Corrected October 14, 2023—see https://doi.org/10.1123/jmpb.2023-0046

*Journal for the Measurement of Physical Behaviour,* 2023, 6, 193-201
https://doi.org/10.1123/jmpb.2023-0016

Human Kinetics
ORIGINAL RESEARCH

# Semiautomatic Training Load Determination in Endurance Athletes

**Christophe Dausin,[1] Sergio Ruiz-Carmona,[2,3] Ruben De Bosscher,[4,5] Kristel Janssens,[2,6] Lieven Herbots,[7,8] Hein Heidbuchel,[9,10] Peter Hespel,[1] Véronique Cornelissen,[11] Rik Willems,[4,5] André La Gerche,[2] Guido Claessen,[4,5] and on behalf of the Pro@Heart Consortium***

[1]Department of Movement Sciences, KU Leuven, Leuven, Belgium; [2]Department of Cardiology, Baker Heart and Diabetes Institute, Melbourne, Australia; [3]Cambridge Baker Systems Genomics Initiative, Baker Heart and Diabetes Institute, Melbourne, Australia; [4]Department of Cardiovascular Sciences, KU Leuven, Leuven, Belgium; [5]Department of Cardiology, University Hospitals Leuven, Leuven, Belgium; [6]Exercise and Nutrition Research Program, The Mary MacKillop Institute for Health Research, ACU, Melbourne, Australia; [7]Department of Cardiology, Hartcentrum, Jessa Ziekenhuis, Hasselt, Belgium; [8]REVAL/BIOMED, Hasselt University, Diepenbeek, Belgium; [9]Department of Cardiovascular Sciences, University of Antwerp, Antwerp, Belgium; [10]Department of Cardiology, University Hospital Antwerp, Antwerp, Belgium; [11]Department of Rehabilitation Sciences, KU Leuven, Leuven, Belgium

***Background:*** Despite endurance athletes recording their training data electronically, researchers in sports cardiology rely on questionnaires to quantify training load. This is due to the complexity of quantifying large numbers of training files. We aimed to develop a semiautomatic postprocessing tool to quantify training load in clinical studies. ***Methods:*** Training data were collected from two prospective athlete's heart studies (Master Athlete's Heart study and Prospective Athlete Heart study). Using in-house developed software, maximal heart rate (MaxHR) and training load were calculated from heart rate monitored during cumulative training sessions. The MaxHR in the lab was compared with the MaxHR in the field. Lucia training impulse score, based on individually based exercise intensity zones, and Edwards training impulse, based on MaxHR in the field, were compared. A questionnaire was used to determine the number of training sessions and training hours per week. ***Results:*** Forty-three athletes recorded their training sessions using a chest-worn heart rate monitor and were selected for this analysis. MaxHR in the lab was significantly lower compared with MaxHR in the field (183 ± 12 bpm vs. 188 ± 13 bpm, $p < .01$), but correlated strongly ($r = .81$, $p < .01$) with acceptable limits of agreement (±15.4 bpm). An excellent correlation was found between Lucia training impulse score and Edwards training impulse ($r = .92$, $p < .0001$). The quantified number of training sessions and training hours did not correlate with the number of training sessions ($r = .20$) and training hours ($r = -.12$) reported by questionnaires. ***Conclusion:*** Semiautomatic measurement of training load is feasible in a wide age group. Standard exercise questionnaires are insufficiently accurate in comparison to objective training load quantification.

***Keywords:*** exercise, automatization, cardiology

Despite the widespread use of heart rate (HR) monitors to precisely quantify external and internal training load (TL), studies in sports cardiology have consistently relied on questionnaires to assess TL. These questionnaires are known to be less valid and reliable to evaluate long-term TL as individuals fail to recall the amount, type, and intensity of physical activity and have the tendency to over- or underreport activities (Helmerhorst et al., 2012; Tran et al., 2020; van Poppel et al., 2010). The limited use of activity trackers in sports cardiology studies is probably due to the challenges associated with data analysis and quantification. Exploring the relationship between exercise TL and the development of clinical symptoms not only requires precise evaluation of symptoms but also the accurate, valid, and reproducible determination of accumulated TL over a given period (van Erp et al., 2020). To date, convenient software to analyze tracking data in a standardized and (semi-)automated manner for the purpose of large epidemiological studies is either unavailable or lacks adequate validation.

