# Associations Between Heart Rate Variability–Derived Indexes and Training Load: Repeated Measures Correlation Approach Contribution

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## Abstract

Davletyarova, K, Vacher, P, Nicolas, M, Kapilevich, LV, and Mourot, L. Associations between heart rate variability–derived indexes and training load: repeated measures correlation approach contribution. *J Strength Cond Res* XX(X): 000–000, 2020—This study aimed to evaluate whether similar associations between indexes derived from heart rate variability (HRV) analyses and training load (TL) could be obtained by using the commonly used Pearson correlation technique and the repeated measures correlation (rmcorr). Fourteen well-trained swimmers (18.5 ± 1.6 years) participated. The training period lasted 4 weeks with a gradual increase in TL. Daily external TL (exTL) and internal TL (inTL) were summed to obtain a weekly TL, and HRV analyses were performed every Saturday morning. During the 4-week period, exTL and inTL increased ($p < 0.05$) together with a decrease ($p < 0.05$) in heart rate and an increase ($p < 0.05$) of cardiac parasympathetic indexes. No significant correlation was found using Pearson correlation while significant associations were found using rmcorr; considering exTL, positive (mean R-R interval [MeanRR], root mean square of differences between successive RR interval [RMSSD], low frequency [LF], high frequency [HF], instantaneous beat-to-beat variability [SD1], continuous beat-to-beat variability [SD2], SD1/SD2; $r$ from 0.59 to 0.46, $p$ value from <0.001 to 0.002) and negative (mean heart rate [meanHR]; $r = -0.55$, $p < 0.001$) associations were found. Considering inTL, positive (MeanRR, RMSSD, LF, HF, HFnu, SD1, SD2, SD1/SD2; $r$ from 0.56 to 0.34, $p$-value from <0.001 to 0.025) and negative (meanHR, LFnu, LF/HF; $r$ from $-0.49$ to $-0.34$, $p$ value from 0.001 to 0.025) associations were found. The rmcorr statistical method was able to show associations between parasympathetic indexes and TL contrary to Pearson correlation analysis. Because rmcorr is specifically designed to investigate within-individual association for paired measures assessed on 2 or more occasions for multiple individuals, it should constitute a tool for future training monitoring researches based on a repeated-measures protocol.

**Key Words:** multiple correlation method, statistic, training monitoring, athletes

## Introduction

Monitoring athletes' external (objective measures of the work performed by the athlete during training or competition; external training load [exTL]) and internal (relative physiological or psycological stressors imposed on the athlete during training or competition; internal training load [inTL]) training load (TL) is crucial for assessing whether they are adapting properly to their training program, for evaluating if the balance between exercise training and recovery is optimal, and, ultimately, for improving sport performance (8,21,25). Depending on the context of the program to which they are applied and the objectives to be achieved, several monitoring methods have been proposed with their own inherent strengths and limitations. Heart rate (HR)-derived indexes, such as HR variability (HRV) or HR recovery, required low cost hardware and software and have the advantage of being independent of location and activity (3,8). Despite having limitations in data interpretation and direct use to prescribe training, they have been highlighted as having a great potential and have been largely used for monitoring training adaptations (2,5,8,13).

Although investigating associations between HR-derived indexes and TL during a training period (i.e., repeated measures of the same variables in the same subjects), regression/Pearson correlation is commonly used. When relative change over a training period is considered (i.e., simple pre-training to post-training evaluation), data from a specific subject are used only one time to evaluate the strength of the correlation (i.e., association between relative pre-post training changes in HRV indices, and a relative pre-post training change in TL is calculated using one data point per subject; e.g., (9)). But most of the time, multiple use of the same data in a specific subject is used for calculation. For example, in the previously cited study, the authors calculated correlations between baseline data and the change over the training period, i.e., using the baseline data a second time in the relative change calculation (9). This procedure is common (15,24,31). The use of multiple recordings on a specific subject could also be performed using absolute data recorded once pre-training and once post-training (26,34) or using relative changes but over multiple time points (10,16). Analyzing nonindependent data

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with techniques that assume independence is a widespread practice. However, such practice has been shown to produce erroneous results (1,22). One common solution is to use the average of the repeated measures data for each subject before performing the correlation. This solution resolves the issue of nonindependence but may lead to misleading results, notably in the case of meaningful individual differences, as previously stated (14,28).

