Recovery and Readiness Monitoring Using Wearable Technology in Young Triathlon Athletes

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Abstract: This study explored the concept of 'readiness to perform' by monitoring twelve youth triathletes (under 23 (U23) and 19 (U19) years old) over three months using the Oura Ring. Physiological data from the wearable were analyzed for all participants; subjective assessments of training intensity (Rating of Perceived Exertion (RPE)) and recovery (Total Quality Recovery (TQR) questionnaire) were conducted only in the U23 subgroup. Stepwise linear regression was used to describe five (Balance) Scores contributing to the Readiness Score (RS). Subsequently, given the limited transparency of Oura's algorithm, the RS was modeled using three approaches: through (1) its real contributors (RMSE = 3.18, R^2 = 0.71), (2) approximated contributors via regression and three additional contributors (RMSE = 4.09, R^2 = 0.52), and (3) directly measured variables with RPE and TQR scores (RMSE = 4.88, R^2 = 0.29). Individual-level analysis was prioritized, though a general model for describing the RS was also developed (RMSE = 3.48, R^2 = 0.60). Sleep emerged as the primary contributor to readiness, followed by physical activity and resting heart rate.

1 INTRODUCTION

Technology has become integral to modern sports, driving advancements in real-time monitoring of athletes' physiological data and performance analysis. However, trust in the reliability and validity of data provided by innovative technology remains a key concern among coaches and practitioners, highlighting the need for critical evaluation and informed use of technological tools (Aerts *et al.*, 2025).

Training load quantifies the overall demand and impact of a training session, both physical and psychological, on an individual's body (Impellizzeri *et al.*, 2023). Readiness and recovery are conceptualized in this study as the readiness to train well and potentially perform well, and the adaptation to the (previous) training load, respectively. These processes are influenced and determined by various factors, with training load and intensity being key factors, as reflected by the fundamental concept of training theory. This concept revolves around the structured and systematic planning of exercise sessions to improve athletic performance.

Furthermore, rest, sleep, nutrition, and various physiological markers are critical determinants of readiness and recovery. Adequate rest and sleep is essential for comprehensive recovery, as also proper nutrition, balanced in macro- and micronutrients and hydration, is fundamental for optimal performance (Walsh *et al.*, 2021; Watson, 2017; Beck *et al.*, 2015). Equally relevant are physiological markers, such as heart rate (variability) (HR(V)) and resting heart rate (RHR), which reflect the state of the autonomic nervous system (Schneider *et al.*, 2018). Lastly, also immunological, biochemical and hormonal markers can be assessed in monitoring an athlete's recovery status. However, no single marker serves as a gold standard in monitoring readiness and recovery.

Effective recovery monitoring of an athlete requires a multidimensional approach, incorporating subjective feedback and social factors to account for non-training related factors, with objective (physiological) data. Context is crucial, as

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physiological measures like HRV are sensitive to non-training related stressors (Flatt *et al*., 2018).

This study investigates recovery and readiness of young triathletes, hypothesizing that data collected by wearable technology (i.e., Oura Ring), combined with reference training load and recovery measures, will demonstrate associations with the overall readiness level of the athletes. Four main objectives are formulated, focusing on the individual athlete.

The first objective is to map the athletes' current sleep, training load, recovery and readiness patterns, and accordingly investigate associations between the corresponding collected variables. The second objective involves modeling and approximating five different (Balance) Scores that contribute to Oura's Readiness Score (RS), using (linear) regression analyses. The third objective is to identify and characterize the most significant contributors to the athlete's readiness, more specifically Oura's RS, by (linear) regression analyses. By this interpretable method, insights into the compilation of the RS and the importance of the most significant contributors are identified. The fourth objective parallels the third, but focuses on approximating the RS by including physiologically measured variables and subjective training load and recovery data in (linear) regression models, rather than Oura's stated contributors.

