history, Anthropometric data indicated a mean body mass of 78.4 ± 18.2 kg, height of 162.7 ± 15.4 cm, and BMI of 29.1 ± 4.7 kg/m². Training experience ranged from less than 10 years (n = 7) to more than 10 years (n = 16).

Training Program

The players were monitored for eight weeks, with 23 players being tracked during their training program at the Jordanian Paralympic Committee. Their program included four training sessions per week, each lasting 60 minutes, with the main goal being to increase maximal strength. Training intensity stayed at 90–95% of each athlete's maximum (1RM), and each session consisted of two to three sets of two to three reps according to the daily plan. Training loads were closely followed. All sessions were supervised by certified national coaches to ensure everyone had a consistent experience and to reduce training differences. The training program wasn't changed for research purposes; it reflected the athletes' regular season schedule, making it more realistic.

Sleep and Physiological Monitoring

Sleep patterns and physical recovery indicators were monitored throughout the eight-week study using the WHOOP 5.0 wearable system (WHOOP Inc., Boston, Massachusetts, USA). This device was chosen due to its proven reliability in continuously tracking sleep and automatic recovery. All players wore the device during the 55-day monitoring period, and data were collected daily. The focus was also on individual changes over time, allowing the analysis to capture differences in sleep habits and their recovery responses and their potential link to injury occurrence. Key variables assessed included:

• Sleep duration (hours)

• Sleep efficiency (%)

• Heart rate variability (HRV, ms)

• Recovery score (%)

Heart rate variability (HRV) readings were taken daily throughout the study using a proven algorithm developed by the monitoring system. This also provided an indicator of autonomic nervous system function. To maintain methodological consistency, data completeness and device usage were verified daily. The dataset was maintained in longitudinal form, allowing for the analysis of repeated daily observations. This facilitated tracking changes in sleep and recovery patterns over time in selected players and monitoring individual variations throughout the observation period.

Injury Monitoring

Injury monitoring combined with daily assessments of sleep and physical recovery served as the primary outcome measure of the study. Musculoskeletal injuries were tracked repeatedly across the observation period and analyzed in relation to recovery indicators By linking injury recurrence with changes in sleep efficiency, HRV and recovery scores the analysis provided a direct view of how fluctuations in sleep and autonomic function may contribute to injury risk over time.

Standardized Procedures

During the monitoring phase consistency was emphasized across all procedures The 23 participants adhered to the same data collection protocols wearing the WHOOP 5.0 device continuously and maintaining their usual sleep routines whenever possible Training programs were not modified ensuring that athletes followed their regular schedules Participants aimed to keep the device on at all times with data synced daily to secure complete recordings Each training session was supervised by national coaching staff providing uniform training conditions and minimizing external differences among athletes Device adherence and compliance with the training plan were carefully documented throughout the study to preserve methodological integrity.

Data Management

All statistical analyses were performed using mixed effects models to account for repeated daily measures from individual participants. Sleep duration, sleep efficiency, HRV and recovery scores were treated as time-varying predictors while recurrent musculoskeletal injury served as the primary outcome variable. Model stability was evaluated through bootstrapping procedures, and variable selection was guided by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). To assess the predictive performance of the Random Forest classifier cross validation was applied with accuracy area under the curve (AUC) and root mean square error (RMSE) reported as evaluation metrics. Missing data were addressed using multiple imputation ensuring that the longitudinal structure of the dataset was preserved throughout the analysis.

Statistical Analysis

All statistical analyses were carried out using IBM SPSS Statistics (version 29.0, IBM Corp, Armonk, NY, USA) together with Python (version 3.11, Python Software Foundation). Descriptive statistics were produced for all study variables including means, standard deviations, and observed ranges. The dataset was structured longitudinally with daily repeated measures nested within participants. Linear mixed-effects models were employed incorporating random intercepts for each athlete to account for variability in daily observations this modeling approach enabled exploration of the relationships between sleep duration, sleep efficiency, HRV, recovery scores and recurrent musculoskeletal injuries while also considering individual differences across the 55-day monitoring period.

A Random Forest classifier was developed to examine injury risk prediction Sleep duration, sleep efficiency, HRV and recovery scores were included as predictor variables and the model generated daily risk estimates. Probabilities of 80% or higher were flagged as high risk outcomes. Model performance was evaluated through cross validation with predictive accuracy assessed using the area under the curve (AUC) root mean square error (RMSE) and overall classification accuracy. Variable importance was analyzed to determine the relative contribution of each predictor in estimating injury risk, in addition linear regression analyses were conducted to explore the individual effects of each variable complementing the machine learning results. Statistical significance was set at $p < 0.05$.