In 1995, Bland and Altman presented an intrasample correlation for analyzing the total intraindividual correlation of pairwise repeated measures (6). Repeated measure correlation (rmcorr) is thus a statistical method for determining the total intraindividual relationships of 2 indicators, assessed in 2 or more cases for several individuals, i.e., typically the case when one wants to assess the association between HR-derived indexes and TL. As Pearson correlation coefficient ($r$), rmcorr coefficient has limitations from $-1$ to 1 and represents the power of the linear relationship between 2 variables but has a much greater statistical power because it does not require averaging or aggregation (4). Complementary, rmcorr conceptual and mathematical development allow analyzing paired repeated measures without averaging or violating the independent and identically distributed assumption, which constitute a clear advantages over simple regression/correlation (4,6).

Hence, the aim of this study was to assess the associations between HRV-derived indexes and exTL and inTL in a group of well-trained swimmers by using and comparing Pearson correlation and rmcorr.

## Methods

### Experimental Approach to the Problem

Subjects were followed throughout a 4-week ecological training period of preparation before the major competition of the year (French championships), which was characterized by a progressive increase in TL. The session rating of perceived exertion has been used to quantify the subjective internal TLs of athletes, as presented elsewhere (18,33,34). At the completion of each training session, athletes provide a 1–10 "rating" on the intensity of the session. The intensity of the session is multiplied by the session duration to provide internal subjective TL (inTL). Swimmers practiced 2 or more training sessions per day; the inTL was summated for each day to create a weekly inTL. In addition, we calculated a weekly exTL as the sum of session volume in kilometers (km). Beat by beat recording of HRV was performed on the Saturday morning (6:30 AM), before any physical activity as a component of the warm-up of morning training session. Swimmers performed a standardized 5-minutes submaximal 9 km·h$^{-1}$ run on the pool deck, followed by 5 minutes of passive recovery by lying on the back (9,33,34). Thereafter, Pearson correlation and rmcorr were performed to evaluate whether any relationships exist between HRV-derived indexes and TLs.

### Subjects

Fourteen national competitive swimmers (6 women; 8 men; Mean ± *SD* age 19.5 ± 0.6 years; 173 ± 6 cm; 63.6 ± 7.1 kg; min–max: 18–20 years) voluntary participated in this study. They competed in swimming for at least 7 years and trained 6 days a week (20.5 ± 2.2 hours per week). All subjects followed a similar training program during the study. None of them smoked or presented cardiovascular or metabolic disease. Swimmers took no medication before or during this study nor were taking any supplements or contraceptive pills. Subjects were informed of the benefits and risks of the investigation before signing an institutionally approved informed consent document to participate in the study. They were informed that the data and results were confidential and that they could withdraw at any time during the study, which was approved by CPP-Est II (2014-A00336-41). All experiments were conducted in accordance with the Declaration of Helsinki.

### Procedures

*Data and Statistical Analyses.* Beat-to-beat HR was recorded using a Suunto t6 Memory Belt (Suunto, Vantaa, Finland). Using the last 2 minutes of the 5 minute-period, mean HR (meanHR), mean R-R interval (MeanRR), root mean square of differences between successive RR intervals (RMSSD), the low frequency (LF; 0.04–0.15 Hz), the high frequency (HF; 0.15–0.40 Hz) (in both absolute and normalized units [nu], i.e., LFnu = LF/[LF + HF] and HFnu = HF/[LF + HF]), and the LF/HF ratio were calculated. We also calculated instantaneous beat-to-beat variability (SD1) and the continuous beat-to-beat variability (SD2) ratio (SD1/SD2) to assess the autonomic interaction with the Poincaré plot method (33).

Results are expressed as means (M) ± *SD*. The Gaussian distribution of the data was verified by the Shapiro-Wilk test. When variables were skewed, they were transformed into their logarithms (ln) for further analyses (10,30,34).

