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SMART RECOVERY: A 36-MONTH CASE STUDY OF WHOOP WEARABLE INTEGRATION IN ELITE SWIMMING

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Abstract. *Wearable technology provides real-time access to crucial physiological parameters without interfering with athletic performance or mobility. This study examines the use of WHOOP fitness band data as a support system for a competitive swimmer and their coach over a 36-month period. By monitoring heart rate variability, strain, and sleep quality, the aim is to demonstrate how wearable technology aids informed decision-making for personalized training and recovery strategies. Key findings indicate that continuous monitoring enabled more precise training load management, with recovery scores averaging 61.6% (±20.3) and showing significant correlation with sleep quality (rs = 0.34, p < 0.001). Sleep disruptions often preceded or accompanied decreases in heart rate variability and recovery scores, offering early warning signs to adjust training. Additionally, maximum heart rate and energy expenditure emerged as primary predictors of day strain measurements. Performance data collected during the WHOOP monitoring period showed consistent improvement patterns across multiple events and course types. Between 2022 and 2025, the swimmer recorded time reductions ranging from 2.5% in the 200m freestyle (short course) to 11.8% in the 400m freestyle (long course), with similarly positive trends across short- and long-course formats. These results align with the implementation of recovery-guided training adjustments and sleep optimization strategies informed by WHOOP data. The findings suggest that integrating wearable technology into coaching frameworks provides substantial benefits for competitive swimmers through individualized training prescription, better recovery management, and measurable performance enhancement. The WHOOP proved to have practical utility in optimizing athletic performance in real-world swimming contexts.*

Keywords*: wearable technology, athlete monitoring, training load, recovery, swimming.*

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Introduction

In recent years, wearable technology has emerged as a transformative force in athlete monitoring, providing coaches and athletes with continuous, non-invasive, and real-time physiological data (Lucas, 2024). Devices such as the WHOOP fitness band are no longer just fitness trackers - they serve as decision-support systems that inform training, recovery, and performance strategies in elite sport (Seçkin et al., 2023). Zhou et al. (2023) present advancements in wearable-based health monitoring using AI-driven models, demonstrating how smart analysis of physiological data may support more informed performance management.

In disciplines like swimming, where minor performance fluctuations can separate podium finishes from missed qualifications, precision monitoring becomes particularly relevant (Migliaccio et al., 2024). The application of marginal gains theory – wherein small, incremental improvements across various physiological parameters may translate into meaningful competitive advantages – has underscored the growing interest in wearables. Additionally, the waterproof design and sensor accuracy of devices like WHOOP 4.0 (rated water-resistant to 10 metres) make them well-suited to aquatic sports (Guppy et al., 2023). WHOOP employs photoplethysmography (PPG) sensors and proprietary algorithms to measure heart rate, heart rate variability (HRV), strain, and sleep parameters continuously. Unlike conventional monitoring tools, it enables daily tracking without interrupting training flow, integrating seamlessly into the athlete's lifestyle (Seçkin et al., 2023). Its capacity to quantify readiness and recovery has generated interest in its use beyond recreational athletes, particularly in elite coaching environments where individualised data can guide micro-adjustments in training intensity, recovery scheduling, and competition tapering. Guppy et al. (2023) describe how such innovations are reshaping elite training environments through real-time feedback loops between athletes and coaches.

McDevitt et al. (2022) discuss the practical benefits of wearable integration in both industrial and sports settings, supporting the view that wearables contribute not just to data collection but also to meaningful intervention in performance management**.** Edriss et al. (2024) reinforce this notion, exploring the role of emerging technologies in the dynamic and kinematic assessment of movement. Zhou (2024) highlights the potential of integrating HRV and body index data into training load adjustment algorithms, supporting a shift from reactive to proactive coaching strategies. Similarly, Hasan et al. (2024) provide a bibliometric analysis reflecting the growing scholarly focus on monitoring training loads via technological tools, while Subramaniam et al. (2023) survey evolving performance analysis technologies evidencing the widespread adoption of wearables and AI-based systems. While this study does not aim to validate the technical accuracy of WHOOP, existing validation research provides important context. Miller et al. (2021) validated the sleep detection capabilities of a commercial wearable device, while Schyvens et al. (2024) confirmed that WHOOP provides reliable, albeit slightly varied, sleep stage estimations compared to polysomnography. Bellenger et al. (2022) evaluated the day-to-day variability of WHOOP-derived HRV data among Olympic water polo athletes, reinforcing its reliability for HRV monitoring. Qian and Kim (2025) further suggest that wearable technology may foster greater athlete engagement and autonomy, while de Zambotti et al. (2024) highlight its potential value in sleep and circadian rhythm research beyond direct performance contexts.