2 MATERIALS AND METHODS

2.1 Participants and Study Design

Twelve young triathletes participated in this study. Six U23 triathletes (3 female, 3 male, aged 19-21 years), with a weekly average amount of training hours between 13 and 19 hours, of which on average 20% of the time is spent on running, 33% on swimming, 40% on cycling and the remainder on strength training. In addition, six U19 triathletes (2 female, 4 male, aged 17-18 years) participated in this study (13 to 17 weekly training hours).

Over the course of three months, the participants wore a personal Oura Ring (Gen3, firmware 2.9.32-2.9.33) throughout both day and night, to monitor key biometrics (i.e., Activity Scores; High/Low Activity; Steps; Total Burn; Sleep Scores; Deep Sleep, Light Sleep, REM Sleep, and Total Sleep Time; Respiratory Rate; Sleep Efficiency; Sleep Latency; Sleep Timing; RHR; Average HRV; Body Temperature; Recovery Index; RS). Oura was selected because of its reported technical quality, wearing comfort, data reporting and data availability, and its functionalities within monitoring readiness. This smart ring provides daily scores (0-100), with the RS being a key metric in this study. It is a composite measure, derived from, inter alia, HRV, and recent sleep and activity levels, providing an indication of the user's readiness to face more challenges, or the need for rest and recovery.

Furthermore, participants were instructed to report an individual rating of perceived exertion (RPE) score per training session, on a 10-point scale, ranging from 'rest' to 'maximal exertion'. The session RPE (sRPE) method, as proposed by Foster *et al*. (2001), was used to calculate the total load index of a session. Additionally, both subjective and objective data regarding recovery were collected via the Total Quality Recovery (TQR) questionnaire (Kenttä & Hassmén, 1998). To maximize compliance of the athletes and to avoid questionnaire fatigue (Halson, 2014), the TQR questionnaire was preferred above longer questionnaires, and no strict daily completion was adopted; instead, participants were instructed to complete the questionnaire at least twice a week, enabling retrospective reporting for multiple past days. The TQR scale consists of two parts: TQR perceived (TQRper) – perceived recovery on a 6-20 scale, ranging from 'no recovery at all' to 'maximal recovery' – and TQR action (TQRact) – a more objective score based on an athlete's engagement in recovery actions across four domains: nutrition, sleep and rest, relaxation and emotional support, and stretching and cooling-down. Research has confirmed the effectiveness of TQR in monitoring training load effects and individual responses, for both daily and less frequent (e.g., microcycle) implementation (Nässi *et al*., 2017; Debien *et al*., 2020). No explicit additional interventions were performed that deviated from their daily routines and training schedules.

RPE and TQR data were not collected for U19 participants due to their late inclusion and the non-routine recording of subjective data. In total, Oura data were recorded over an average of 77.83 (± 6.70) days, with ~8% missing data due to, inter alia, device non wear. For the U23 population, an average number of 76.67 (± 19.55) TQRper, 70.00 (± 14.30) TQRact, and 168.83 (± 50.23) RPE datapoints were obtained. The study was approved by the Social and Societal Ethics Committee of KU Leuven (G-2023-7108-R2).

2.2 Data Processing and Analysis

Data processing comprised three main phases (Figure 1), focusing on (linear) regression analysis. While the true relationships may be non-linear, linear models – which additionally allow the inclusion of interaction terms – were chosen for their interpretability and alignment with the study's exploratory objectives.