Results

Descriptive Statistics

Descriptive stats for the key study variables, like sleep duration, sleep efficiency, heart rate variability (HRV), repeated musculoskeletal injuries, and certain anthropometric traits, are shown in Table 2.

Table 2. Descriptive stats of the study variables for paralympic powerlifters (N = 23).

Variable	Mean ± SD	Minimum	Maximum
Sleep Duration (hours)	6.42 ± 1.87	1.5	11.96
Sleep Efficiency (%)	74.2 ± 18.3	9	97
HRV (ms)	78.6 ± 28.4	27	133
Injury Recurrence (count)	2.2 ± 1.9	0	5
Body Mass (kg)	78.8 ± 31.2	48	133
Height (cm)	148 ± 22.0	128	181

The descriptive analysis showed a lot of variation between individuals in sleep and recovery measures. Average sleep duration was 6.42 ± 1.87 hours, but it varied from very short sleep (1.5 h) to long sleep (11.96 h). Sleep efficiency also varied widely, averaging 74.2 ±

18.3%. HRV values were pretty spread out (78.6 ± 28.4 ms), pointing to differences in autonomic recovery status among athletes. Injury recurrence was from 0 to 5 incidents, with a mean of 2.2 ± 1.9 injuries per athlete. This suggests that recurring musculoskeletal injuries were common in this group. Anthropometric measures showed variability, with body mass ranging from 1648-1660 kg and height between 128 and 181 cm, which matches the diversity of disability classifications and physical profiles present among Paralympic powerlifters.

Figure 1. Spread of sleep length, sleep quality, variability in heart rate (HRV), and recurring musculoskeletal injuries in Paralympic powerlifters.

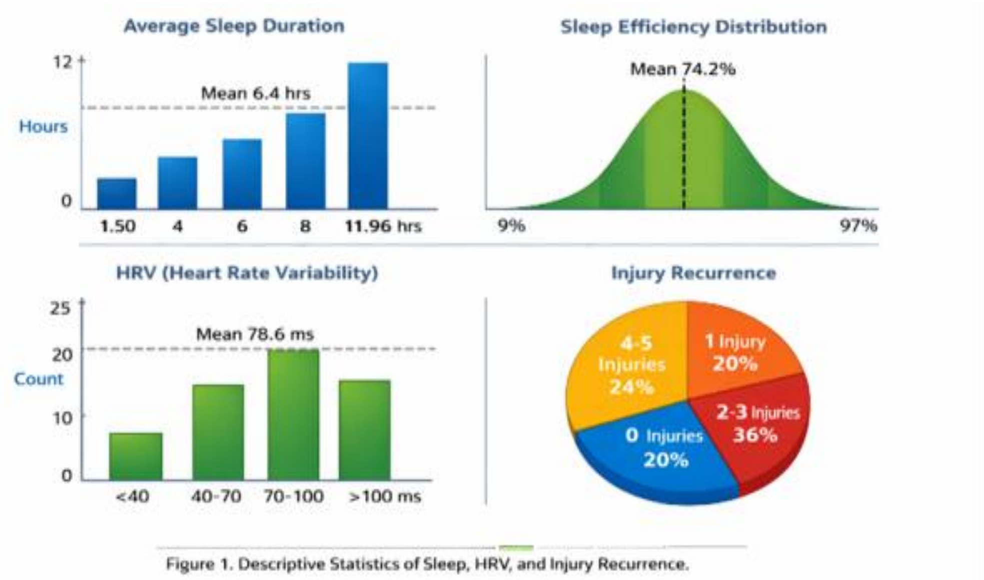

Figure 1 displays the distribution of key study variables across 23 athletes. The charts highlight significant variations in sleep patterns, recovery states, and injury recurrence among individuals-these insights complement the descriptive stats in Table 2. This graphic underscores the diversity in the sample, offering a clearer perspective on the variability in the longitudinal dataset.

