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Received04/07/2023
Accepted19/12/2023

Printed ISSN: 2352-989X
Online ISSN: 2602-6856

**Comparison of Training Load Models for
Predicting Heart Rate Variability Changes**

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ABSTRACT

The aim of this study is to compare different training load (TL) models to predict changes in heart rate variability (HRV). TL was evaluated using the heart rate stress score (HRSS), while HRV was measured in the morning using a Polar H7 chest strap and an Android application during a 2-minute period for an individual adult engaged in recreational running. The results indicate that the REDI model exhibits the highest correlation with HRV indices. Specifically, the REDI model's Lambda values of 0.1, 0.03, and 0.02 demonstrate the strongest correlations with low frequency (LF), high frequency (HF), and Ln_RMSSD_RA ($p < 0.001$), respectively. The Acute and Chronic load of both the EWMA and Coggan models exhibit similar correlations with LF ($p < 0.05$). Conversely, no linear correlation was observed between any of the models' Training Stress Balance (TSB) and HRV. In non-linear regression, the Chronic_EWMA showed stronger relationship with Ln_RMSSD_RA compared to other models.

Keywords : Training Load Monitoring ;Heart Rate Variability ; Modeling

INTRODUCTION

Training load monitoring plays a vital role in effectively planning and monitoring the fitness levels of athletes. In a comprehensive survey conducted among top-tier European clubs, the quantification of training load emerged as the most critical factor contributing to athletic success and injury prevention (McCall et al., 2016). While some studies have proposed using biological markers to assess training load, such as oxygen consumption or blood lactate concentration, these methods are often limited to scientific research settings due to the need for specialized equipment (Hopkins, 1991). Alternatively, approaches based on heart rate (HR) monitoring or perceived exertion (RPE) evaluation appear to be more practical for everyday use (Saboul et al., 2016).

To address the need for quantifying training load, various indices of training stress have been developed, including the widely utilized "TRaining IMPulse" (TRIMP) and session RPE methods (Banister, 1991; Foster, 1998). These methods provide a means of assessing acute and chronic training loads. Gabbett (2016) proposed the use of the acute-to-chronic workload ratio as a reference for effective load management, finding that a ratio between 0.8 and 1.3 reduces the risk of injury, while values below 0.5 or above 1.5 indicate a high risk of injury.

Heart rate variability (HRV) refers to the measurement of the variation in time intervals between consecutive heartbeats and is controlled by the autonomic nervous system (ANS), which regulates essential physiological functions (Harvard Health, 2021). HRV can serve as a non-invasive means of assessing imbalances in the autonomic nervous system. Studies have demonstrated the benefits of utilizing HRV as a monitoring tool in sports training programs, showing improvements in athletes compared to standard training protocols (Bahenský et al., 2021; Carrasco-Poyatos et al., 2020; Kiviniemi et al., 2010). Furthermore, HRV has been found to parallel changes in variables such as VO₂ max, lactate levels, and vagal modulation, making it an effective tool for measuring critical indicators that are challenging to monitor in routine settings (Kiviniemi et al., 2010; Kiviniemi et al., 2007; Makivić et al., 2013).

Moreover, shifts in HRV from parasympathetic dominance to sympathetic dominance have been observed in parallel with overtraining, providing insights into autonomic activity imbalances during overreaching phases (Hottenrott et al., 2006; Mourot et al., 2004; Uusitalo et al., 2000). These findings suggest that HRV monitoring can be valuable in tracking athletic performance and

training load dynamics for both amateur and professional athletes (Makivić et al., 2013) .

Numerous studies have demonstrated the benefits of utilizing HRV as a monitoring tool in sports training programs. Recent research has shown that using HRV as a training guide leads to improvements in athletes compared to standard training protocols (Bahenský et al., 2021; Carrasco-Poyatos et al., 2020; Kiviniemi et al., 2010). These studies have shown that scaling back exercise intensity when HRV is decreased does not decrease overall performance, and in some groups (men), performance was even better compared to standard training regimes. Other studies (Kiviniemi et al., 2010; Kiviniemi et al., 2007; Makivić et al., 2013) have demonstrated that changes in HRV parallel changes in variables such as VO2 max, lactate levels, and vagal modulation. Training based on HRV can be an effective means of measuring these critical indicators that are typically challenging to monitor in routine settings. Given that HRV monitoring can accurately detect these key indicators of overtraining, it is not surprising that HRV is also a valuable tool for monitoring overtraining itself. Multiple studies (Hottenrott et al., 2006; Mourot et al., 2004; Uusitalo et al., 2000) have indicated that shifts in HRV from parasympathetic dominance to sympathetic dominance occur in parallel with overtraining. Researchers (Altini et Plews, 2021; Bosquet et al., 2003; Hedelin, Kenttä, et al., 2000; Hedelin, Wiklund, et al., 2000; Hynynen et al., 2006; Mourot et al., 2004; Natarajan et al., 2019; Tian et al., 2013; Uusitalo et al., 2000) have been able to detect the autonomic activity imbalance that occurs during overreaching phases through HRV in both non-athletes (training camp participants) and athletes. These findings may offer another application of HRV monitoring for tracking athletic performance and training load dynamics in both amateur and professional athletes (Makivić et al., 2013). In this perspective, we posed the following question: What is the best model that can predict changes in heart rate variability?

1 Methods

1.1 Method and tools:

The subject is 40 years old male and engages in recreational sports, with 2 to 3 running sessions per week. The subject has a BMI of 24.2, indicating a normal body weight (according to the World Health Organization, 2021).

For each training session, the training load (CE) is calculated based on the heart rate (FC) data measured by the Polar H7 chest strap and recorded on a Garmin watch (Forerunner 245). The training load is estimated using the

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relative TRIMP method, known as HRSS (Heart Rate Stress Score). This method involves normalizing (dividing) the Banister's TRIMP (Banister, 1991) by a theoretical TRIMP for a one-hour session at a heart rate equal to the lactate threshold (TRIMP threshold).

$$\text{HRSS} = (\text{TRIMP}_{\text{Banister}} / \text{TRIMP}_{\text{threshold}}) * 100$$
$$\text{TRIMP}_{\text{Banister}} = T * \Delta\text{HR} * K$$

T = duration in minutes of the session

$\Delta\text{HR} = (\text{HR session} - \text{HR rest}) / (\text{HR max} - \text{HR rest})$

K = $0.86 * e^{(1.67 * \Delta\text{HR})}$ for women; $0.64 * e^{(1.92 * \Delta\text{HR})}$ for men

$$\text{TRIMP}_{\text{threshold}} = 60 * \Delta\text{HR} * K$$

Heart rate variability (HRV) measurements are taken using a Polar H7 heart rate monitor (Polar Electro Oy), which has been scientifically validated for recording beat-to-beat intervals (Hernández-Vicente et al., 2021). The heart rate monitor is connected to an Android application via Bluetooth. The specific application used, "Hrv4Training," has also been scientifically validated for HRV measurement and analysis compared to the golden standard Kubios software (Stone et al., 2021).