While numerous studies validate the technical performance of wearable devices, fewer have emphasised their practical application as decision-support tools in long-term athlete development. Drawing on frameworks established by Zhou (2024) and Hasan et al. (2024), this case study investigates how continuous monitoring through the WHOOP system may help coaches adjust training intensity, manage recovery periods, and support performance across an extended period in a competitive swimming context.

Methodology

Research Aim and Objectives

The primary aim of this study was to examine how continuous physiological monitoring through the WHOOP wearable system can inform individualized training and recovery strategies for a competitive swimmer over a 36-month period.

The specific objectives were:

- To demonstrate how WHOOP-derived physiological data (heart rate variability, resting heart rate, strain, and sleep metrics) support informed coaching decisions.
- To evaluate how continuous monitoring contributes to optimizing workload management, recovery scheduling, and performance improvement across multiple training seasons.
- To identify correlations between physiological indicators and competition performance trends, highlighting the adaptive response of the athlete throughout different phases of training.

Based on prior research and the objectives of this study, the following hypotheses were formulated:

H1: Recovery scores are positively associated with sleep performance and heart rate variability and negatively associated with resting heart rate.

H2: Day Strain is positively associated with training-related metrics such as MaxHR and Energy Burned.

H3: Sleep quality indicators (e.g., Sleep Performance, Sleep Efficiency) show moderate positive correlations with Recovery scores but weaker associations with Day Strain.

H4: A neural network model using physiological (MaxHR), behavioral (Recovery, Energy Burned), and sleep-related variables (Sleep Efficiency, Sleep Consistency, Sleep Performance) will accurately predict Day Strain.

Participant

The study followed a single national-level junior swimmer, male, aged approximately 15 to 17 years over the course of the 36-month data collection period (17 years old at the completion). At study onset, the athlete had over 8 years of competitive experience and a well-defined specialization in freestyle and individual medley events, competing in both short- and long-course formats.

Key background details:

Training experience: continuous structured training from age 9, including club and national team levels.

Training load: approximately 8–9 swimming sessions per week plus 2 dryland conditioning sessions.

Competition history: regular participation in national championships and multiple international events across the 36-month period.

Performance evolution: time reductions between 2.5% (200m freestyle) and 11.8% (400m freestyle), aligned with the progressive integration of recovery-guided training strategies.

These characteristics support the case study's focus on the longitudinal adaptation of a trained, performance-oriented athlete.

Instruments

The WHOOP 4.0 fitness band was employed for continuous monitoring of physiological and recovery parameters. The following metrics were automatically recorded and synchronized with the WHOOP cloud platform:

- Recovery Score (% based on HRV, resting heart rate, and sleep quality)
- Strain Score (a cumulative measure of cardiovascular load)
- Heart Rate Variability (HRV)
- Resting Heart Rate (RestHR)
- Sleep Stages and Duration (including REM sleep, SWS, and total sleep time)
- Energy Burn (caloric expenditure)

These metrics are calculated by WHOOP's proprietary algorithms that process physiological data to generate three primary indices: Recovery, Strain, and Sleep scores (WHOOP, n.d.). The Recovery score (0-100%) integrates resting heart rate, heart rate variability, respiratory rate, and sleep performance to quantify the body's readiness for exertion. The Strain score (0-21) quantifies cardiovascular load accumulated through daily activities and workouts, including swimming sessions. The Sleep score evaluates sleep quality and efficiency based on time in various sleep stages, disturbances, and respiratory rate (WHOOP, n.d.).

Data were collected automatically and synced with the WHOOP platform without manual intervention, ensuring minimal disruption to the athlete's training or lifestyle.

All measurements were performed non-invasively and continuously, with data automatically uploaded via Bluetooth connection to the WHOOP application.

Work Protocol

Over the 36-month monitoring period, the 17-year-old national-level swimmer followed a periodized training program with approximately 8–9 swim sessions per week. During general preparation phases, training emphasized aerobic conditioning and technical skill acquisition – focusing on building an endurance base and refining stroke efficiency. As the season progressed into competition phases (especially during taper periods), the program shifted to prioritize high-intensity efforts, with greater emphasis on speed work and race-pace sets while overall volume was strategically reduced to promote peak performance. Training was closely aligned with WHOOP-derived recovery and strain metrics to adjust daily loads; in practice, the athlete’s daily WHOOP recovery score (a composite index of autonomic nervous system readiness derived from measures like heart rate variability, resting heart rate, and sleep quality) guided the day-to-day training intensity and volume. This data-driven approach to autoregulation ensured that on days when the athlete was well-recovered, they could safely handle higher training strain, whereas on days of low recovery or elevated fatigue the coaching staff scaled back the workload - with the aim of supporting adaptation and minimizing the risk of overtraining or injury.