First, two-way analyses of variance (ANOVAs) for repeated measures were performed to assess the effect of time (i.e., T1, T2, T3, and T4) × the effect of sex. When appropriate (violation of sphericity assumption), we applied Greenhouse-Geisser corrections (12). As no significant sex effect was observed, the data were pooled and analyzed together. Post hoc Tukey's tests were applied to determine a difference between 2 mean values if the ANOVA revealed a significant effect. Second, Pearson correlations were performed between inTL, exTL, and HRV indexes (a) based on athlete's average data over the 4 time points of measurements (b) and based on average of the relative changes over time. Finally, repeated measures correlations were performed using the R package labeled "rmcorr" (4). Like a Pearson correlation coefficient ($r$), the rmcorr coefficient ($r_{\text{rm}}$) is bounded by $-1$ to 1 and represents the strength of the linear association between 2 variables (the null hypothesis for rmcorr is $\rho_{\text{rm}} = 0$, and the research/alternative hypothesis is $\rho_{\text{rm}} \neq 0$) (4). Confidence intervals (CIs) were computed by using the optional parameter proposed by the rmcorr package. Finally, both mean correlations and repeated measures correlations CIs were estimated using parametric bootstrapping (1,000 samples), and the following criteria were adopted to interpret the magnitude of the correlation between test measures: <0.1, trivial; 0.1–0.3, small; 0.3–0.5, moderate; 0.5–0.7, large; 0.7–0.9, very large; and 0.9–1.0, almost perfect (20). A $p$ value of <0.05 was considered statistically significant.

## Results

During the 4-week training period (Table 1), both inTL (week 1: 1964 ± 1,182, week 2: 4,978 ± 1,323, week 3: 6,642 ± 1,484, week 4: 6,865 ± 1,209; $F(3, 39) = 36.01$, $p < 0.001$, $\eta^2 = 0.74$) and exTL (week 1: 19.2 ± 6.0 km, week 2: 41.8 ± 10.2 km, week 3: 41.9 ± 11.5 km, week 4: 54.8 ± 4.8 km; $F(3, 39) = 42.94$, $p < 0.001$, $\eta^2 = 0.77$) progressively increased.

**Table 1**

**Heart rate variability indexes.***

| | Week 1 | Week 2 | Week 3 | Week 4 |
|---|---|---|---|---|
| inTL (a.u) | 1964 ± 1,182 | 4,978 ± 1,323† | 6,642 ± 1,484†,‡ | 6,865 ± 1,209†‡ |
| exTL (km) | 19.2 ± 6.0 | 41.8 ± 10.2† | 41.9 ± 11.5† | 54.8 ± 4.8†‡ |
| MeanRR (ms) | 770.5 ± 79.2 | 811.7 ± 104.1 | 827.9 ± 77.1 | 866.2 ± 113.9† |
| MeanHR ($1 \cdot min^{-1}$) | 79.0 ± 8.1 | 75.4 ± 9.6 | 73.4 ± 7.0 | 70.7 ± 8.3† |
| RMSSD (ms) | 32.9 ± 22.4 | 40.1 ± 23.5 | 53.0 ± 31.0† | 57.1 ± 35.3† |
| LF ($ms^{2)}$ | 504.3 ± 381.6 | 808.2 ± 682.5 | 675.4 ± 368.2 | 1,136.8 ± 563.9† |
| HF ($ms^{2)}$ | 454.1 ± 643.6 | 731.5 ± 896.8 | 1,365.8 ± 1757.3† | 1,629.7 ± 1889.8† |
| LFnu (nu) | 60.4 ± 18.2 | 56.6 ± 17.2 | 44.1 ± 20.5 | 53.5 ± 24.2 |
| HFnu (nu) | 39.6 ± 18.2 | 43.4 ± 17.2 | 55.9 ± 20.5 | 46.5 ± 24.2 |
| LF/HF | 2.3 ± 2.2 | 2.0 ± 2.2 | 1.2 ± 1.5 | 2.0 ± 2.1 |
| SD1 (ms) | 23.3 ± 15.9 | 28.4 ± 16.7 | 37.6 ± 22.0† | 40.5 ± 25.1† |
| SD2 (ms) | 58.2 ± 19.3 | 68.6 ± 25.2 | 68.4 ± 20.2 | 78.0 ± 20.1† |
| SD1/SD2 (ms) | 0.4 ± 0.1 | 0.4 ± 0.1 | 0.5 ± 0.2†‡ | 0.5 ± 0.2 |