1.1 Procedural definition of the concepts

Training load (TL): The physiological or internal response of an individual to a specific training session or physical activity.

TL metrics: Heart Rate Stress Score (HRSS) uses TRIMP of the session which include the session heart rate mean, reserve heart rate and an exponential scaling factor to account for higher intensity, divided by theatrical session of 60-minute duration at lactate threshold (also known as relative TRIMP). **Heart rate variability (HRV):** The variation in the time intervals between successive heartbeats, reflecting the constant adjustments made by the autonomic nervous system (ANS). The measurement was performed in the morning, while in a supine (lying) position, for a duration of 2 minutes, using a Polar H7 chest strap coupled with Android App. **HRV metrics** 1) time domain: the Root mean square of the successive differences is used as absolute value (RMSSD), natural logarithm(Ln_RMSSD) and rolling average of the natural logarithm (RMSSD_LN_RA); 2) frequency domain: Low frequency (0.04 to 0.15 Hz), high frequency (0.15 to 0.4 Hz).

1.1 Determination of parameters inherent to different training load calculations:

Resting Heart Rate: the moving average of the resting heart rates from the past 7 days. Resting heart rate is automatically measured by the Garmin Forerunner 245 watch every morning. **Maximum Heart Rate:** automatically

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recorded during a maximal effort test "30 MTT: 30-minute time trial". **Lactate Threshold Heart Rate:** The determination of the heart rate is performed during the 30 MTT test, which entails engaging in a 30-minute running activity at maximum exertion. The lactate threshold heart rate, corresponding to a lactate concentration of 4mmol, is derived from the average heart rate recorded during the final 20 minutes of the test. Notably, the results obtained from this test exhibit comparability to direct lactate measurements conducted in a laboratory setting (McGehee et al., 2005).

Table 1. Training load models and their metrics equation

Model	Author	Formula
Coggan	(Allen et Coggan, 2010)	$ATL = ATL_{Yesterday} + (TL_{Today} - ATL_{Yesterday}) / 7$ $CTL = CTL_{Yesterday} + ((TL_{Today} - CTL_{Yesterday}) / 42)$ $TSB = ATL - CTL$
Rolling average	(Gabbett, 2016)	ATL : Rolling average over the past 7 days. CTL : Rolling average over the past 28 days. $TSB = ATL - CTL$
Exponential Weighted Moving Average (EWMA)	Williams et al., 2017	$EWMA_{today} = TL_{Today} * \lambda a + (1 - \lambda a) * EWMA_{yesterday}$ <i>Where:</i> $\lambda a = 1/(N+2)$ $N = 7$ (for Acute) or 28 (for Chronic) $TSB = ATL - CTL$
Robust Exponential Decreasing Index (REDI)	Moussa et al., 2019	$REDI_{Today}^{\lambda} = \frac{1}{\sum_{i=0}^{1v} \alpha_i^{\lambda}} \sum \alpha_i^{\lambda} * TL_i$ <i>Where</i> $\alpha_i^{\lambda} = \begin{cases} 0 & \rightarrow TL \text{ missing} \\ e^{-\lambda} & \text{Otherwise} \end{cases}$ λ : 0.1 ; 0.3 and 0.02

NB: we use negative values of the REDI calculated with Lambda (λ) of 0.1 to simulate an acute component for this model as proposed by original author.

1.1 Statical analysis

The data are expressed as mean $\pm$ standard deviation. The Pearson correlation coefficient is used to assess the strength and direction of a linear relationship between variables. Curve fitting technique was used to fit data with different equations. Root Mean Square Error (RMSE) was used to assess the average magnitude of the differences between predicted values and observed values in non-linear regression models. A significance level of 0.05 was chosen for the analysis.

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2. Results

Table 2. The descriptive statistics of training load models metrics and heart rate variability metrics

	Metrics	N	Mean $\pm$ SD
Training load metrics			
HRSS		29	51.03 $\pm$ 33.18
Rolling average	Acute_RA	120	12.4 $\pm$ 10.7
	Chronic_RA	100	11.8 $\pm$ 7.51
	TSB_RA	100	2.31 $\pm$ 6.84
EWMA	Acute_EWMA	127	12.8 $\pm$ 8.28
	Chronic_EWMA	127	13.2 $\pm$ 4.53
	TSB_EWMA	127	0.4 $\pm$ 4.96
Coggan	Acute_Cog	127	12.7 $\pm$ 8.98
	Chronic_Cog	127	13.2 $\pm$ 4.76
	TSB_Cog	127	0.48 $\pm$ 5.74
REDI	REDI+0.02	127	17 $\pm$ 7.54
	REDI-0.1	127	-14.4 $\pm$ 10.5
	REDI+0.3	127	18.1 $\pm$ 17.6
HRV metrics			
RMSSD		76	45.5 $\pm$ 20
Ln_RMSSD		76	3.73 $\pm$ 0.42
LF		76	0.07 $\pm$ 0.04
HF		76	0.08 $\pm$ 0.05
LF/HF		76	0.92 $\pm$ 0.42
RMSSD_LN_RA		123	3.76 $\pm$ 0.22

The data contains 29 training sessions with an effective average training load of (51.03 $\pm$ 33.18). Days without training are given a load of zero and are not included in this mean. 75 HRV measurements were conducted during the 127-day monitoring of the athlete. The calculated values (Acute, Chronic, and TSB) do not have any missing values, except for the rolling average model, which requires 7 and 28 days to start calculating acute and chronic values, respectively.

2.1 Linear association

Table 3. correlation matrix of training load and heart rate variability metrics.