The swimmer's performance data demonstrates a pattern of consistent improvement across multiple events and course types during the WHOOP monitoring period. From 2022 to 2025, all recorded events showed positive progression, ranging from 2.5% improvement in 200m freestyle to a remarkable 11.8% reduction in 400m freestyle times. This pattern of enhancement coincides with the implementation of recovery-guided training adjustments and sleep optimization strategies informed by WHOOP metrics.

Table 1. *Calculated improvement percentages for each event category*

Event	Competition course	Improvement percentages	Time improvements (seconds)	Time period for the improvements
200 freestyle	Short course	2.5 %	2.85	12 months
	Long course	0.83%	0.95	12 months
400 freestyle	Short course	3.67%	9.01	12 months
	Long course	11.8%	30.33	36 months
200 backstroke	Short course	3.37%	4.25	23 months
	Long course	2.85%	3.76	25 months
200 individual medley	Short course	1.96%	2.51	11 months
	Long course	5.88%	8.09	14 months

Data were exported directly from the WHOOP platform as daily entries, with each observation representing one calendar day, resulting in a longitudinal daily-level dataset spanning 36 months. Of the 994 total observations, 223 were subsequently excluded from the neural network analysis due to incomplete records attributable to device malfunction, non-wear days, or other causes unrelated to the athlete's physiological status. All remaining observations were used as exported, with no additional transformations applied prior to analysis.

A combination of descriptive statistics, correlation analysis, and trend analysis was performed on the collected data:

- Descriptive statistics (mean, standard deviation, ranges) characterized the overall physiological and sleep behavior of the athlete.
- Spearman correlation coefficients were calculated to explore the relationships between recovery status, strain, sleep metrics, and performance-relevant indicators. Given that all variables significantly deviated from normality (Shapiro-Wilk $p < .001$ for all variables), Spearman's rank correlation was selected as the appropriate non-parametric measure of monotonic association. No correction for multiple comparisons was applied to the correlation matrix; results should therefore be interpreted with appropriate caution given the large number of pairwise tests conducted.
- Time series analysis examined how physiological trends evolved over the 36 months, identifying patterns aligned with periods of increased training loads, competition phases, and tapering.

All analyses were focused on understanding how real-time monitoring influenced coaching decisions, such as:

- Adjustments in training intensity based on recovery scores and HRV fluctuations.
- Scheduling of active recovery sessions when signs of accumulated fatigue were detected.
- Modifications in sleep hygiene practices to optimize recovery based on sleep performance trends.

The athlete and their legal guardians provided informed consent for the use of anonymized data in scientific research. Data handling procedures respected confidentiality, and participation was voluntary, with the option to withdraw at any time.

Monitoring training load and recovery has become a central theme in contemporary sports science, especially in the context of endurance sports where balancing stress and adaptation is essential for optimal performance and injury prevention (Halson, 2014; Meeusen et al., 2013; Chowdhary et al., 2024). The increasing availability of wearable technology enables practitioners to collect detailed physiological, performance, and recovery data on a daily basis, offering a unique opportunity to apply machine learning techniques to predict performance-related outcomes.

Statistical Analysis

The selection of a two-layer Multilayer Perceptron (MLP) with a single neuron per hidden layer represents a deliberately constrained design. Although this configuration is highly unconventional and lacks the complexity of standard deep learning architectures, it was chosen for three primary reasons: (1) dataset size limitations, as the final sample (n = 771) is relatively small for high-dimensional modeling; (2) risk mitigation for overfitting, since larger architectures could easily memorize patterns in such a limited dataset rather than generalizing; and (3) an emphasis on explanatory modeling rather than purely predictive optimization. By restricting the model's capacity, we forced it to identify and amplify only the most robust and systematic relationships among variables, thereby enhancing interpretability. This approach aligns with the study’s objective of highlighting dominant predictors of Day Strain - particularly physiological versus sleep-related factors - rather than achieving marginal gains in predictive accuracy through increased model complexity.

Ethical Considerations

Participation was voluntary and conducted with the informed consent of the athlete and her legal guardians. Data were anonymized prior to analysis, and the study complied with institutional and ethical standards regarding privacy and research involving minors.

Results

Over the 36-month monitoring period, a large volume of physiological and sleep-related data was collected using the WHOOP fitness band. Key findings from descriptive statistics include:

- Average Recovery Score: 61.6% (± 20.3), with notable fluctuations corresponding to periods of increased training intensity and competition.
- Mean Heart Rate Variability (HRV): 104 ms (± 21.7), showing variations aligned with training load adjustments and recovery phases.
- Average Day Strain Score: 16.0 (± 4.56), indicating moderate-to-high cardiovascular workload during peak training periods.
- Average Sleep Duration: 6.7 hours per night, with significant variations during competition phases.