Inferential Statistics

Linear mixed-effects models revealed significant connections between recovery signs and repeated injuries. Poor sleep efficiency and lower HRV often pointed to a greater risk of injury in repeated assessments. Sleep duration had a lesser, but still relevant, link to repeated injuries. The Random Forest classifier achieved an overall predictive accuracy of 82%. It had an AUC of 0.79 and an RMSE of 0.21. The variable importance analysis showed that HRV and sleep efficiency were the key predictors of injury risk. Recovery score and sleep duration followed closely behind. Predicted probabilities of 80% or higher indicated high-risk events-these mostly aligned with actual injury occurrences. Multiple linear regression analyses supported the separate contributions of HRV and sleep efficiency in injury recurrence, which matched what the machine learning model suggested. Statistical significance was defined as $p < 0.05$, and every observed association met this criterion.

Inferential Statistical Analysis

Initial correlation analyses used Spearman's rank correlation coefficient in IBM SPSS Statistics (version 29.0, IBM Corp., Armonk, NY, USA) to examine the relationships between sleep-related factors, HRV, and recurring musculoskeletal injuries. Check out Table 3 for the correlation coefficients.

Table 3. Spearman's rank correlation coefficients among sleep parameters, HRV, and recurrent musculoskeletal injuries in paralympic powerlifters (N = 23).

Variable	Sleep Duration	Sleep Efficiency	HRV	Injury Recurrence
Sleep Duration (hours)	1	0.52*	0.47*	−0.62*
Sleep Efficiency (%)	0.52*	1	0.68*	−0.71**
HRV (ms)	0.47*	0.68*	1	−0.39
Injury Recurrence (count)	−0.62*	−0.71**	−0.39	1

*p < 0.05; **p < 0.01.

The first look at the data showed that more sleep and better sleep efficiency went hand in hand with fewer injuries coming back. Sleep efficiency had the strongest connection to not getting hurt again ($\varrho = -0.71$, $p < 0.01$). But this was just the start; since the data spanned over time, mixed effects models and predictive machine learning methods were used to dig deeper. They confirmed that both sleep efficiency and HRV had their own impact on injury risk.

Mixed-Effects Model Results

Given the dataset's setup-daily measures over 55 days-the primary analyses used linear mixed-effects models in Python (version 3.11, from the Python Software Foundation). These models considered the variability among individuals and revealed that lower sleep efficiency and reduced HRV were significantly tied to a higher rate of injuries ($p < 0.05$). Sleep duration also had a weaker but still meaningful link to the risk of injury.

Predictive Modeling

I ran a random forest classifier in Python to check how well it predicts. The model achieved an overall accuracy of 82%, with an AUC of 0.79 and an RMSE of 0.21. It went through internal validation using cross-validation, but testing on independent datasets is still needed to confirm its generalizability. The variable importance analysis highlighted sleep efficiency and HRV as the top predictors of injury risk; recovery score and sleep duration came next. We marked predicted probabilities of 80% or higher as high-risk events, mostly aligning with actual injury occurrences.

Inferential Statistical Analysis

Correlation Heatmap

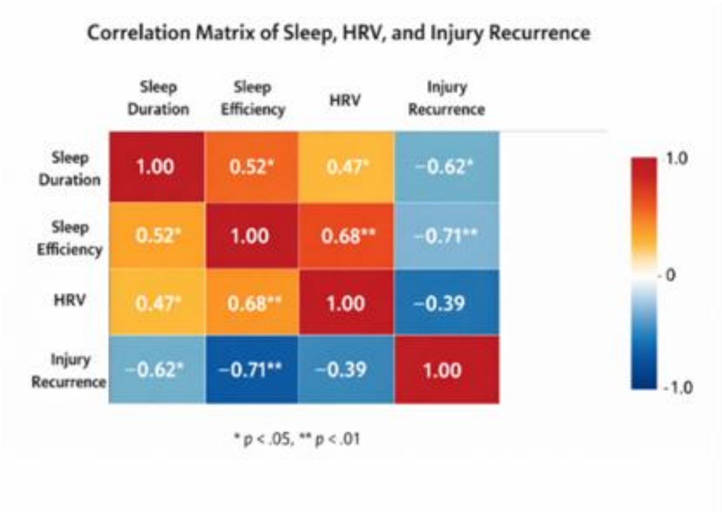

Figure 2. Correlation heatmap showing the connections between sleep duration, sleep efficiency, variability in heart rate (HRV), and recurring musculoskeletal injuries in paralympic powerlifters

The heatmap reveals the relationships among the primary study variables. There was a significant negative correlation between sleep efficiency and injury recurrence. Conversely, sleep efficiency and HRV showed a positive relationship-suggesting that sleep quality is connected to better autonomic recovery. These early results support the Spearman correlation findings displayed in Table 3.