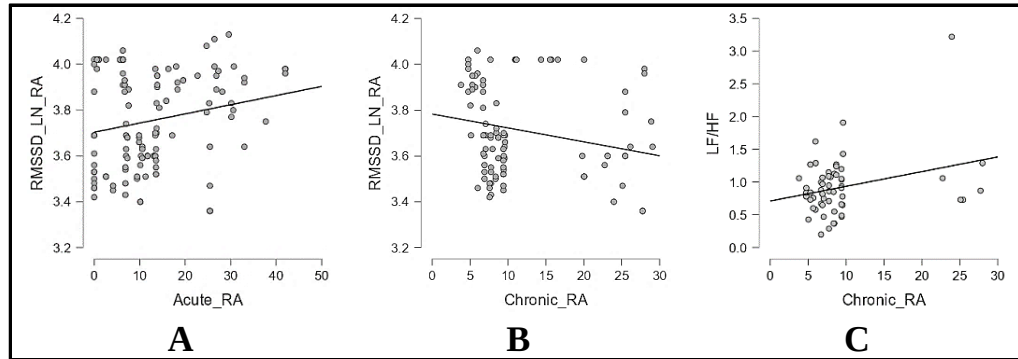
		RMSSD	Ln_RMSSD	LF	HF	LF/HF	RMSSD_LN_RA
HRSS		0.066	0.057	0.129	0.139	-0.017	0.159
Rolling average	ATL	-0.032	0.029	0.221	0.074	0.106	0.202*
	CTL	-0.208	-0.223	-0.131	-0.229	0.291*	-0.221*
	TSB	0.126	0.066	0.051	0.104	0.221	-0.143
EWMA	ATL	0.022	0.056	0.243*	0.109	0.212	0.101
	CTL	0.041	0.074	0.239*	0.068	0.277*	0.105
	TSB	-0.002	-0.031	-0.208	-0.129	-0.118	-0.072
Coggan	ATL	0.021	0.059	0.250*	0.12	0.196	0.131
	CTL	0.042	0.074	0.241*	0.073	0.274*	0.103
	TSB	0.001	-0.034	-0.211	-0.139	-0.092	-0.119
REDI	REDI+0.02	0.221	0.267*	0.432***	0.430***	0.065	0.369***
	REDI-0.1	-0.215	-0.264*	-0.439***	-0.426***	-0.041	-0.338***
	REDI+0.3	0.123	0.169	0.334***	0.279*	0.07	0.274**

* :P<0.05 ;** :P<0.01 ;*** :P<0.001

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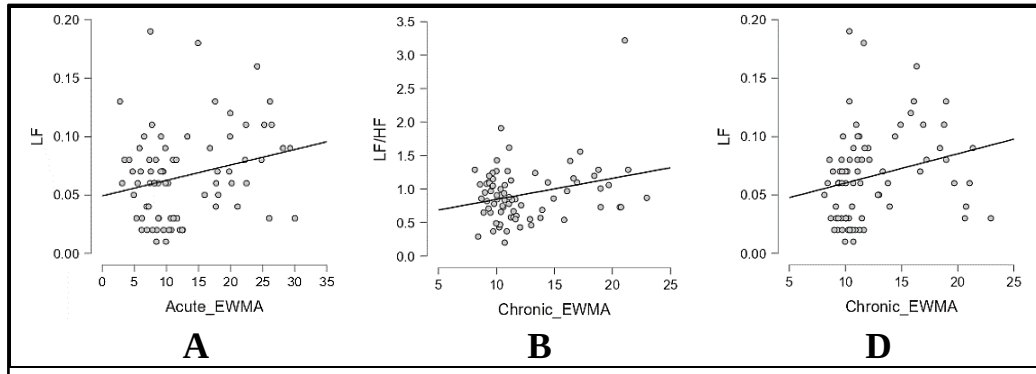
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Fig. 1 Significant correlation between metrics of the Rolling average training load model and HRV metrics



For the rolling average model, the results show a positive significant correlation between acute TL and the rolling average of natural logarithm of RMSSD ($P < 0.05$). the chronic TL shows a negative correlation with RMSSD_LN_RA ($P < 0.05$) and positive correlation with the ratio LF/HF ($P < 0.05$).

Fig. 2. Significant correlations between metrics of the EWMA model and HRV metrics

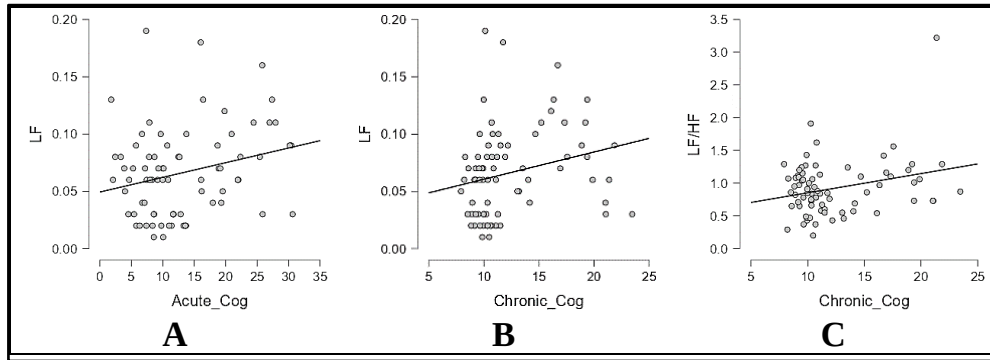


In the EWMA model, we have identified three significant positive correlations. The first correlation is between Acute TL and LF, indicating statistical significance ($p\text{-value} < 0.05$). The second correlation is between Chronic and LF, also showing statistical significance ($p\text{-value} < 0.05$). Additionally, we found a significant positive correlation between Chronic and the ratio LF/LH, with both variables having a $p\text{-value}$ less than 0.05.