The training and strain data correctly show high variability, with Day Strain displaying μ=16, δ=4.56 and a skewed distribution based on the W=0.812 value. Moving to heart rate metrics, the data provide clear patterns, particularly revealing the strongly non-normal distribution of RestHR (W=0.677) likely due to outliers, while HRV (W=0.978) is closest to normal distribution. The sleep parameter analysis is comprehensive, correctly showing that REM sleep is closest to normal distribution, consistent with Table 2 showing REM with the highest W value (0.996). The observation about extreme non-normality in Efficiency, Awake, Debt, and Need variables suggests these metrics have highly skewed or irregular distributions. Lastly, the HR zone data provide valuable context, showing that the middle zones (2, 3, and 4) have distributions closer to normal (W ~0.95) compared to the extreme zones (1 and 5).

Table 2. *Descriptive statistics and normality assessment of whoop-derived variables (n = 994)*

Variable	Mean	SD	Min	Max	Shapiro-Wilk W	p-value
Recovery Metrics						
Recovery (%)	61.6	20.3	1	98	0.974	< .001
RestHR (bpm)	55.8	6.38	46	120	0.677	< .001
HRV (ms)	104	21.7	21	160	0.978	< .001
Skin Temperature (°C)	34.3	0.413	31.9	36.8	0.970	< .001
Blood Oxygen (%)	96.0	1.30	91.0	99.3	0.993	< .001
Respiratory Rate (brpm)	15.6	0.696	13.5	18.5	0.989	< .001
Activity Metrics						
Day Strain	16.0	4.56	0	20.6	0.812	< .001
Energy Burn (kcal)	3272	999	138	6564	0.970	< .001
MaxHR (bpm)	173	18.6	91	207	0.887	< .001
AvgHR (bpm)	80.0	6.73	52	115	0.974	< .001
Strain	15.0	2.61	4.2	20.0	0.791	< .001
Heart Rate Zone Distributions						
HRZone1 (%)	13.0	11.0	0	74	0.772	< .001
HRZone2 (%)	27.5	9.29	0	77	0.954	< .001
HRZone3 (%)	35.6	11.4	0	65	0.950	< .001
HRZone4 (%)	18.8	11.8	0	66	0.952	< .001
HRZone5 (%)	0.735	1.71	0	18	0.464	< .001
Sleep Metrics						
Sleep Performance (%)	68.3	12.9	7	100	0.963	< .001
Asleep (min)	418	72.8	0	709	0.916	< .001
In Bed (min)	468	81.1	60	737	0.927	< .001
Light Sleep (min)	224	54.6	0	696	0.955	< .001
SWS (min)	85.7	21.6	0	154	0.980	< .001
REM (min)	108	36.5	0	236	0.996	0.007
Awake (min)	50.6	18.7	0	323	0.842	< .001
Sleep Need (min)	617	67.5	70	772	0.788	< .001
Sleep Debt (min)	95.4	32.8	0	247	0.932	< .001
Sleep Efficiency (%)	89.2	4.09	7	100	0.630	< .001
Sleep Consistency (%)	66.0	14.5	8	97	0.976	< .001
Duration Workout (min)	126	39.4	14	287	0.949	< .001

Table 2 presents detailed descriptive statistics and normality results, providing a comprehensive view of the distributions of physiological, performance, and sleep-related variables across 994 observations. Shapiro-Wilk test results indicate that all variables significantly deviate from normal distribution ($p < .001$ for all variables except REM sleep, which has p = .007). SD = Standard Deviation; Min = Minimum; Max = Maximum; bpm = beats per minute; ms = milliseconds; brpm = breaths per minute; kcal = kilocalories; min = minutes.

Table 3 presents a correlation matrix showing pairwise Spearman correlations among a large set of physiological, sleep, heart rate, and performance-related variables for 994 observations. The Spearman coefficient (rs usually range between -1 to +1). Green = stronger negative/positive correlations. Yellow = median correlation and red = weak. It should be noted that these observations constitute a longitudinal repeated-measures dataset from a single individual, with each row representing one calendar day. As such, consecutive observations are likely not independent, and autocorrelation within the time series was not formally assessed. The correlation coefficients reported below should therefore be interpreted with caution, as the assumption of independence underlying standard Spearman correlation is not fully met in this context.