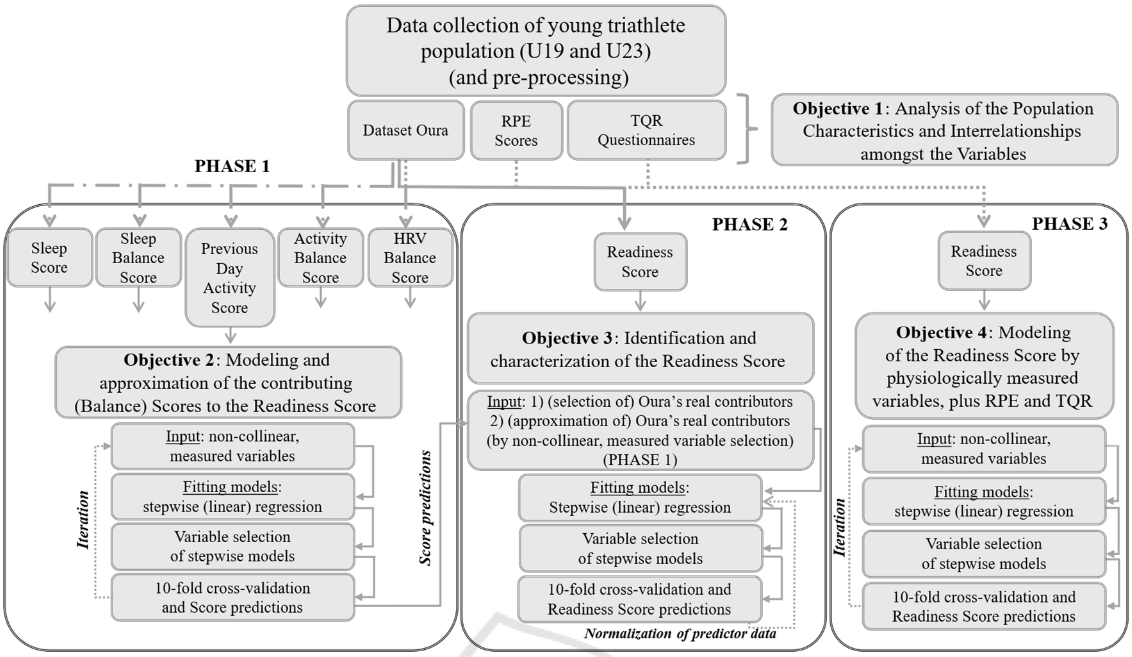

Figure 1: Overview of the implemented three-phase data processing flow for analyzing Oura's Readiness Score. RPE = Rating of Perceived Exertion; TQR = Total Quality Recovery.

Model performance for fitting and predicting the investigated scores per individual athlete was assessed using the (adjusted) coefficient of determination ($R_{(a)}^2$) and root mean squared error (RMSE). Overall model significance was assessed through a global F-test, as were individual estimated regression coefficients evaluated for significance (with α = 0.05). Model validation for each athlete's scores was performed using 10-fold cross-validation. Prior to regression analysis, the assumption of independence among predictor variables was assessed by investigating for multicollinearity, with a condition index tolerance level of 30 and a variance-decomposition proportion tolerance of 0.5

Phase 1 (Figure 1) analyzed five scores provided by Oura, each contributing to the RS. For these scores, individual regression models were constructed, using non-collinear, actual measured variables from the Oura dataset (i.e., no composite measures) that best represent the respective score, as predictor data. Oura's Recovery Index was not approached as no measured variables allowed approaching this score. Following data-fitting, athlete-specific predictor variable sets were defined. Subsequently, in a cross-validation loop, a regression model was reconstructed for each individual score and athlete, based on the aforementioned selection of predictor variables. Through iterative variable subsetting, an average performance of $R^2 > 0.75$ and RMSE < 4.00 for each of the five investigated scores was pursued. The resulting predictions from this phase served as inputs for Phase 2.

In Phase 2 (Figure 1), Oura's RS was analyzed in more detail, adopting a structure analogous to Phase 1. Regression models were developed distinguishing between two predictor sets: (1) Oura's real contributors, and (2) approximations of these contributing scores derived from Phase 1 combined with three additional factors (i.e., RHR, Temperature Deviation, and Recovery Index). These eight variables collectively represent Oura's official RS contributors. After the final cross-validation step and obtaining a model with a proper accuracy, a second model fitting on the corresponding, this time normalized, predictor data was performed. This process was performed for the models based on the real contributors only, where variable importance was derived from the fraction of its estimated model coefficient to the total absolute sum of the different coefficients, excluding the intercept. Moreover, an attempt was made to obtain a general model that might approximate the RS for each of the athletes.