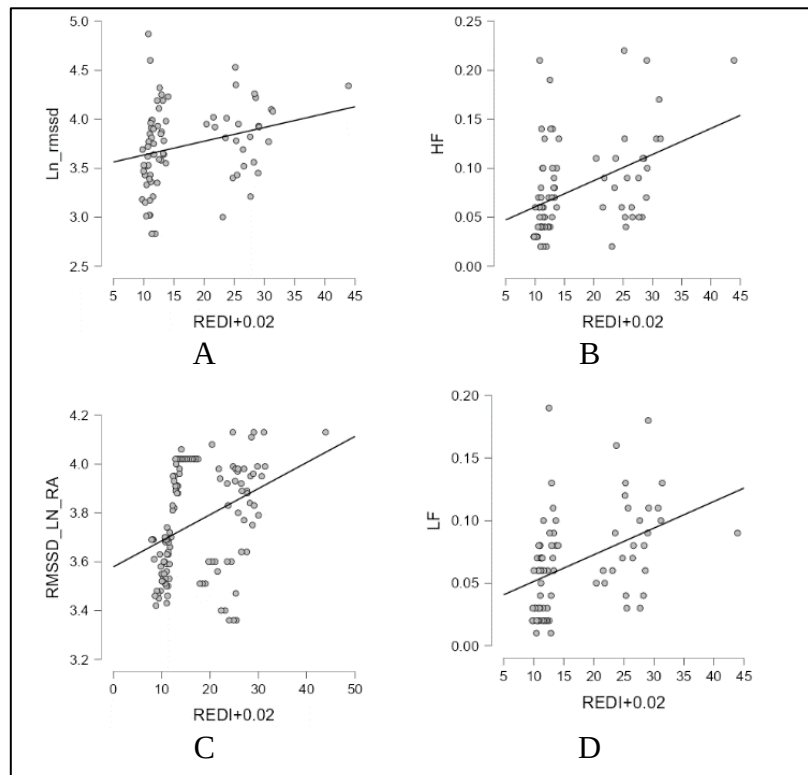
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Fig. 3. Significant correlations between metrics of the Coggan model and HRV metrics.

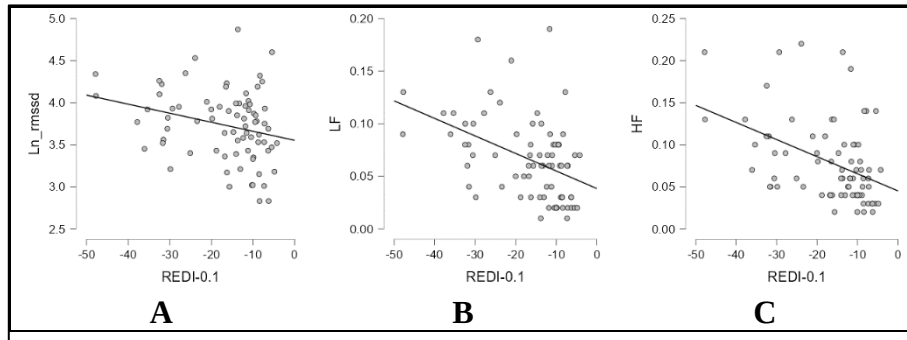


In the Coggan model, we observed three significant positive correlations. The first correlation is between Acute TL and LF, which shows statistical significance ($p\text{-value} < 0.05$). The second correlation is between Chronic and LF, also demonstrating statistical significance ($p\text{-value} < 0.05$). Lastly, we found a significant positive correlation between Chronic and the ratio LF/LH, with both variables having a $p\text{-value}$ less than 0.05.



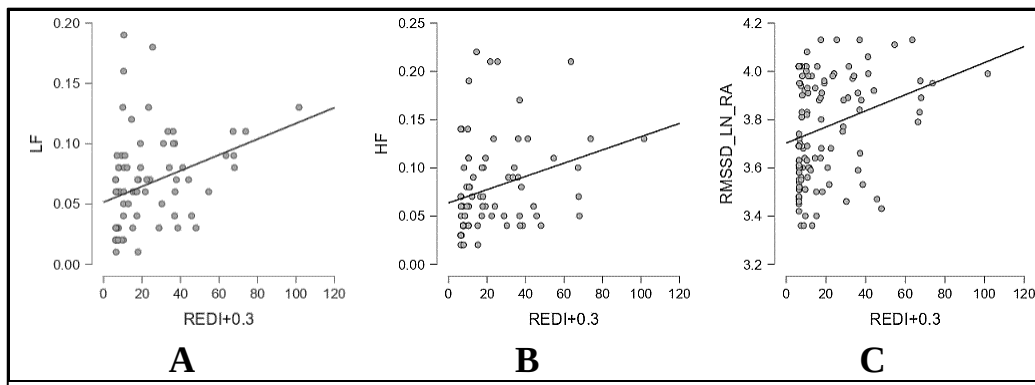
In the REDI model, using a lambda value of 0.02, we have identified four significant positive correlations. Specifically, we found that Ln_Rmsd has a correlation coefficient with statistical significance ($p\text{-value} < 0.05$), along with RMSSD_LN_RA, LF, and HF, which also exhibit significant a strong positive correlation ($p\text{-value} < 0.001$).

Fig. 4. Significant correlations between negative values of the REDI model with lambda of 0.1 and HRV metrics.



In the REDI model, using a lambda value of 0.1 and negative values, we have identified three significant negative correlations. Specifically, we found that Ln_Rmssd has a correlation coefficient with statistical significance (p -value < 0.05), along with RMSSD_LN_RA, LF, and HF, which also exhibit a strong positive correlation (p -value < 0.001).

Fig. 5. Significant correlations between metrics of the REDI model with lambda of 0.3 and HRV metrics.



The REDI+0.3 model exhibits several significant correlations with HRV metrics. Specifically, we observed a positive and statistically significant correlation between REDI+0.3 and LF ($p < 0.001$). Furthermore, there was a significant positive correlation between REDI+0.3 and HF ($p < 0.05$). However, other HRV metrics, such as RMSSD, Ln_RMSSD, LF/HF, and RMSSD_LN_RA, did not show significant correlations with the REDI+0.3 model.

2.2 Non-linear association

In this section, a non-linear curve fitting technic was performed to find the best predictor to the rolling average of the natural logarithm of RMSSD (Ln_RMSSD_RA).

▪ TSB_EWMA vs Ln_RMSSD_RA

With R^2 of 0.33 and RMSE of 0.18, The polynomial quartic equation was the best fit of the TSB_EWMA and HRV changes.

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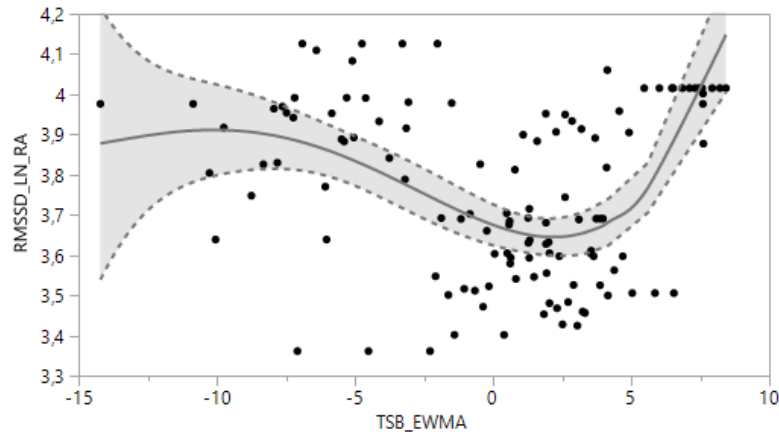
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Table 4. parameters estimate of the quartic model between TSB_EWMA and HRV.