TL quantification methods that integrate individual physiological responses, such as the Lucia or Edwards training impulse (LuTRIMP or eTRIMP), yield the strongest dose–response relationships between TL and changes in performance (Sanders et al., 2017). However, these methods are impractical to use in large samples of athletic populations because calculation of the indices requires the determination of lactate thresholds (LuTRIMP) or maximal HR (MaxHR; eTRIMP) by means of a maximal incremental exercise test (Sanders et al., 2017). Hence, software allowing for automated calculation of MaxHR from wearables could facilitate accurate calculation of TL based on eTRIMP in the context of epidemiological studies (Cardinale & Varley, 2017).

The primary objective of this study was to develop a semiautomated tool to quantify MaxHR and TL using electronically



*Authors from the consortium are listed in the Acknowledgments section.
Ruiz-Carmona https://orcid.org/0000-0003-4920-5915
De Bosscher https://orcid.org/0000-0002-3163-4781
Janssens https://orcid.org/0009-0004-3176-6751
Herbots https://orcid.org/0000-0001-7784-3610
Heidbuchel https://orcid.org/0000-0001-9301-8127
Hespel https://orcid.org/0000-0003-1283-2229
Cornelissen https://orcid.org/0000-0002-0578-4954
Willems https://orcid.org/0000-0002-5469-9609
La Gerche https://orcid.org/0000-0002-3906-3784
Claessen https://orcid.org/0000-0001-8261-6666
Dausin (christophe.dausin@kuleuven.be) is corresponding author, https://orcid.org/0000-0001-7864-2968

tracked training data. We evaluated the agreement between MaxHR calculated from wearables compared with MaxHR from exercise testing. Furthermore, we compared TL quantification based on HR monitoring during exercise (eTRIMP), with a method that integrates individual physiological responses (i.e., lactate thresholds) from maximal incremental exercise testing (i.e., LuTRIMP). Finally, given the widespread use of questionnaires in the field of sports cardiology, we compared measured TL with reported TL obtained by questionnaires.

# Methods

## Study Participants

Training data were collected from two international multicenter studies: the Prospective Athlete Heart study (Pro@Heart) and the Master Athlete's Heart study (Master@Heart; de Bosscher, Dausin, et al., 2022; de Bosscher et al., 2021). Pro@Heart is a prospective study in which young male and female endurance athletes (cycling, distance running [≥1,500 m], duathlon, triathlon, rowing, swimming [≥400 m], or cross-country skiing) competing at national or international level are recruited at a starting age between 16 and 23 years, with the aim to characterize cardiac remodeling during 20 years of follow-up (de Bosscher, Dausin, et al., 2022). Master@Heart is a cohort study including middle-aged men between 45 and 70 years participating in endurance sports, aiming to assess the impact of endurance sport on cardiac and vascular function (de Bosscher et al., 2021). For the current study, we included male athletes in whom ≥1 year of training data were available, of which at least 100 training sessions included HR monitoring. A list of supported devices is presented in Supplementary Material S1 (available online). At a minimum, 80% of the training data should have been registered via a chest-worn HR monitor. All participants gave written informed consent. The studies were approved by the ethics committee research of University Hospitals Leuven (S57241 and S61336).

## Aerobic Power Assessment and Lab MaxHR

All participants underwent an incremental cardiopulmonary exercise test on a cycle ergometer to assess peak oxygen consumption, including a 12-lead electrocardiogram (Avantronic Cylcus2, or Lode Excalibur Sport, Lode BV Medical Technology; de Bosscher, Dausin, et al., 2022; de Bosscher et al., 2021). The initial workload was set at 30 W or 60 W and increased by 30 W per minute until exhaustion. Respiratory gas exchange was analyzed using a breath-by-breath open-circuit ergospirometry system. Peak oxygen consumption was determined as the highest mean oxygen consumption measured over 30 s (CORTEX MetaLyzer IIIB R2, or Vyntus CPX, CareFusion). MaxHR was determined as the highest HR registered during a 5-s interval at the end of the test and was used for further analyses (Lab MaxHR).

## Aerobic and Anaerobic Threshold Test

In a selection of participants, an additional incremental exercise test was performed to determine both the aerobic and anaerobic threshold using lactate measures. During all tests, the subject's HR was monitored continuously using a chest strap HR monitor. The protocols are explained in detail in Supplementary Material S2 (available online).