*inTL = internal training load, exTL = external training load, MeanRR = mean R-R interval, meanHR = mean heart rate, RMSSD = root mean square of differences between successive RR intervals, LF = low frequency, HF = high frequency, nu = normalized units, SD1 = instantaneous beat-to-beat variability, SD2 = continuous beat-to-beat variability.

†$p < 0.05$ difference vs. week 1.

‡$p < 0.05$ difference vs. week 2.

Heart rate variability indexes are presented in Table 1. Mean R-R interval ($F(3, 39) = 4.28$, $p = 0.01$, $\eta^2 = 0.25$), RMSSD ($F(3, 39) = 5.85$, $p = 0.002$, $\eta^2 = 0.31$), LF ($F(3, 39) = 4.44$, $p = 009$, $\eta^2 = 0.25$), HF ($F(3, 39) = 6.64$, $p < 0.001$, $\eta^2 = 0.34$), SD1 ($F(3, 39) = 5.85$, $p = 0.002$, $\eta^2 = 0.31$), SD2 ($F(3, 39) = 3.93$, $p = 0.015$, $\eta^2 = 0.23$), and SD1/SD2 ($F(3, 39) = 5.25$, $p = 0.004$, $\eta^2 = 0.29$) progressively increased during the training program. By contrast, meanHR ($F(3, 39) = 4.41$, $p = 0.009$, $\eta^2 = 0.25$) significantly decreased during the 4 weeks. No significant changes were observed for LFnu ($F(3, 39) = 2.56$, $p < 0.07$, $\eta^2 = 0.16$), HFnu ($F(3, 39) = 2.56$, $p < 0.07$, $\eta^2 = 0.16$), and LF/HF ($F(3, 39) = 2.53$, $p < 0.07$, $\eta^2 = 0.16$).

Using Pearson correlations on average absolute data and on average of relative changes over the course of time, no significant association was found between HRV indexes and neither inTL nor exTL ($p > 0.08$; Tables 2 and 3 for more details).

Using repeated measures correlations (Table 4), the results showed that exTL was largely and positively correlated with MeanRR ($r_{rm} = 0.54$, $p < 0.001$), RMSSD ($r_{rm} = 0.57$, $p < 0.001$), HF ($r_{rm} = 0.59$, $p < 0.001$), SD1 ($r_{rm} = 0.57$, $p < 0.001$), and SD2 ($r_{rm} = 0.50$, $p < 0.01$). External training load was also moderately and positively correlated with LF ($r_{rm} = 0.46$, $p < 0.01$) and SD1/SD2 ($r_{rm} = 0.46$, $p < 0.01$). External training load was largely and negatively correlated with meanHR ($r_{rm} = -0.55$, $p < 0.001$).

Internal training load was largely and positively correlated with RMSSD ($r_{rm} = 0.52$, $p < 0.001$) and SD1 ($r_{rm} = 0.52$, $p < 0.001$). Internal training load was moderately and positively correlated with MeanRR ($r_{rm} = 0.48$, $p < 0.01$), LF ($r_{rm} = 0.37$, $p < 0.05$), HFnu ($r_{rm} = 0.34$, $p < 0.05$), SD2 ($r_{rm} = 0.48$, $p < 0.01$), and SD1/SD2 ($r_{rm} = 0.48$, $p < 0.01$). Internal training load was moderately and negatively correlated with MeanRR ($r_{rm} = -0.49$, $p < 0.01$), LFnu ($r_{rm} = -0.34$, $p < 0.05$), and with LF/HF ($r_{rm} = -0.35$, $p < 0.05$).