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	3,6747653	0,025865	142,07	<,0001*
TSB_EWMA	-0,021646	0,008961	-2,42	0,0172*
(TSB_EWMA-0,3965)^2	0,004413	0,001216	3,63	0,0004*
(TSB_EWMA-0,3965)^3	0,0005811	0,000187	3,11	0,0024*
(TSB_EWMA-0,3965)^4	0,0000168	1,523e-5	1,10	0,2721

The R-squared value of 0.33 suggests that approximately 33% of the variation in Ln_RMSSD_RA can be explained by the TSB_EWMA and its higher-order polynomial terms in the model. The root mean squared error (RMSE) of 0.18 represents the average difference between the predicted Ln_RMSSD_RA values from the model and the actual Ln_RMSSD_RA values in the dataset, Which can be considered as very acceptable.

Fig. 6. Polynomial quartic curve fitting of the relation TSB_EWMA and Ln_RMSSD_RA



The regression analysis model examines the relationship between TSB_EWMA (Training Stress Balance Exponential Weighted Moving Average) and Ln_RMSSD_RA (Natural Logarithm of RMSSD Relative to Acute Stress). The estimated intercept of the model is 3.67, indicating the expected value of Ln_RMSSD_RA when TSB_EWMA is zero. The coefficient for TSB_EWMA is -0.021646, suggesting that for every unit increase in TSB_EWMA, Ln_RMSSD_RA is expected to decrease by approximately 0.021646 units. This coefficient is statistically significant with a t-ratio of -2.42 and a p-value of 0.0172, indicating a significant relationship between TSB_EWMA and Ln_RMSSD_RA. The model also includes higher-order polynomial terms of TSB_EWMA, denoted as $(TSB_EWMA - 0.3965)^2$, $(TSB_EWMA - 0.3965)^3$, and $(TSB_EWMA - 0.3965)^4$. These terms capture the non-linear relationship between TSB_EWMA and Ln_RMSSD_RA. The coefficients associated with these terms are all statistically significant,

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indicating that the non-linear relationship between TSB_EWMA and Ln_RMSSD_RA is meaningful.

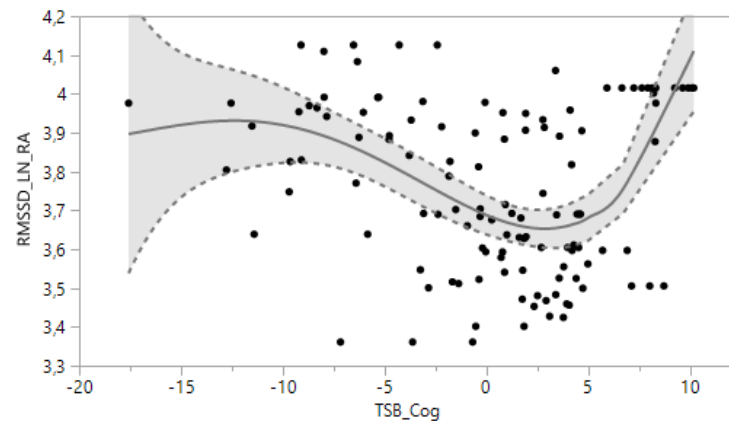
▪ TSB_Coggan vs Ln_RMSSD_RA

With R² of 0.27 and RMSE of 0.19, The polynomial quartic equation was the best fit of the TSB_Coggan and HRV changes.

Table 5. Parameters estimate of the quartic model between TSB_Coggan and HRV.

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	3,6874018	0,025476	144,74	<,0001*
TSB_Cog	-0,019133	0,007427	-2,58	0,0112*
(TSB_Cog-0,48108)^2	0,0028449	0,00083	3,43	0,0008*
(TSB_Cog-0,48108)^3	0,0003142	0,000109	2,88	0,0047*
(TSB_Cog-0,48108)^4	7,4814e-6	6,974e-6	1,07	0,2856

Fig. 7. polynomial quartic curve fitting of the relation TSB_Coggan and Ln_RMSSD_RA



The R-squared value of 0.27 indicates that approximately 27 % of the variation in Ln_RMSSD_RA can be explained by the TSB_Coggan and its higher-order polynomial terms in the model. The root mean squared error (RMSE) of 0.19 represents the average difference between the predicted Ln_RMSSD_RA values from the model and the actual Ln_RMSSD_RA values in the dataset.

The estimated intercept of the model is 3.6874018, indicating the expected value of Ln_RMSSD_RA when TSB_Coggan is zero. The coefficient for TSB_Cog is -0.019133, suggesting that for every unit increase in TSB_Coggan, Ln_RMSSD_RA is expected to decrease by approximately 0.019133 units. This coefficient is statistically significant with a t-ratio of -2.58 and a p-value of 0.0112, indicating a significant relationship between TSB_Coggan and Ln_RMSSD_RA.

Similar to the previous model, higher-order polynomial terms of TSB_Coggan are included in the model to capture the non-linear relationship.

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The terms $(TSB_Cog-0.48108)^2$, $(TSB_Cog-0.48108)^3$, and $(TSB_Cog-0.48108)^4$ represent the non-linear effects. The coefficients associated with these terms are statistically significant, suggesting a meaningful non-linear relationship between TSB_Cog and Ln_RMSSD_RA .

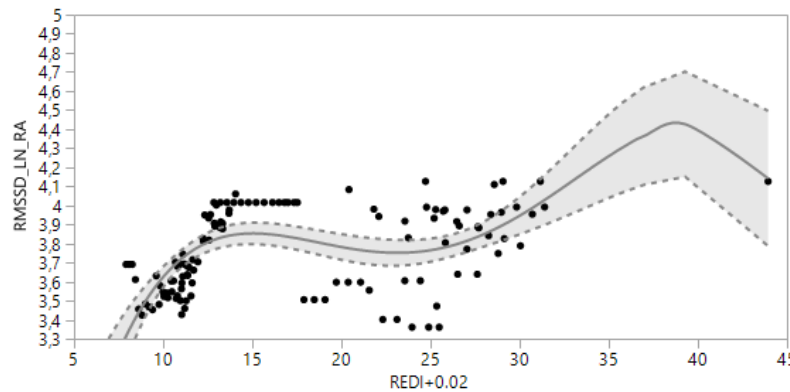
▪ REDI+0.02 vs Ln_RMSSD_RA

With R^2 of 0.27 and RMSE of 0.19, The polynomial quartic equation was the best fit of the TSB_Cog and HRV changes.