Random Forest Injury Risk Prediction

Researchers examined injury risk trends over time using a Random Forest machine learning model in Python (version 3.11, Python Software Foundation). They included sleep duration, sleep efficiency, HRV, and recovery score as predictor variables. The model generated personalized daily injury risk predictions for the entire 55-day monitoring period.

Figure 3. Daily predicted injury risk scores generated by the random forest model during the 55-day monitoring period.

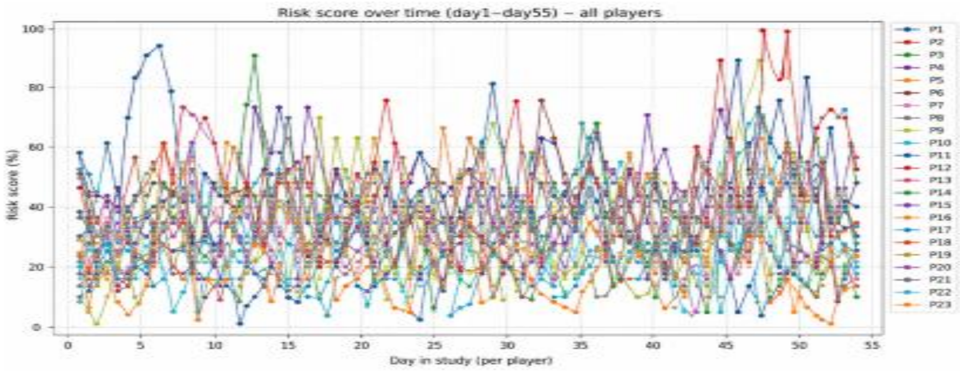

Figure 3. Daily predicted injury risk scores tracked for 23 elite Paralympic powerlifters over 55 days. Each colored line represents one athlete's daily injury risk percentage, calculated using the random forest model. There were notable day-to-day shifts and differences between athletes in their risk patterns. A few athletes went over the high-risk threshold (≥80%) several times; others stayed at lower risk consistently. These trends highlight the personal nature of recovery and injury vulnerability in Paralympic powerlifting. The risk changes matched with periods of poor sleep efficiency and HRV, supporting the mixed model insights.

Supplementary Regression Analysis

I conducted another exploratory analysis-a multiple linear regression analysis in IBM SPSS Statistics (version 29.0, IBM Corp., Armonk, NY, USA). The goal? To examine how sleep duration, sleep efficiency, and HRV each influence recurrent musculoskeletal injuries, as outlined in Table 4.

Table 4. Multiple linear regression analysis of sleep parameters and HRV predicting recurrent musculoskeletal injuries (N = 23).

Predictor Variable	β (Standardized)	SE	t-value	p-value
Sleep Duration (hours)	−0.41	0.12	−3.42	0.018*
Sleep Efficiency (%)	−0.58	0.15	−4.87	0.006**
HRV (ms)	−0.19	0.11	−1.72	0.142
Model R^2	0.62			

*$p < 0.05$; **$p < 0.01$.

Regression results showed that sleep efficiency was the strongest independent predictor of injury recurrence ($\beta = -0.58$, $p < 0.01$). Sleep duration came next ($\beta = -0.41$, $p < 0.05$). HRV had a negative correlation, but it didn't hold up statistically ($\beta = -0.19$, $p = 0.142$). The overall model accounted for 62% of the variance ($R^2 = 0.62$) in recurrent musculoskeletal injuries. This underscores how sleep quality and duration affect injury risk among Paralympic powerlifters.

Discussion

This study aimed to explore the relationship between athletes' sleep duration and efficiency and their variability in heart rate (HRV) and injuries in elite Paralympic powerlifters. By using traditional statistics and machine learning, findings indicated a connection between sleep traits-particularly efficiency-and injury recurrence over a 55-day period. Athletes who enjoyed better sleep efficiency and longer sleep durations experienced fewer injuries. Sleep quality is vital for recovery and injury prevention.