## Discussion

The aim of this study was to compare 2 different statistical methods to evaluate the association between exTL, inTL, and indexes derived from HRV in athletes, i.e., Pearson correlation and repeated measures correlation. To the best of our knowledge, this study is the first that used the repeated measures correlation to investigate the cardiac autonomic nervous system—TL associations during a real 4-week training periodization, with weekly evaluation. The results highlighted that using Pearson correlation or repeated measures correlations led to different results,

**Table 2**

**Pearson correlations between training load markers and HRV markers.***

| | External training load (km) | | | | Internal training load (a.u) | | | |
|---|---|---|---|---|---|---|---|---|
| | *r* | *n* | *p* | CI | *r* | *n* | *p* | CI |
| MeanRR | −0.14 | 14 | 0.644 | −0.58 to 0.39 | −0.02 | 14 | 0.940 | −0.69 to 0.69 |
| MeanHR | 0.15 | 14 | 0.617 | −0.35 to 0.63 | 0.048 | 14 | 0.870 | −0.68 to 0.69 |
| RMSSD | 0.22 | 14 | 0.444 | −0.27 to 0.64 | 0.14 | 14 | 0.639 | −0.66 to 0.64 |
| LF | −0.34 | 14 | 0.239 | −0.70 to 0.25 | 0.01 | 14 | 0.972 | −0.46 to 0.42 |
| HF | 0.16 | 14 | 0.589 | −0.39 to 0.64 | 0.12 | 14 | 0.686 | −0.62 to 0.67 |
| LFnu | −0.25 | 14 | 0.382 | −0.66 to 0.52 | −0.09 | 14 | 0.757 | −0.63 to 0.70 |
| HFnu | 0.25 | 14 | 0.382 | −0.47 to 0.69 | 0.09 | 14 | 0.757 | −0.63 to 0.70 |
| LF/HF | −0.31 | 14 | 0.278 | −0.72 to 0.42 | −0.13 | 14 | 0.663 | −0.64 to 0.70 |
| SD1 | 0.22 | 14 | 0.453 | −0.28 to 0.69 | 0.14 | 14 | 0.628 | −0.67 to 0.64 |
| SD2 | −0.25 | 14 | 0.932 | −0.44 to 0.49 | 0.05 | 14 | 0.851 | −0.47 to 0.47 |
| SD1/SD2 | 0.31 | 14 | 0.280 | −0.22 to 0.70 | 0.14 | 14 | 0.621 | −0.83 to 0.69 |

*HRV = heart rate variability; CI = confidence intervals; MeanRR = mean R-R interval; meanHR = mean heart rate; RMSSD = root mean square of differences between successive RR intervals; LF = low frequency; HF = high frequency; nu = normalized units; SD1 = instantaneous beat-to-beat variability; SD2 = continuous beat-to-beat variability.

**Table 3**

**Pearson correlations between training load markers and HRV markers based on relative changes over the course of time.***

| | External training load (km) | | | | Internal training load (a.u) | | | |
|---|---|---|---|---|---|---|---|---|
| | *r* | *n* | *p* | CI | *r* | *n* | *p* | CI |
| MeanRR | 0.30 | 14 | 0.299 | −0.27 to 0.71 | 0.48 | 14 | 0.081 | −0.07 to 0.81 |
| MeanHR | −0.31 | 14 | 0.277 | −0.72 to 0.26 | −0.48 | 14 | 0.085 | −0.81 to 0.07 |
| RMSSD | 0.21 | 14 | 0.482 | −0.36 to 0.67 | 0.34 | 14 | 0.236 | −0.23 to 0.74 |
| LF | 0.10 | 14 | 0.743 | −0.45 to 0.60 | 0.24 | 14 | 0.413 | −0.33 to 0.68 |
| HF | 0.15 | 14 | 0.617 | −0.41 to 0.63 | 0.36 | 14 | 0.209 | −0.21 to 0.75 |
| LFnu | −0.28 | 14 | 0.340 | −0.70 to 0.29 | −0.31 | 14 | 0.288 | −0.72 to 0.26 |
| HFnu | 0.11 | 14 | 0.712 | −0.45 to 0.61 | 0.18 | 14 | 0.539 | −0.39 to 0.65 |
| LF/HF | −0.28 | 14 | 0.339 | −0.71 to 0.29 | −0.30 | 14 | 0.300 | −0.72 to 0.27 |
| SD1 | 0.20 | 14 | 0.483 | −0.37 to 0.66 | 0.34 | 14 | 0.236 | −0.23 to 0.74 |
| SD2 | 0.37 | 14 | 0.191 | −0.20 to 0.75 | 0.47 | 14 | 0.094 | −0.08 to 0.80 |
| SD1/SD2 | 0.24 | 14 | 0.410 | −0.33 to 0.68 | 0.36 | 14 | 0.208 | −0.21 to 0.75 |