## Data Extraction and Analysis

All individual training data were uploaded and stored on an electronic data recording platform (Training Peaks, Peaksware). Raw data files (FIT, GPX, or TCX format) were exported and pseudonymized. An in-house developed code in R was used for the postprocessing of the files (Supplementary Material S3 [available online]). This code is open source and is publicly accessible at https://github.com/sruizcarmona/trainingpeaks.

All files were screened for duplicates and possible erroneous data. Duplicated sessions were filtered out based on their unique identification, the starting time, and the distance covered. Files with unsupported formats (PWX and SRM), corrupted files, or activities shorter than 1 min were discarded. Files were excluded if the following errors were found: average speed >65 km/hr, missing date of the activity, missing identification of the activity, and unclear type of sport (Table 1). Activities with at least 50% adequate HR measurements were used for further analysis. Satisfactory activity files were processed using a two-step approach to avoid noise and artifacts that could lead to inaccurate outliers. First, the initial and the last 10 s of each session were removed to prevent GPS and other sensor pairing errors. This exclusion window was automatically extended by another 10 s if the HR on the first 20 s was >180 bpm, likely due to artifacts upon starting the training. Second, the raw HR data were smoothed using a 10-s moving average. Noise from speed data was eliminated using a 20-s moving average. A longer time window was used for smoothing

**Table 1 General Errors Found in the Activity Files Exported From Training Peaks**

| Total activities | Definition | Count |
|---|---|---|
| Total activities collected | | 17,304 |
| Activity errors | | |
| Multiple sports/rows | The activity contains multiple sports (triathlon or duathlon) within the same file | 2 |
| Short/no data | Activity with no data or <60 s | 356 |
| Speed avg. too high | Speed above 65 km/hr | 3 |
| Unknown | Unknown error, impossible to process | 157 |
| Wrong year | Years in the future | 3 |
| File errors | | |
| PWX format | PWX format not compatible | 242 |
| Reading | Corrupted file, can't be opened | 64 |
| SRM format | SRM format is not compatible | 0 |

speed data, because of higher variability than in the HR data. These thresholds were defined in a pilot study in 21 athletes to avoid bias, reduce data variability, and yet keep pertinent and valid information on TL without impacting average values. The data extracted per athlete and per training session are described in Supplementary Material S4 (available online).

## Automatic Determination of MaxHR and Calculation of eTRIMP and LuTRIMP

The determination of MaxHR is crucial for the calculation of TL. To exclude the need to perform a maximal exercise test, we developed an algorithm to extract MaxHR from HR registrations during training (Tangent MaxHR). First, the kernel density estimate of the MaxHR for all the training sessions of every athlete was computed. The kernel density estimation is a smoothed linear version of a histogram of the MaxHR reached during each training session (Figure 1, black line). Next, the first derivative for the density estimate curve was calculated to identify the peak value of the first derivative of the curve, whereafter the tangent to the downward slope of the curve was drawn to determine MaxHR (Figure 1, gray line). We postulated that the intersection of the downward tangent slope with the $x$-axis yields a valid estimation of MaxHR. Because in some cases the density plot resulted in two different peaks, and the tangent method was prioritizing the highest one, to improve our calculations, the number of activities with an HR above the estimated MaxHR after the steepest downward slope intersection was taken into account (Figure 1, Example 2). A mathematical function was designed and optimized using a grid search machine learning algorithm to optimize the cutting point and limit the number of activities with an HR above the calculated MaxHR. This algorithm was validated in 150 athletes and their expected MaxHR based on the density plots. The best set of parameters of the grid search machine learning algorithm was chosen given the minimum possible error between the expected and calculated values.

For each athlete, we calculated the internal TL based on the total time (in minutes) spent in predefined HR zones. These zones were determined based on (a) percentages of their Tangent MaxHR (eTRIMP) and (b) physiological thresholds obtained from an incremental exercise test (LuTRIMP). Both methods have previously been described in detail (Lucía et al., 2003; van Erp et al., 2020). Detailed determination of eTRIMP and LuTRIMP is explained in Supplementary Material S5 (available online).

## Training Questionnaires

The 22 participants from the Master@Heart study were asked to fill out a questionnaire on the type of sports, weekly training hours, and level of competition (Supplementary Material S6 [available online]; de Bosscher et al., 2021).