Table 3. *Spearman Correlation Coefficients (rs) Between Key WHOOP Variables (N=994)*

	Code	V 1	V 2	V 3	V 4	V 5	V 6	V 7	V 8	V 9	V 10	V 11	V 12	V 13	V 14	V 15	V 16	V 17	V 18	V 19	V 20
Recovery	V1	-																			
RestHR	V2	-0.43	-																		
HRvar	V3	0.66	-0.81	-																	
Day Strain	V4	0.01	-0.10	0.05	-																
Energy_burn	V5	0.02	-0.16	0.11	0.96	-															
MaxHR	V6	0.02	-0.11	0.08	0.79	0.74	-														
AvgHR (bpm)	V7	-0.13	0.15	-0.16	0.76	0.73	0.55	-													
Sleep_perf	V8	0.34	0.12	-0.06	-0.14	-0.17	-0.08	-0.20	-												
Light_sleep	V9	0.34	0.09	0.13	-0.06	-0.06	-0.01	-0.08	0.53	-											
REM	V10	0.13	0.05	-0.11	-0.04	-0.06	-0.02	-0.12	0.43	-0.17	-										
Efficiency	V11	0.13	-0.21	0.21	0.08	0.11	0.08	0.06	0.06	0.08	0.07	-									
Strain	V12	0.06	-0.02	0.03	0.51	0.44	0.47	0.28	0.06	0.01	0.11	0.00	-								
Energy_burn /activity	V13	0.05	-0.06	0.06	0.40	0.36	0.35	0.20	0.06	-0.01	0.11	0.04	0.93	-							
MaxHR/ activity	V14	0.03	-0.01	0.03	0.38	0.32	0.63	0.21	0.01	0.04	0.03	0.01	0.60	0.51	-						
AvgHR/ activity	V15	0.03	0.13	-0.10	0.36	0.25	0.34	0.24	0.03	0.06	0.04	-0.09	0.58	0.39	0.46	-					
HRZone1	V16	-0.04	-0.26	0.24	-0.28	-0.18	-0.19	-0.26	-0.10	-0.13	-0.10	0.16	-0.33	-0.16	-0.13	-0.66	-				
HRZone2	V17	-0.02	0.01	-0.01	-0.14	-0.07	-0.14	-0.07	-0.01	0.00	0.03	-0.01	-0.26	-0.11	-0.22	-0.49	0.23	-			
HRZone3	V18	0.00	0.07	-0.11	0.03	0.03	-0.08	0.09	-0.03	0.02	0.01	-0.03	0.04	0.00	-0.13	0.34	-0.57	-0.21	-		
HRZone4 %	V19	0.05	0.22	-0.17	0.26	0.12	0.20	0.14	0.11	0.10	0.09	-0.17	0.51	0.31	0.40	0.73	-0.62	-0.47	0.19	-	
HRZone5	V20	-0.04	0.24	-0.20	-0.08	-0.18	0.05	-0.10	0.14	0.07	0.11	-0.11	0.30	0.22	0.49	0.33	-0.17	-0.18	-0.16	0.45	-

Note: Color coding indicates correlation strength: green = strong correlations (|rs| > 0.7), yellow = moderate correlations (0.5 < |rs| < 0.7), red = weak correlations (|rs| < 0.5). Values represent Spearman's rank correlation coefficients. All highlighted correlations are significant at p < 0.001.

Regarding heart rate and performance relationships, Day Strain correlates positive and strong/very strong with MaxHR (rs=0.789), AvgHR (rs=0.756), Energy Burn (rs=0.959), Energy_burn/activity (0.925). These relationships confirm that higher cardiovascular demand and energy expenditure are strongly associated with increased training strain.

Looking at sleep duration and quality metrics, very strong positive correlation might be observed between Asleep – In_bed (rs=0.971), potentially indicating redundancy between these metrics. Another strong positive correlation appears between Sleep_perf – Asleep (0.818) that emphasize the idea of more sleep associated with a better performance. Moderate positive correlations appear between REM – Asleep/In_bed (0.56–0.59) and an expected negative correlation between Awake – Efficiency (rs=-0.804) showing that the more time awake the lower sleep efficiency.

In terms of HRV and recovery patterns, Recovery scores correlated positively with HRV (rs = 0.663), supporting the relationship between higher heart rate variability and better recovery. A negative correlation between Recovery and RestHR (rs = -0.434) confirmed that lower resting heart rates were associated with better recovery status. HRV also showed a strong inverse correlation with RestHR, representing a classic autonomic nervous system pattern where higher parasympathetic activity is reflected in higher HRV and lower resting heart rate.

Finally, examining training load and intensity zones, heart rate zone analysis revealed that Zone 4 (high-intensity) showed a strong positive correlation with AvgHR (rs = 0.725) and a moderate correlation with Strain (rs = 0.51), while Zone 1 (low-intensity) showed a negative correlation with Strain (rs = -0.326).

H1 was supported. Recovery scores showed significant positive correlations with HRV (rs = 0.663, $p < 0.001$) and Sleep Performance (rs = 0.344, $p < 0.001$), and a negative correlation with Resting Heart Rate (rs = –0.434, $p < 0.001$), suggesting an association between higher recovery scores, better autonomic function, and sleep quality.