In Phase 3 (Figure 1), again an analogous structure was adopted. Unlike previous phases, this phase expanded the potential predictor variables beyond Oura's stated contributors by including all measured, non-collinear Oura variables, alongside RPE and TQR scores. This allowed the construction and evaluation of regression models representing the RS by using an alternative subset of variables.

3 RESULTS AND DISCUSSION

3.1 Population Characteristics and Variable Interrelationships

3.1.1 Sleep Features

Adequate sleep is vital for comprehensive recovery, encompassing physical, psychological, immune, and endocrine functions, whereby insufficient sleep can impair performance and hinder recovery (Walsh *et al*., 2021; Watson, 2017). On average, the U23 athletes slept 7.94 (± 0.58) hours, and the U19 athletes 7.86 (± 0.33) hours, including daytime naps. Our observations align with previous research suggesting that athletes often report sleep durations below recommended levels, which may be associated with poorer sleep efficiency and quality compared to non-athletes. Contributing factors include demanding training and competition schedules, travel, and increased stress levels (Roberts *et al*., 2019).

The U23 population averaged a Sleep Score of 80.45 (± 5.72), while the U19 athletes averaged 79.79 (± 3.91). The lowest average Sleep Score (i.e., 71.39 ± 8.68) was associated with the least sleep hours, while the highest average Sleep Score (i.e., 86.53 ± 4.01) was associated with the most sleep hours. This strong association between sleep duration and Sleep Score was confirmed by significant positive correlations in all U23 athletes ($p < 0.05$), yielding daily and seven-day average r values of 0.74 and 0.65, respectively. Furthermore, Sleep Scores were significantly correlated with RS for two U23 athletes ($p < 0.05$), with daily r values of 0.70 and 0.75 (seven-day average r values of 0.68 and 0.87).

Due to collinearity among several sleep features, total sleep duration was selected at the beginning of the regression analyses without prioritizing collinear variables with this variable.

3.1.2 Cardiac Features

Two overnight RHR variables – lowest and average – were analyzed. As anticipated, these variables showed an average daily and seven-day average correlation of $r = 0.85$, and $r = 0.90$, respectively. The average RHR was on average 49.96 (± 4.68) bpm for the U23 athletes, and 51.35 (± 2.80) bpm for the U19 athletes. These lower values reflect exercise-induced cardiac adaptations that enhance blood-pumping efficiency, commonly observed in athletes compared to non-athletes (Nystoriak and Bhatnagar, 2018).

The average HRV, as measured overnight and provided as the rMSSD, ranged between 57.45 (± 9.51) ms and 170.73 (± 26.95) ms. Due to significant inter-individual variability in HRV, focusing on individual trends is a more meaningful approach than comparison to others. Furthermore, since inconsistent findings have been observed in scientific literature when based on daily measurements, it has been suggested that weekly or seven-day moving averages offer a more valid approach (Plews *et al*., 2013).

The average RHR exhibited a significant correlation ($p < 0.05$) with the average HRV for two U23 athletes (i.e., $r = -0.71$ and $r = -0.94$ for daily measurements, respectively, $r = -0.89$ and $r = -0.95$ for seven-day averages). One U19 athlete showed a significant seven-day average correlation of $r = -0.70$ between the average RHR and HRV. Hence, average RHR and HRV appear to be inversely related. Moreover, with consistently negative (significant) correlation results, it was observed that the RS and average RHR are likewise inversely correlated (i.e., daily and seven-day average correlation values up to $r = -0.68$ and $r = -0.87$, respectively).

Due to collinearity between average and lowest RHR, the average RHR was preferred for further analysis due to its greater robustness and reliability.

3.1.3 Readiness Score

An average RS of 79.31 (± 2.19) was observed. The RS exhibited no significant high correlations with other variables, besides these previously mentioned.