*HRV = heart rate variability; CI = confidence intervals; MeanRR = mean R-R interval; meanHR = mean heart rate; RMSSD = root mean square of differences between successive RR intervals; LF = low frequency; HF = high frequency; nu = normalized units; SD1 = instantaneous beat-to-beat variability; SD2 = continuous beat-to-beat variability.

supporting the interest of rmcorr for investigating the longitudinal links between TL and HRV indexes.

Monitoring the load placed on athletes in both training and competition is of primary importance to reach the best performance possible and to avoid nonfunctional overreaching and injuries (8). The pursuit of the best (psychological, biological, and physiological) methods has produced an exponential increase in empirical and applied research. Among them, the use of HRV has been facilitated by technological advances in HR monitors that allow the collection of ECG tracings conveniently. Accordingly, a continuous increase in the number of publications using indexes derived from HR recordings have been reported (23).

Studies investigating associations between variables around 2 or more time points generally used regression/Pearson correlation [e.g. (9,10,15,24,31,34)]. Indeed, significant positive correlations between TL and parasympathetic HRV indexes (e.g., RMSSD) recorded before and after a specific training program design, to reach an adequate level of fitness after the holidays have been showed in swimmers and judokas (34). The same type of associations has been reported in different sports, using relative changes in the data over different time points (e.g., multiple daily (10) or weekly changes (15,24)). In these examples, the authors used nonindependent data (absolute data or relative changes in TL and HRV indexes were recorded in the same group of subjects at different time points of the training cycle) and performed analyzes with techniques that assume independence (4). This is a widespread practice but such practice could lead to erroneous results (1,4). One common solution is to use either the average of the repeated measures data or the average of relative changes over the course of time for each subject before performing the correlation (as conducted in this study, Tables 2 and 3). Despite it solves the issue of nonindependence, this technique may lead to misleading results, notably in the case of meaningful individual differences (14,28), as it is likely the case when considering the autonomic nervous system response to exercise training (7,19).

In our study, using Pearson technique on both mean values and mean relative changes over the course of time lead to nonsignificant association between inTL, exTL, and any of the calculated HRV indexes. These results were obtained based on weekly data, averaged into one single point, and the regression line was plotted with these averaged data (4). This result suggests that, at a between-subject level, no association exists in our sample between the TL stressor and athletes' parasympathetic markers. Such a result is not consistent with several studies that repeatedly showed associations between HRV indexes and TLs based on the Pearson's correlations methodology [e.g., (9,10,15,34)]. This could be due to the specific design of our study and athletes 'responses to training. This could also be due to a different methodological approach to find association between training monitoring variables. In our study, Pearson correlations were performed between inTL, exTL, and HRV indexes based on athlete's average data over the four time points of measurements. In the previous studies, data were averaged (as in