H2 was strongly supported. Day Strain exhibited very strong positive correlations with MaxHR (rs = 0.789, $p < 0.001$) and Energy Burned (rs = 0.959, $p < 0.001$), suggesting that cardiovascular demand and energy expenditure are strongly associated with training strain.

H3 was supported. Sleep quality indicators, particularly Sleep Performance, had moderate positive correlations with Recovery (rs = 0.344, $p < 0.001$), while their associations with Day Strain were negligible (rs between –0.144 and 0.06), indicating that sleep contributes more to readiness than to training load.

Based on the correlation patterns, a quartet of variables (HRV, MaxHR, HR Zone 4 time, and Sleep Performance) emerged as potentially strong predictors of training readiness and response, capturing distinct aspects of physiological status with minimal redundancy.

The neural network analysis utilized 994 total observations, with 656 cases (85.1%) allocated to training and 115 cases (14.9%) dedicated to testing, while 223 cases were excluded due to algorithm filtering (Table 4). All 994 observations contributed to at least some of the correlation calculations. The filtering of 223 rows was not due to an empty field. The issue is strictly related to missing values in the six predictor variables used for the neural network model: Recovery, Energy Burned, MaxHR, Sleep Efficiency, Sleep Consistency, Sleep Performance, and the dependent variable: Day Strain. A deliberately constrained architecture was implemented, consisting of two hidden layers with one neuron each, using hyperbolic tangent activation functions for the hidden layers and an identity function for the output layer.

Table 4. *Case Processing Summary*

Item	Value	Interpretation
Total cases	994	Good dataset size for neural modeling
Training cases	656 (85.1%)	Large enough for pattern learning
Testing cases	115 (14.9%)	Smaller but still acceptable for validation
Excluded	223	Filtering applied

The model included six input variables: Recovery (behavioral factor), Energy Burned (behavioral factor), MaxHR (physiological covariate), Sleep Efficiency, Sleep Consistency, and Sleep Performance (sleep-related covariates). All covariates were standardized to ensure comparable scaling. Day Strain served as the dependent variable, with the model using sum of squared errors.

Table 5. *Network Information*

Layer	Parameter	Details
Input Layer	Factors	1) Recovery (Behavioral variable)
		2) Energy burned (Behavioral variable)
	Covariates	1) MaxHR (Physiological variable)
		2) Sleep Efficiency (Sleep variable)
		3) Sleep Consistency (Sleep variable)
		4) Sleep performance (Sleep variable)
	Number of Units	512
	Rescaling Method for Covariates	Standardized
Hidden Layer(s)	Number of Hidden Layers	2
	Number of Units in Hidden Layer 1	1
	Number of Units in Hidden Layer 2	1
	Activation Function	Hyperbolic tangent
Output Layer	Dependent Variables	1) Day Strain (Target variable)
	Number of Units	1
	Rescaling Method for Scale Dependents	Standardized
	Activation Function	Identity
	Error Function	Sum of Squares

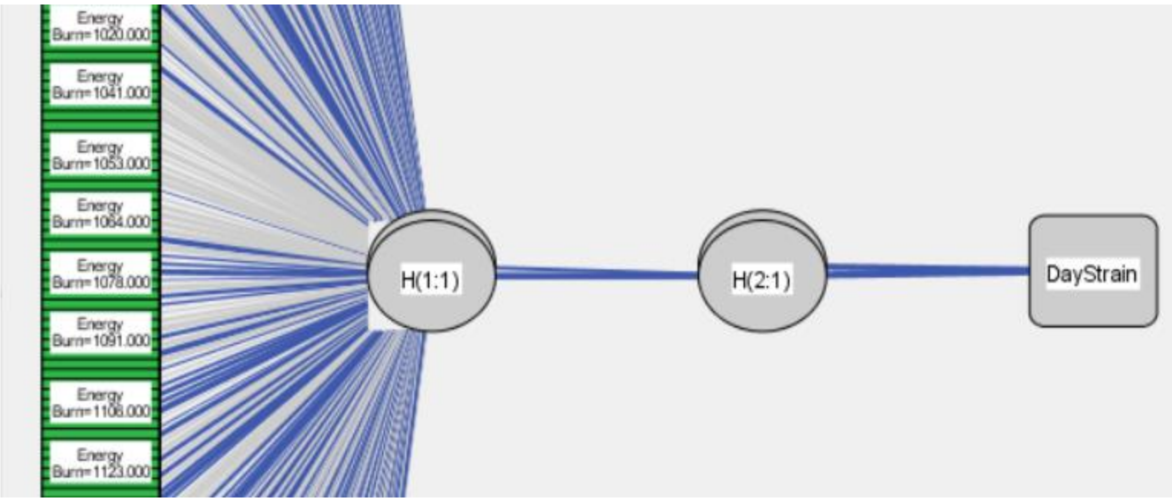

Figure 1. Neural Network model

This highly constrained neural network architecture, despite utilizing six input variables, incorporates only one neuron per hidden layer. This design functions similarly to a non-linear regression, applying a soft mapping function rather than operating as a deep or wide neural network (Table 5, Figure 1). The minimalist structure reduces the risk of overfitting, particularly given the limited test size, by forcing the model to identify and prioritize only the most robust relationships in the data. Consequently, the model is particularly well-suited for explanatory modeling objectives rather than solely maximizing predictive performance, as it highlights dominant predictors and underlying patterns without introducing unnecessary complexity (Table 6).