Given the extremely low and mostly non-significant individual correlations, and daily average values of $r = 0.01$, $r = 0.07$ and $r = 0.16$ between the RS and sRPE, TQRact and TQRper, respectively, in the U23 group, the RS did not correlate with these variables. This suggests that the RS was not reflected in the athletes' training load or recovery ratings. Since training schedules were pre-determined, without considering Oura data on the actual training day, the lack of correlation likely stems from the absence of RS data integration into the decision-making process. Notably, it may be assumed that a recovery score is linked to a readiness score for the athlete. However, the results indicated no significant link between the RS and TQR scores. Due to the lack of data, no conclusions could be drawn for the U19 group.

3.1.4 Recovery Measures

The U23 athletes had an average TQRper score of 14.14 (± 1.42), indicating a 'reasonable' to 'good' recovery, and an TQRact score of 14.62 (± 1.42).

The two-part TQR questionnaire provides comprehensive insight into training responses, as a discrepancy between perceived recovery and recovery actions can indicate maladaptation to training load. Moreover, a practical guideline suggests aligning TQRact and TQRper scores with RPE ratings (reported on or converted to a 0-20 scale) for adequate recovery (Kenttä & Hassmén, 1998). However, in this study, consistently low and non-significant correlations were observed between TQR scores and the (s)RPE scores on the one hand, and the two TQR scores among themselves on the other hand.

3.2 Investigation of Oura's (Balance) Scores Contributing to the Readiness Score

3.2.1 Sleep Score and Sleep Balance Score

Oura's Sleep Score claims to reflect how well the athlete slept each night, and is determined by the total sleep duration, sleep efficiency, restless sleep, REM sleep duration, deep sleep duration, sleep latency and sleep timing. For the U23 population, the cross-validation of the established models yielded an RMSE between 2.07 and 3.85, with the exception of one athlete (RMSE = 8.62). Hence, the model made an overall error of 2 to 4 units out of 100. Equally, a large fraction of the variance in the Sleep Score was explained by all models, represented by an R^2 of 0.69-0.86, with the exception of one athlete's model that performs worse than a simple mean-based prediction. For the U19 population, an average RMSE of 2.86 and R^2 of 0.77 were obtained from cross-validation.

Total and deep sleep duration consistently emerged as the key determinants of the Sleep Score across all models, whether or not with an additional interaction effect. Sleep efficiency was also a crucial predictor, excluded from the model for only one athlete. The primarily positive regression coefficients for these three predictor variables indicate their positive impact on the Sleep Score. Conversely, sleep latency and timing were the least incorporated into the models. Sleep latency consistently exhibited negative regression coefficients, suggesting that longer nocturnal wakefulness negatively impacts the Sleep Score. The effect of sleep timing was inconsistent. These findings underscore the critical importance of sleep quantity and the deep sleep stage for Sleep Score determination, aligning with their recognized roles in physical recovery.

The Sleep Balance Score was approximated by a combination of total sleep duration with sleep efficiency. Given it is a Balance Score, time-shifted data from the last 14 days, were presented as predictor data. The validated models for the U23 population exhibited an average RMSE of 3.98 and an R^2 of 0.75. The U19 models demonstrated a considerable lower performance (i.e., average RMSE of 5.30 and R^2 of 0.56, excluding one athlete). It is reasonable that the excluded athlete's model exhibited substantial overfitting, as indicated by an RMSE > 20 and an $R^2 < 0$. The inclusion of 17 predictor variables in this athlete's model likely introduced model complexity beyond the data's explanatory capacity.

The significantly explanatory variables included in the descriptive models mainly corresponded to the athlete's sleep duration from one up to ten days prior, aligning with Oura's assignment of greater weight to recent sleep patterns in computing the score. Regression coefficients for recent sleep duration (1-5 days) were consistently positive, indicating their positive effect. Furthermore, sleep efficiency was only included in one U23 athlete's model, indicating that the sleep efficiency of the last day, as well as nine to thirteen days prior were determinant. In contrast, all U19 models incorporated at least one sleep efficiency variable, ranging from the athlete's sleep efficiency from one to thirteen days before the score.