Table 6. parameters estimate of the quartic model between REDI+0.02 and HRV.

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	4,0643905	0,106338	38,22	<,0001*
REDI+0.02	-0,013412	0,006401	-2,10	0,0383*
$(REDI+0.02-16,6441)^2$	-0,002846	0,000624	-4,56	<,0001*
$(REDI+0.02-16,6441)^3$	0,0005198	9,931e-5	5,23	<,0001*
$(REDI+0.02-16,6441)^4$	-0,000014	3,141e-6	-4,46	<,0001*

Fig. 8. polynomial quartic curve fitting of the relation REDI+0.02 and Ln_RMSSD_RA



The R-squared value of 0.27 indicates that approximately 27% of the variation in Ln_RMSSD_RA can be explained by the REDI+0.02 and its higher-order polynomial terms in the model. The root mean squared error (RMSE) of 0.19 represents the average difference between the predicted Ln_RMSSD_RA values from the model and the actual Ln_RMSSD_RA values in the dataset. The estimated intercept of the model is 4.064, indicating the expected value of Ln_RMSSD_RA when REDI+0.02 is zero. The coefficient for REDI+0.02 is -0.013, suggesting that for every unit increase in REDI+0.02, Ln_RMSSD_RA is expected to decrease by approximately 0.013 units.

These findings indicate that REDI+0.02 has a significant relation to Ln_RMSSD_RA , and the inclusion of higher-order polynomial terms improves the model's ability to capture the non-linear relationship. However, it is important to note that the magnitude of the effect is relatively small, as indicated by the coefficient estimates.

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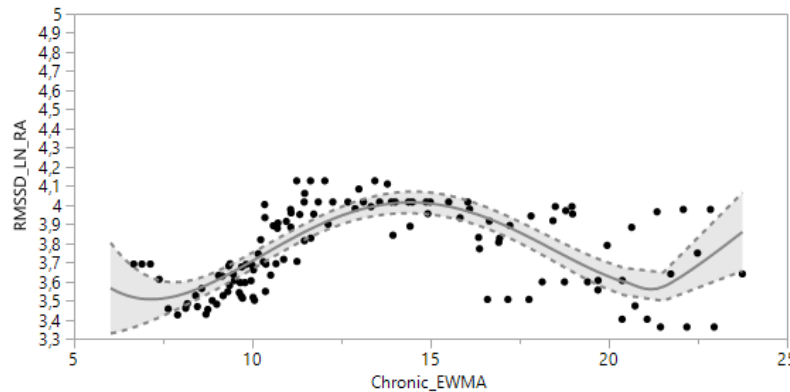
▪ Chronic_EWMA vs Ln_RMSSD_RA

With R^2 of 0.50 and RMSE of 0.15, The polynomial quartic equation was the best fit of the Chronic_EWMA and HRV changes.

Table 7. parameters estimate of the quartic model between Chronic_EWMA and HRV.

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	3,3813343	0,108179	31,26	<,0001*
Chronic_EWMA	0,0456726	0,008716	5,24	<,0001*
(Chronic_EWMA-13,1986)^2	-0,017396	0,001986	-8,76	<,0001*
(Chronic_EWMA-13,1986)^3	-0,000837	0,000311	-2,70	0,0081*
(Chronic_EWMA-13,1986)^4	0,0001867	0,000038	4,91	<,0001*

Fig. 9. Polynomial quartic curve fitting of the relation Chronic_EWMA and Ln_RMSSD_RA



The R-squared value of 0.50 indicates that approximately 50% of the variation in Ln_RMSSD_RA can be explained by the Chronic_EWMA and its higher-order polynomial terms in the model. The root mean squared error (RMSE) of 0.15 represents the average difference between the predicted Ln_RMSSD_RA values from the model and the actual Ln_RMSSD_RA values in the dataset.

The estimated intercept of the model is 3.38, indicating the expected value of Ln_RMSSD_RA when Chronic_EWMA is zero. The coefficient for Chronic_EWMA is 0.046, suggesting that for every unit increase in Chronic_EWMA, Ln_RMSSD_RA is expected to increase by approximately 0.0456726 units.

These findings indicate that Chronic_EWMA has a significant relation to Ln_RMSSD_RA, and the inclusion of higher-order polynomial terms improves the model's ability to capture the non-linear relationship. The relatively high R-squared value suggests that Chronic_EWMA explains a substantial portion of the variation in Ln_RMSSD_RA.

Discussion

The present study aimed to investigate the associations between HRV metrics and various training load models. Training load models provide valuable insights into the dynamic nature of training load, allowing coaches and athletes to monitor and manage training intensity effectively. In this study, we examined the relation between HRV metrics and different training load models, including Rolling Average, EWMA, Coggan, and REDI.

The first approach aims to search for a linear relation with a simple bivariate correlation. This approach will highlight the best model that can fit a real dynamic of the HRV response to training.

With the Rolling Average model, we observed significant positive correlations between HRV metrics and the Acute_RA, Chronic_RA, but not TSB_RA. Specifically, there were significant positive correlations between Acute_RA and LF ($p < 0.05$), as well as Chronic_RA and LF ($p < 0.05$). These findings suggest that LF is associated with the rolling average estimates of training load within the Rolling Average model. The model failed to predict HRV changes in a linear relation way. Especially when the TSB, the most important metric that should give a sight on the athlete freshness did not match HRV changes.

Moving on to the EWMA model, we found significant positive correlations between Acute_EWMA and LF ($p < 0.05$), as well as between Chronic_EWMA and LF ($p < 0.05$). These findings suggest that LF is positively associated with the acute and chronic estimates of training load within the EWMA model. However, no significant correlations were observed between HRV metrics and other variables in the EWMA model.

Within the Coggan model, a significant positive correlation was found between Acute_Cog and LF ($p < 0.05$). This indicates that LF is associated with the acute estimate of training load in the Coggan model. However, no other HRV metrics in this model showed significant correlations.