Table 6. *Model Summary*

Phase	Metric	Value	Interpretation
Training	Sum of Squares Error	38.218	Very good fit on training data
	Relative Error	.117	
	Stopping Rule Used	1 consecutive step(s) with no decrease in error	
	Training Time	0:00:00.19	
Testing	Sum of Squares Error	13.827	Acceptable generalization, slight increase in error (normal)
	Relative Error	.178	

Note: Dependent Variable - Day Strain

This highly constrained neural network acted similarly to a non-linear regression with a soft mapping function, rather than a deep or wide neural network, which had the advantage of reducing the risk of overfitting given the limited test size. The Training Relative Error of 0.117 indicated a strong fit (values between 0.10–0.20 are considered good), while the Testing Relative Error of 0.178 indicated good generalization capacity. The model converged after just one step with no decrease in error, stabilizing almost instantly, with the training time of 0.19 seconds further confirming the model's simplicity and efficiency.

H4 was confirmed. The neural network demonstrated good predictive accuracy (Relative Error = 0.117 in training, 0.178 in testing). Variable importance analysis revealed MaxHR as the dominant predictor (100% normalized importance), followed by Energy Burned (29.5%) and Recovery (24.5%), with sleep metrics playing a minor role.

Variable importance analysis revealed that MaxHR was by far the strongest determinant of Day Strain, accounting for 100% of normalized importance. Energy Burned (29.5%) and Recovery (24.5%) also contributed meaningfully, likely reflecting workload and readiness dynamics. In contrast, sleep-related variables such as Sleep Efficiency (6.1%), Sleep Performance (16.9%), and Sleep Consistency (2.0%) showed limited predictive power (Table 7, Figure 2).

Table 7. *Variable importance analysis*

Variable	Importance	Normalized Importance	Interpretation
MaxHR	0.559	100.00%	*Dominant Predictor* — Cardiac ceiling effect
Energy Burned	0.165	29.50%	Strong contributor — workload variable
Recovery	0.137	24.50%	Moderate readiness signal effect
Sleep Performance	0.094	16.90%	Small but relevant influence
Sleep Efficiency	0.034	6.10%	Minimal effect
Sleep Consistency	0.011	2.00%	Almost negligible

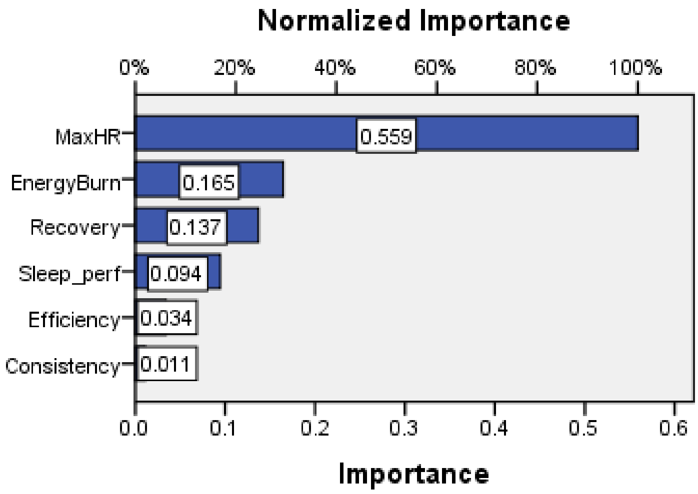

Figure 2. Factor importance

While the present neural network model – built using six key input variables (e.g., Recovery, MaxHR, Sleep Efficiency) – performed well in predicting Day Strain for a single athlete, its application in broader athletic contexts, such as team settings or multi-athlete cohorts, requires thoughtful adaptation. Generalizing such a model entails both methodological expansion and contextual calibration. The minimalist architecture (1 neuron per hidden layer) worked well for a single subject but would likely underfit more complex, heterogeneous datasets.

Generalization also requires incorporating new variables: demographics (age, gender, training experience), contextual features: Phase of training cycle (e.g., taper, overload), recent competition participation, travel disruptions, menstrual cycle (in female athletes).