**Table 4**

**Intraindividual repeated measures correlation scores between training loads and heart rate variability indexes.***

| | External training load (km) | | | | Internal training load (a.u) | | | |
|---|---|---|---|---|---|---|---|---|
| | $r_{rm}$ | df | *p* | CI | $r_{rm}$ | df | *p* | CI |
| MeanRR | 0.54 | 41 | <0.001 | 0.28 to 0.73 | 0.48 | 41 | 0.001 | 0.20 to 0.69 |
| MeanHR | −0.55 | 41 | <0.001 | −0.73 to −0.29 | −0.49 | 41 | 0.001 | −0.69 to −0.22 |
| RMSSD | 0.57 | 41 | <0.001 | 0.31 to 0.74 | 0.52 | 41 | <0.001 | 0.26 to 0.71 |
| LF | 0.46 | 41 | 0.002 | 0.18 to 0.67 | 0.37 | 41 | 0.014 | 0.07 to 0.61 |
| HF | 0.59 | 41 | <0.001 | 0.34 to 0.76 | 0.56 | 41 | <0.001 | 0.30 to 0.74 |
| LFnu | −0.29 | 41 | 0.062 | −0.55 to 0.02 | −0.34 | 41 | 0.025 | −0.59 to −0.04 |
| HFnu | 0.29 | 41 | 0.062 | −0.02 to 0.55 | 0.34 | 41 | 0.025 | 0.04 to 0.59 |
| LF/HF | −0.3 | 41 | 0.052 | −0.55 to 0.01 | −0.35 | 41 | 0.022 | −0.59 to −0.05 |
| SD1 | 0.57 | 41 | <0.001 | 0.31 to 0.74 | 0.52 | 41 | <0.001 | 0.26 to 0.71 |
| SD2 | 0.5 | 41 | 0.001 | 0.23 to 0.70 | 0.46 | 41 | 0.003 | 0.16 to 0.66 |
| SD1/SD2 | 0.46 | 41 | 0.002 | 0.18 to 0.67 | 0.44 | 41 | 0.003 | 0.15 to 0.66 |

*rrm = Repeated measurement correlation coefficient; CI = confidence intervals; meanRR = mean R-R interval; meanHR = mean heart rate; RMSSD = root mean square of differences between successive RR intervals; LF = low frequency; HF = high frequency; nu = normalized units; SD1 = instantaneous beat-to-beat variability; SD2 = continuous beat-to-beat variability.

our study) or were used as independent data. This may constitute an issue in the understanding of the interpretation of the results that have been obtained because this approach could lead to erroneous results (1).

By contrast, the repeated measures technique highlighted significant positive associations between TLs and parasympathetic HRV indexes. These significant results were obtained because repeated measures correlations take advantage of multiple data points per subject. Indeed, this methodology has much greater statistical power than a standard Pearson correlation using average data (4), limiting the risks of overestimated effect sizes and making them of particular interest for small population cohorts (11), as regularly observed in sport science. Based on these results, we can say that at an intraindividual level, exTL or inTL was positively associated with MeanRR and cardiac parasympathetic indexes (RMSSD, HF, HFnu, and SD1) while they were negatively associated with meanHR and cardiac sympathovagal balance index (LF/HF). It must be underlined that the rmcorr approach is quite different than using pooled data. Indeed, the repeated measures correlations answered to the longitudinal links between variable and considers the intraindividual level, whereas Pearson's correlations based on pooled data address hypothesis focused on the variation association between 2 variables at a between-subject perspective.

Interestingly, the results of this study confirmed the significant associations between TL and HRV-derived indexes, showing an increase of cardiac parasympathetic control during the course of a well-tolerated increase in TL as repeatedly observed (5,9,10,13,29,30,33,34). It should be noted that this is not always reported (27,32). We can thus hypothesize that such opposite findings or conflicting results obtained with very similar methodology such as e.g., presence (16) or absence (17) of relationship between parasympathetic index (RMSSD) and performance or between various training impulse indexes and the percentage of changes in aerobic performance (24,31) could be resolved using statistical methodology specifically developed for repeated measures, such as rmcorr. Hence, our results extended the well-known association between a parasympathetic index and TL by showing that the rmcorr statistical method led to different results compared with the more commonly used Pearson correlation. In the context of repeated measures in the same subjects, we strongly recommend using repeated measures correlations.

## Practical Applications

Our results showed that different results were obtained depending on the correlation method used. Pearson correlation could be used when relative changes between 2 time points are considered. However, when absolute data are considered or when multiple relative changes are considered, using rmcorr will contribute to better detect indicators adapted to training monitoring and will help to improve our understanding of the underlying mechanisms at an intraindividual level, especially when small cohort of athletes are involved. Our results showed that over a 4-week training program with weekly evaluation of inTL and exTL, an increase in TL is longitudinally linked with an increase in parasympathetic indexes, such as RMSSD, HR, or SD1, or a decreased in meanHR calculated during the recovery of a 5′/5′ test. These indexes could be used for inTL monitoring.

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