Finally, regarding the REDI model, which assesses the ratio of acute to chronic training load, we found significant positive correlations between REDI+0.02 and LF ($p < 0.001$), as well as between REDI-0.1 and LF ($p < 0.001$). Additionally, REDI+0.3 exhibited a significant positive correlation with LF ($p < 0.01$). These findings indicate that LF is strongly associated with different variations of the REDI model, suggesting that LF is influenced by the acute to chronic training load ratio.

In the non-linear curve fitting we found the following:

The results of the polynomial quartic models between TSB_EWMA, TSB_Coggan, REDI+0.02, Chronic_EWMA, and HRV provide valuable

insights into the relationship between these training load models and Ln_RMSSD_RA.

With TSB_EWMA, the model exhibited an R-squared value of 0.33, indicating that approximately 33% of the variation in Ln_RMSSD_RA can be explained by TSB_EWMA and its higher-order polynomial terms. The coefficient for TSB_EWMA was -0.022, indicating that with each unit increase in TSB_EWMA, Ln_RMSSD_RA is expected to decrease by approximately 0.022 units. The statistically significant coefficients associated with the higher-order polynomial terms indicate a meaningful non-linear relationship between TSB_EWMA and Ln_RMSSD_RA.

For the TSB_Coggan, the model showed an R-squared value of 0.27, suggesting that around 27% of the variation in Ln_RMSSD_RA can be explained by TSB_Coggan and its higher-order polynomial terms. The coefficient for TSB_Cog was -0.019, indicating that an increase in TSB_Coggan is associated with a decrease in Ln_RMSSD_RA. Similarly, the significant coefficients associated with the higher-order polynomial terms highlight the presence of a non-linear relationship between TSB_Coggan and Ln_RMSSD_RA.

Next, the model between REDI+0.02 and Ln_RMSSD_RA demonstrated an R-squared value of 0.27, indicating that approximately 27% of the variation in Ln_RMSSD_RA can be explained by REDI+0.02 and its higher-order polynomial terms. The coefficient for REDI+0.02 was -0.013, indicating that an increase in REDI+0.02 is associated with a decrease in Ln_RMSSD_RA.

Lastly, the model between Chronic_EWMA and Ln_RMSSD_RA returned an R-squared value of 0.50, suggesting that approximately 50% of the variation in Ln_RMSSD_RA can be explained by Chronic_EWMA and its higher-order polynomial terms. The coefficient for Chronic_EWMA was 0.046, indicating that an increase in Chronic_EWMA is associated with an increase in Ln_RMSSD_RA. The significant coefficients associated with the higher-order polynomial terms indicate a meaningful non-linear relationship between Chronic_EWMA and Ln_RMSSD_RA.

Comparing the models, the Chronic_EWMA model exhibited the highest R-squared value of 0.50, indicating a relatively stronger relationship with Ln_RMSSD_RA compared to the other models. Additionally, the RMSE value of 0.15 for the Chronic_EWMA model suggests a smaller average difference between the predicted and actual Ln_RMSSD_RA values compared to the other models. Therefore, based on these results, the Chronic_EWMA model appears to be the most favorable in capturing the relationship between training load and HRV.

Conclusion

This study aimed to explore the associations between HRV metrics and different training load models, including Rolling Average, EWMA, Coggan, and REDI. The results revealed that the Rolling Average model showed positive correlations between HRV metrics and Acute_RA, Chronic_RA, but not TSB_RA. However, the model failed to predict HRV changes accurately. The EWMA model exhibited positive correlations between HRV metrics and Acute_EWMA, Chronic_EWMA, but no significant correlations with other variables. The Coggan model showed a positive correlation between HRV metrics and Acute_Cog, while the REDI model demonstrated strong associations between HRV metrics and different variations of the acute to chronic training load ratio.

Furthermore, the non-linear curve fitting indicated that TSB_EWMA, TSB_Coggan, REDI+0.02, and Chronic_EWMA had significant relationships with Ln_RMSSD_RA. The Chronic_EWMA model showed the highest R-squared value of 0.50, suggesting a stronger relationship with Ln_RMSSD_RA compared to other models. Additionally, the Chronic_EWMA model had a smaller average difference (RMSE of 0.15) between predicted and actual Ln_RMSSD_RA values.

In summary, the Chronic_EWMA model emerged as the most favourable in capturing the relationship between training load and HRV, exhibiting a stronger association and better predictive performance compared to the other models examined in this study.

It is important to note that further research is necessary to validate these findings and understand the underlying physiological mechanisms driving the observed relationships. Additionally, considering the limitations of the study, such as the sample size and potential confounding factors, caution should be exercised when interpreting and generalizing these results.

References

- Allen, H. et Coggan, A. R. (2010). Training and racing with a power meter. VeloPress.
- Altini, M. et Plews, D. (2021). What is behind changes in resting heart rate and heart rate variability? A large-scale analysis of longitudinal measurements acquired in free-living. *Sensors*, 21(23), 7932.
- Bahenský, P. et Grosicki, G. J. (2021). Superior Adaptations in Adolescent Runners Using Heart Rate Variability (HRV)-Guided Training at Altitude. *Biosensors*, 11(3). <https://doi.org/10.3390/bios11030077>
- Banister, E. W. (1991). Modeling elite athletic performance. Dans *Physiological testing of elite athletes* (vol. 347, p. 403-422). Kinanthropometry Champaign IL: Human Kinetics Books.
- Bosquet, L., Papelier, Y., Leger, L. et Legros, P. (2003). Night heart rate variability during overtraining in male endurance athletes. *Journal of sports medicine and physical fitness*, 43(4), 506.