Throughout the 36-month monitoring period, WHOOP data informed day-to-day and weekly coaching strategies. Recovery scores and heart rate variability metrics guided the modulation of training intensity, particularly during high-load phases and tapering. Sleep-related insights – such as accrued sleep debt and reduced REM sleep – prompted targeted behavioral interventions, including sleep routine optimization and psychological recovery protocols. Strain scores and heart rate zone distributions informed the timing of deloads and rest days, helping maintain performance capacity while reducing injury risk. These interventions illustrate how wearable technology enabled a responsive and individualized coaching approach, transforming data into actionable decisions that supported coaching decisions related to performance monitoring and athlete well-being.

Discussions

This study examined the longitudinal integration of WHOOP-derived physiological data into the training process of a single competitive swimmer over a 36-month period. The findings indicate consistent associations between recovery-related metrics, cardiovascular load indicators, and training strain, as well as a progressive improvement in performance outcomes observed across multiple events during the monitoring period.

The correlation analysis revealed expected physiological patterns. Recovery scores were moderately associated with heart rate variability and inversely related to resting heart rate, reflecting established autonomic regulation mechanisms. Similarly, Day Strain showed strong associations with MaxHR and energy expenditure, indicating that cardiovascular demand and workload metrics are closely aligned within the WHOOP framework. Consistent with this, heart rate zone analysis showed that Zone 4 (high intensity) was more strongly associated with training load than Zone 1 (low intensity). Sleep-related variables demonstrated moderate relationships with recovery but minimal association with strain, suggesting that sleep contributes more to readiness than to acute training load.

The neural network model further supported these observations by identifying MaxHR and Energy Burned as the most influential predictors of Day Strain, while sleep variables contributed less to model performance. This finding is consistent with previous research highlighting the role of cardiovascular capacity in regulating exercise tolerance and performance (Bosquet et al., 2008), suggesting that objective training load and physiological ceiling play a more substantial role in deterining day Strain than sleep patterns in this dataset. Given the deliberately constrained architecture, the model functioned primarily as an explanatory tool, highlighting dominant relationships rather than maximizing predictive complexity. This approach is consistent with the exploratory nature of the study and the limited sample size.

From an applied perspective, the continuous monitoring of recovery and strain metrics coincided with day-to-day adjustments in training intensity and recovery strategies. Periods characterized by higher recovery scores were generally aligned with higher training loads, while lower recovery values were followed by reduced intensity or recovery-focused sessions. Over the observation period, performance improvements were recorded across all events, occurring alongside the implementation of these monitoring-informed adjustments.

However, these observations must be interpreted with caution. The study design does not allow causal inference. The absence of a control condition, the involvement of a single athlete, and the natural progression associated with training, maturation, and coaching interventions all represent plausible alternative explanations for the observed performance improvements. Therefore, the results should be understood as descriptive of a specific applied context rather than evidence of effectiveness.

Several methodological limitations should be considered. First, the dataset consists of repeated daily measurements from a single individual, and the assumption of independence is not met. Although this issue is acknowledged, no formal time-series or mixed-effects modeling was applied, and the reported correlations may therefore be influenced by autocorrelation. Second, while missing data were excluded from the neural network analysis, a comprehensive preprocessing protocol, including outlier handling and sensitivity analysis, was not fully implemented. Third, multiple comparisons were conducted within the correlation matrix without statistical correction, increasing the risk of type I error. Finally, the use of proprietary WHOOP algorithms limits transparency regarding the derivation of key variables.

Despite these limitations, the study provides a detailed account of how wearable-derived metrics can be integrated into daily coaching practice over an extended period. The value of the approach lies primarily in its ecological validity, illustrating how continuous monitoring may support individualized decision-making in a real-world training environment.

Future research should extend this work using multi-athlete designs, appropriate longitudinal statistical models, and controlled comparisons to better distinguish between training effects, technological support, and natural performance progression.

Conclusions

This case study describes the longitudinal use of WHOOP wearable data in the training process of a competitive swimmer over 36 months. The findings indicate that physiological and behavioral metrics derived from the device are systematically associated with training load and recovery patterns within this context.

The observed performance improvements occurred alongside the implementation of monitoring-informed training adjustments. However, given the observational design and lack of control conditions, no causal relationship between wearable use and performance outcomes can be established.

The results support the potential utility of wearable technology as a practical tool for monitoring and guiding training decisions in applied settings. At the same time, they highlight the need for cautious interpretation and for further research using more robust methodological designs to evaluate effectiveness.

In its current form, the study should be understood as an exploratory contribution that documents applied practice rather than providing confirmatory evidence.

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Informed Consent Statement: Written informed consent was obtained for the participant involved in this study.

Data Availability Statement: Data can be made available upon request to the contact author.

Conflicts of Interest: The authors declare no conflict of interest.

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