3.2.2 Previous Day Activity Score and Activity Balance Score

The Previous Day Activity Score quantifies an athlete's (in)activity relative to their long-term average. Initial model fitting identified burned calories, inactive, low (HR < 60% of maximum), and high active time (HR 80-100% of maximum) as the consistently selected explanatory variables for this score. The validation results exhibited an average RMSE of 5.59 and 6.40 for the U23 and U19 population, respectively, indicating deviations of 5 to 6 units from true values. However, an overall average R^2 of 0.80 was obtained from the validation process. Almost all estimated regression coefficients were negative, but a true interpretation is challenging as the (regression coefficient of the) intercept for the majority of athletes started with a value above 100.

Oura's Activity Balance Score was analyzed using burned calories, steps and high activity time, from the preceding 14 days, shifted in time, as predictor data. The cross-validation process yielded an average RMSE of 6.56 (R^2 = 0.68) for the U23 population and 8.41 (R^2 = 0.49) for the U19 population. Ultimately, no adequate desired performance was achieved for this score.

3.2.3 HRV Balance Score

The HRV Balance Score compares the athlete's average HRV from the past 14 days relative to their long-term average, thereby giving greater emphasis on recent data. Due to limited long-term data, the athlete's average RHR over the past 14 days was also included as predictor data alongside 14-day HRV data, significantly improving model representation.

Cross-validation of the descriptive models for the U23 group yielded RMSE values between 1.51 and 4.15 and R^2 values between 0.46 and 0.95, with the largest prediction error coinciding with the greatest explained variation in the score. For the U19 group, cross-validation yielded an average RMSE of 2.76 and an R^2 of 0.84. Model analysis revealed that all but one athlete's model included at least one RHR variable. Proportionally, more HRV variables were included, generally exhibiting positive coefficients, indicating higher HRV correlated with an increased HRV Balance Score. In contrast, RHR coefficients exhibited both positive and negative values, precluding unambiguous interpretation.

3.3 Investigation of the Readiness Score

3.3.1 RS Approximated by Its Real Contributors

A first approximation of the RS by regression analysis was conducted based on its real reported contributors (i.e., Sleep Score, Sleep Balance Score, Previous Day Activity Score, Activity Balance Score, average RHR, HRV Balance Score, Temperature Deviation and Recovery Index). Validation of the fitted regression models yielded an RMSE between 2.05 and 4.67, and an R^2 between 0.28 and 0.90. The lowest explained variation by the validated regression models ($R^2 = 0.28$) was obtained for the athlete with the second highest estimated error (RMSE = 4.38).

Stepwise regression consistently selected the Sleep Score across all athletes. Four U23 athletes showed a significant positive regression coefficient for this variable. Among the U19 athletes, five times a positive regression coefficient, and one non-significant negative one was observed. Hence, an overall positive association with the RS was found. The second contributor assessed was the Sleep Balance Score. Likewise, this variable exhibited a positively estimated regression coefficient for the same four U23 athletes. For the U19 population, this score was three times included with a positively estimated coefficient, once with a negative coefficient. Likewise, an overall positive association with the RS was assumed. Using subsequently normalized predictor data, it was shown that the Sleep Score determined 15-35% of the RS among the U23 population, and 20-30% for the U19 population, with one exception (<15%). For both populations, the Sleep Score was one of the strongest contributors to the RS. For the Sleep Balance Score, a contribution to the RS of 5-15% for the U23, and 5-20% for the U19 athletes, respectively, was found.