The random forest model provided deeper insights, tracking daily variations in injury risk. Injury risk is not static; it depends significantly on the quality of recovery. This highlights the necessity for regular monitoring through wearables to identify early signs of inadequate recovery and modify interventions accordingly. What stands out in this study? The connection between sleep efficiency and injury recurrence is more robust than sleep duration alone. Yes, enough sleep is essential, but quality and consistency seem to play a more critical role in healing, tissue repair, and neuromuscular recovery. Athletes may spend countless hours in bed, but if their sleep patterns fluctuate, they lose out on the restorative benefits that aid in managing training stress. These findings resonate with previous research emphasizing the importance of sleep quality for athlete health and injury prevention. (Silva et al., 2022; Madaleno et al., 2026; Fullagar et al., 2019).

Sleep quality is critical for Paralympic powerlifters. They often struggle with chronic pain, irregular muscle function, and spasticity. Finding comfortable sleep positions Definitely a challenge. These factors disrupt both sleep and recovery. The variability in athletes' sleep patterns-along with their physiological responses and injury histories-reveals the complexity of recovery in Paralympic sports. This underscores the need for personalized monitoring that transcends basic recovery suggestions.

HRV demonstrated a positive correlation with sleep efficiency. Better sleep quality appears linked to enhanced autonomic recovery. However, in regression analyses, HRV did not emerge as a strong independent predictor of injury recurrence. This indicates that while HRV provides valuable insights alongside sleep-related measures, it should not be viewed in isolation. Given that HRV is influenced by many factors-such as training load, mental stress, and environmental conditions-it should be interpreted within a broader monitoring framework (Chennaoui et al., 2021; Stanley et al., 2013; Hauser et al., 2021).

Wearable technology-like WHOOP devices-offers effective ways to track athletes. Continuous data collection during training reduces the need for sporadic checks. This paves the way for predictive analytics, identifying athletes at heightened risk. Coaches and medical teams can harness these data to customize recovery strategies, modify training intensity, and address sleep issues. Such an approach enhances both athlete safety and performance.

Limitations and Future Directions

Despite these optimistic results, there are limitations to consider. First, the sample size is small-representing just a handful of elite Paralympic powerlifters from a national team. So, it's prudent to approach these results cautiously-they're more like preliminary findings than sweeping conclusions. Also, since all participants belonged to the same national team, variables like disability classification, training background, and environmental factors could affect the applicability of these findings to larger populations. While the 55-day monitoring period allowed for continuous data collection, extending follow-up over multiple seasons could shed light on the long-term connections between sleep and injury recurrence.

They implemented bootstrapping and mixed effects modeling for enhanced parameter stability. Yet, that small sample size might still limit the strength of those estimates. Sure, cross-validation was done to assess the random forest model's predictive capability. Still, validating with independent datasets would be beneficial to truly gauge the model's generalizability. Moreover, despite their analysis of daily repeated measures with longitudinal mixed effects models, the intricate dynamics of recovery and injury risk call for further exploration-perhaps with more advanced longitudinal methods.

Future research should focus on larger, more diverse samples-encompassing different disability types, female athletes, and participants from various countries. Validating those machine learning prediction models with separate datasets would also be wise. Moreover, incorporating elements such as training load, psychological stress, pain levels, and nutrition would likely enhance the precision and relevance of tailored injury risk predictions.

Conclusion

This study highlights that sleep efficiency is vital for recurrent musculoskeletal injuries in elite Paralympic powerlifters. More sleep hours correlated with fewer injuries, but sleep quality emerged as the key player in recovery. HRV provided some insights into recovery but did not strongly predict sleep factors. Wearable technology and machine learning help monitor and anticipate injury risk on a personal level. This suggests that recovery and injury risk can evolve over time. The findings emphasize the need for tailored recovery strategies tailored to each athlete's unique physiology and sleep patterns.

There are limitations-like sample size and scope. Yet, this study suggests that sleep efficiency plays a significant role in injury prevention within Paralympic sports. Future research must focus on larger, more diverse groups, validate predictive models with different datasets, and integrate additional recovery-related factors to better understand injury risk.

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AI Use Disclosure

In accordance with the latest publishing ethics and transparency standards, AI tools were utilized solely for translation and language editing to enhance the manuscript's clarity and readability. There was no AI involvement in the development of scientific content-this included study design, data collection, analysis, interpretation of results, or conclusions. The author retains full responsibility for the content of the manuscript, ensuring its originality, integrity, and accuracy.

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Formal analysis: The author

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Writing–Original Draft: The author

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