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-
- Carrasco-Poyatos, M., González-Quílez, A., Martínez-González-Moro, I. et Granero-Gallegos, A. (2020). HRV-Guided Training for Professional Endurance Athletes: A Protocol for a Cluster-Randomized Controlled Trial. *International Journal of Environmental Research and Public Health*, 17(15). <https://doi.org/10.3390/ijerph17155465>
- Foster, C. (1998). Monitoring training in athletes with reference to overtraining syndrome. *Medicine and Science in Sports and Exercise*, 30(7), 1164-1168.
- Friel, J. (2022). Estimating Training Stress Score (TSS) | TrainingPeaks. <https://www.trainingpeaks.com/learn/articles/estimating-training-stress-score-tss>
- Gabbett, T. J. (2016). The training-injury prevention paradox: should athletes be training smarter and harder? *British journal of sports medicine*, 50(5), 273-280. <https://doi.org/10.1136/bjsports-2015-095788>
- Harvard Health. (2021). Heart rate variability: How it might indicate well-being - Harvard Health. <https://www.health.harvard.edu/blog/heart-rate-variability-new-way-track-well-2017112212789>
- Hedelin, R., Kenttä, G., Wiklund, U., Bjerle, P. E. R. et Henriksson-Larsén, K. (2000). Short-term overtraining: effects on performance, circulatory responses, and heart rate variability. *Medicine and Science in Sports and Exercise*, 32(8), 1480-1484.
- Hedelin, R., Wiklund, U., Bjerle, P. et Henriksson-Larsén, K. (2000). Cardiac autonomic imbalance in an overtrained athlete. *Medicine and Science in Sports and Exercise*, 32(9), 1531-1533.
- Hernández-Vicente, A., Hernando, D., Marín-Puyalto, J., Vicente-Rodríguez, G., Garatachea, N., Pueyo, E. et Bailón, R. (2021). Validity of the polar h7 heart rate sensor for heart rate variability analysis during exercise in different age, body composition and fitness level groups. *Sensors*, 21(3), 902.
- Hopkins, W. G. (1991, 1991/09/01). Quantification of Training in Competitive Sports. *Sports Medicine*, 12(3), 161-183. <https://doi.org/10.2165/00007256-199112030-00003>
- Hottenrott, K., Hoos, O. et Esperer, H. D. (2006). Heart rate variability and physical exercise. *Current status. Herz*, 31(6), 544-552.
- Hulin, B. T., Gabbett, T. J., Caputi, P., Lawson, D. W. et Sampson, J. A. (2016). Low chronic workload and the acute: chronic workload ratio are more predictive of injury than between-match recovery time: a two-season prospective cohort study in elite rugby league players. *British journal of sports medicine*, 50(16), 1008-1012.
- Hynynen, E. S. A., Uusitalo, A., Kontinen, N. et Rusko, H. (2006). Heart rate variability during night sleep and after awakening in overtrained athletes. *Medicine and Science in Sports and Exercise*, 38(2), 313.
- Kiviniemi, A. M., Hautala, A. J., Kinnunen, H., Nissilä, J., Virtanen, P., Karjalainen, J. et Tulppo, M. P. (2010). Daily exercise prescription on the basis of HR variability among men and women. *Medicine and Science in Sports and Exercise*, 42(7), 1355-1363.
- Kiviniemi, A. M., Hautala, A. J., Kinnunen, H. et Tulppo, M. P. (2007). Endurance training guided individually by daily heart rate variability measurements. *European journal of applied physiology*, 101(6), 743-751.
- Maheshwari, A., Norby, F. L., Soliman, E. Z., Adabag, S., Whitsel, E. A., Alonso, A. et Chen, L. Y. (2016). Low heart rate variability in a 2-minute electrocardiogram recording is associated with an increased risk of sudden cardiac death in the general population: the atherosclerosis risk in communities study. *PLOS ONE*, 11(8), e0161648.
- Makivić, B., Nikić Djordjević, M. et Willis, M. S. (2013). Heart Rate Variability (HRV) as a tool for diagnostic and monitoring performance in sport and physical activities. *Journal of Exercise Physiology Online*, 16(3).
- McCall, A., Dupont, G. et Ekstrand, J. (2016). Injury prevention strategies, coach compliance and player adherence of 33 of the UEFA Elite Club Injury Study teams: a survey of teams' head medical officers. *British journal of sports medicine*, 50(12), 725. <https://doi.org/10.1136/bjsports-2015-095259>

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- McGehee, J. C., Tanner, C. J. et Houmard, J. A. (2005). ACOMPARISON OF METHODS FOR ESTIMATING THE LACTATE THRESHOLD. *The Journal of Strength & Conditioning Research*, 19(3), 553-558.
- Mourot, L., Bouhaddi, M., Perrey, S., Cappelle, S., Henriët, M. T., Wolf, J. P., Rouillon, J. D. et Regnard, J. (2004). Decrease in heart rate variability with overtraining: assessment by the Poincaré plot analysis. *Clinical physiology and functional imaging*, 24(1), 10-18.
- Moussa, I., Leroy, A., Saulière, G., Schipman, J., Toussaint, J.-F. et Sedeaud, A. (2019). Robust Exponential Decreasing Index (REDI): adaptive and robust method for computing cumulated workload. *BMJ Open Sport & Exercise Medicine*, 5(1), e000573.
- Natarajan, A., Pantelopoulos, A., Emir-Farinas, H. et Natarajan, P. (2019). Heart rate variability with photoplethysmography in 8 million individuals: results and scaling relations with age, gender, and time of day. *bioRxiv*, 772285.
- OMS, o. m. d. l. s. (2021). Obésité et surpoids. World Health Organization: WHO. <https://www.who.int/fr/news-room/fact-sheets/detail/obesity-and-overweight>
- Saboul, D., Balducci, P., Millet, G., Pialoux, V. et Hautier, C. (2016, 2016/02/17). A pilot study on quantification of training load: The use of HRV in training practice. *European Journal of Sport Science*, 16(2), 172-181. <https://doi.org/10.1080/17461391.2015.1004373>
- Stone, J. D., Ulman, H. K., Tran, K., Thompson, A. G., Halter, M. D., Ramadan, J. H., Stephenson, M., Finomore Jr, V. S., Galster, S. M. et Rezai, A. R. (2021). Assessing the accuracy of popular commercial technologies that measure resting heart rate and heart rate variability. *Frontiers in Sports and Active Living*, 37.
- Tian, Y., He, Z.-h., Zhao, J.-x., Tao, D.-l., Xu, K.-y., Earnest, C. P. et Mc Naughton, L. R. (2013). Heart rate variability threshold values for early-warning nonfunctional overreaching in elite female wrestlers. *The Journal of Strength & Conditioning Research*, 27(6), 1511-1519.
- Uusitalo, A. L. T., Uusitalo, A. J. et Rusko, H. K. (2000). Heart rate and blood pressure variability during heavy training and overtraining in the female athlete. *International Journal of Sports Medicine*, 21(01), 45-53.
- Williams, S., West, S., Cross, M. J. et Stokes, K. A. (2017). Better way to determine the acute:chronic workload ratio? *British journal of sports medicine*, 51(3), 209. <https://doi.org/10.1136/bjsports-2016-096589>