A third variable examined, and the second variable included in the descriptive model for all athletes, was the Previous Day Activity Score, consistently showing a positive regression coefficient, except for one athlete, indicating a positive association with the RS. This may reflect a confounding effect, where increased activity correlates with higher readiness. However, Oura posits that maintaining 5-8 hours of inactivity daily would have a positive impact on the athlete's activity score, and subsequently RS, while both excessive inactivity and overexertion will reduce the score. The recurrent positive regression coefficient for the Previous Day Activity Score in the descriptive models of the RS is thus a rational finding. The Activity Balance Score was included in ten athletes' models, with nine showing a positive and one a non-significant negative regression coefficient, likewise suggesting a positive association with the RS. Across the entire population, these two activity scores contributed 7-15% (Previous Day Activity Score) and 7-25% (Activity Balance Score) to the RS models.

The athlete's average RHR is the third variable included in all regression models, with a consistently negatively estimated regression coefficient, except one positive but non-significant one, indicating an inverse relation with the RS. An overall contribution to the RS of 8-35% was observed. Furthermore, the regression coefficient for the HRV Balance Score showed mixed results. With five positive and three times a negative regression coefficient, an overall positive effect predominated. A relative importance in describing the RS of 5-10%, up to 20%, for the U23 and U19 population, respectively, was found.

Temperature Deviation was the least frequently included predictor variable, and by this considered as the least contributing variable in describing the RS. The variable appeared in only two models, with positive coefficients, contributing from virtually 0 to 15%. In contrast, the Recovery Index was included in all U23 models and three U19 models, consistently showing a positive coefficient, indicating a positive association with the RS. The relative importance in determining the RS was 5-15%. Finally, for all athletes, generally none to three interaction terms were included in their model, but these terms' importance did not prevail over the main effects.

In addition to the individual approach, a general model was constructed to investigate whether also this model could adequately describe the RS of all athletes. For this general model, the following criteria were applied: once a variable's main effect was included for at least four out of the six U23 athletes, this variable was included in the general model. For interaction terms, a required occurrence for at least two out of the six athletes was applied. Accordingly, it was found that the Temperature Deviation variable was the only RS contributor variable that did not meet the selection criteria. However, this variable was still included in the general model as an interaction term associated with this variable was selected.

This led to the general regression model ([Eq. (1)]):

$$
\begin{gathered}
\text{Readiness Score} = \text{Intercept} + A{*}\text{Sleep Score} \\
+ B{*}\text{Sleep Balance Score} + C{*}\text{Previous Day} \\
\text{Activity Score} + D{*}\text{Activity Balance Score} \\
+ E{*}\text{Average RHR} + F{*}\text{HRV Balance Score} \\
+ G{*}\text{Temperature Deviation} + H{*}\text{Recovery Index} \\
+ I{*}\text{ Sleep Score}{*}\text{Sleep Balance Score} \\
+ J{*}\text{Sleep Score}{*}\text{Average RHR} \\
+ K{*}\text{Sleep Score}{*}\text{Temperature Deviation}
\end{gathered} \tag{1}
$$

With the values of the RS contributors and the coefficients A to K being individual-specific.

The U23 models were used for variable selection, whereupon the general model ([Eq. (1)]) was tested on both the U23 and U19 group for its descriptive capability. Because of the explicit requirement to include the aforementioned selected variables in the general model, not all variables had a significant regression coefficient for each athlete. Positive associations with the RS were found for sleep and activity scores, as well as for the HRV Balance Score and Recovery Index, while average RHR showed consistently negative effects. Temperature Deviation and interaction terms showed no clear pattern.

Model validation yielded RMSE values between 1.40 and 3.98, with the exception of one athlete (RMSE = 7.10). Overall, the explained variation in the RS by the general model (R^2) ranged between 0.58 and 0.95, excluding one athlete. This athlete was the only athlete for whom the general model exhibited a poor performance in the validation process. These results suggest that the proposed general model has strong potential for describing and predicting the RS but individual adjustments should not be excluded.

3.3.2 RS Approximated by Approximations of Its Real Contributors

This regression analysis aimed to examine whether models based on predicted (Balance) Scores could adequately describe the RS. Consequently, the RS, along with its contributors, would be uncovered and identified in its totality, as opposed to the black-box nature of the score that previously dominated.

It was found that sleep-related variables, particularly the approximated Sleep Score and Sleep Balance Score, were strong positive predictors of the athletes' RS, underscoring the importance of sleep for recovery and readiness. Likewise, activity-related variables, especially the Previous Day Activity Score, showed primarily positive associations with the RS. Average RHR appeared inversely related to the RS, while the HRV Balance Score and Recovery Index had positive effects. Consistent with previous findings, Temperature Deviation was the least significant predictor of the RS. Model validation yielded RMSE values between 2.60 and 5.44, with badly an average predictive accuracy R^2 of 0.56, excluding one athlete (RMSE = 7.74 and R^2 = 0.18). In a one-to-one comparison of validation statistics, models based on the true contributors exhibited superior performance for all but two athletes.

3.3.3 RS Approximated by an Alternative Subset of Predictor Variables

To meet the fourth objective, regression models using multiple non-collinear, directly measured Oura variables, in combination with sRPE and TQR scores, were developed. Due to missing data, sRPE and TQR scores were excluded for the U19 group. The models exhibited poor performance (average validation R^2 = 0.29), with sleep-related variables, average RHR and HRV, and respiratory rate most frequently included. The models failed to adequately describe and predict the RS, indicating that the subset of contributor variables to the RS proposed by Oura is needed to adequately describe the RS using regression models which only allow the inclusion of main effects and first-degree interaction terms.

3.4 Limitations

While devices like the Oura Ring show high validity for directly measured metrics (e.g., RHR, HRV; Kinnunen *et al.*, 2020), their proprietary scores lack transparency and gold-standard validation, without which it remains unclear how well the RS reflects actual physiological readiness. Therefore, caution is advised when interpreting wearable-derived – black-box – metrics for modeling purpose, as compounded estimation errors may reduce accuracy – especially for inferred parameters like readiness.

This study's effort to deconstruct Oura's scores into interpretable models offers valuable insights, yet also highlights the need for prioritizing directly measured, well-contextualized data. However, due to the assumption of linearity, multicollinearity among physiological variables, the inclusion of interaction terms that may increase the risk of overfitting, and the hierarchical structure and limited size of the dataset, linear regression may not be the most robust modeling approach for this context. Therefore, future research should consider alternative modeling techniques, and pursue external validation using larger independent datasets and comparisons with established physiological reference measurements to assess the validity and generalizability of both the model and underlying wearable metrics.

While the sRPE method is widely used and correlates well with HR zones (up to r = 0.84 for endurance athletes (Borresen & Lambert, 2008)), it lacks precision in time quantification, as it includes total session duration regardless of pauses (Halson, 2014). Despite this, the simplicity, reliability, and demonstrated agreement of the (s)RPE method with more complex metrics support its continued use. In addition, the TQR questionnaire lacked specificity for triathlon, with outdated or not clearly defined items (e.g., cooling down, stretching), limiting its relevance and score potential. A sport-specific and updated version, aligned with modern recovery strategies, is recommended for future research. Noteworthy is the unavailability of (s)RPE and TQR data for the U19 subgroup which restricts the generalizability of findings, which are based on only six (U23) athletes.

Lastly, this study focused on twelve youth pre-elite triathletes monitored over three months, limiting generalizability to other populations or long-term trends. Individualized monitoring prevailed over a generalized approach due to varied physiological responses among the athletes.

4 CONCLUSION

Readiness and recovery levels of young triathletes can (potentially) be monitored using wearable technology in combination with reference training load and recovery measures. The primary focus should be on the individual athletes' responses, rather than general trends, and their sleep patterns, both in the short- and long-term. Beside objectively collected data, the significance of subjective data should not be underestimated. A novel contribution is presented, as no prior published work has approximated the RS by using simple regression analysis based on Oura's stated contributing factors, nor based on other (physiological) wearable data or subjective measures.

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