## Statistics

Statistical analyses were performed using GraphPad Prism (GraphPad Software). Data are presented as mean ± $SD$ unless otherwise specified. The estimated MaxHR by the tangent method and the assessed MaxHR during cycle ergometry were compared using Bland–Altman analyses. Pearson's correlation was calculated between eTRIMP, LuTRIMP, Lab MaxHR, and Tangent MaxHR. Normality was ensured using the Shapiro–Wilk test. Differences between both studies were evaluated using Student's $t$ test or a Wilcoxon test as appropriate. Outliers were screened using the robust regression and outlier removal tool in

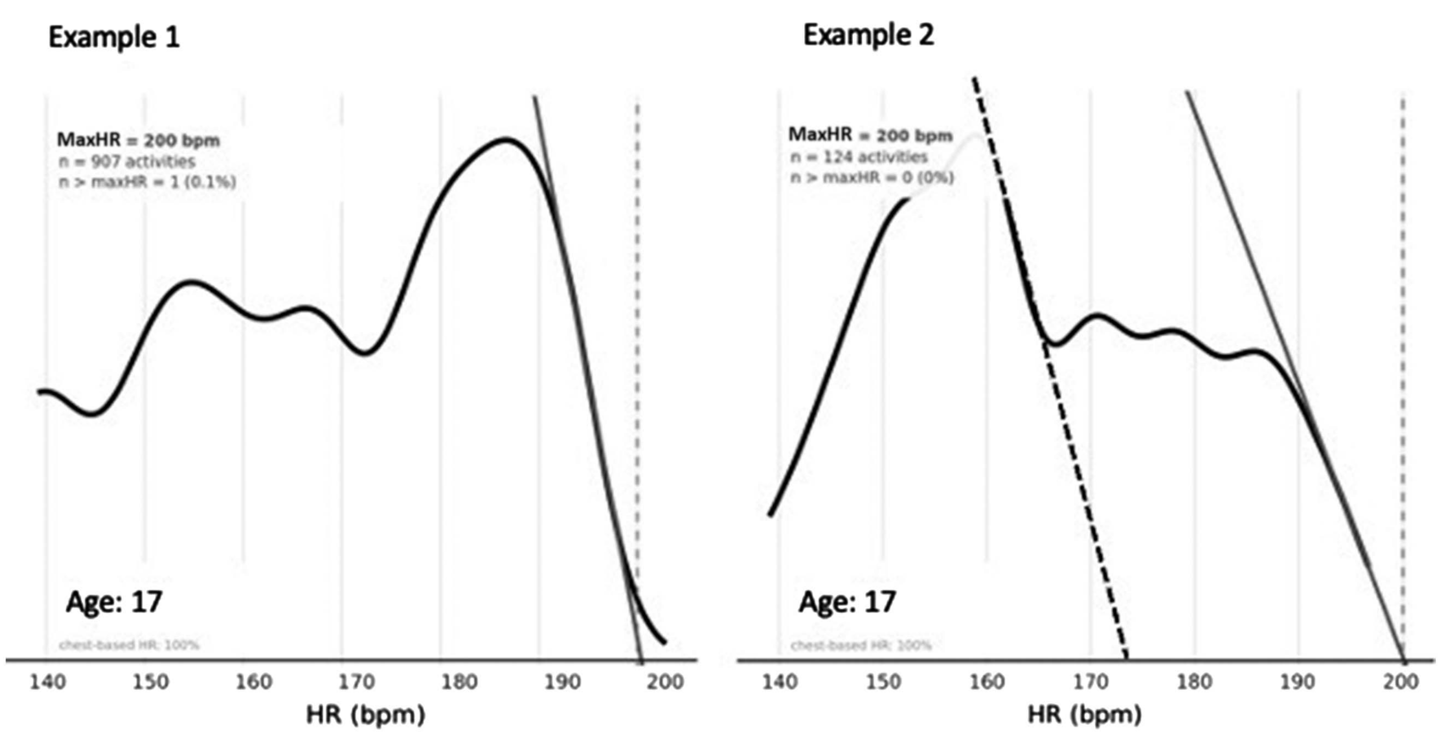


**Figure 1** — MaxHR density curve showing the tangent on the steepest downward tangent slope (gray line). The intersection with the baseline axis is represented by the gray dotted line. Informative annotations, such as number of activities, type of heart rate monitor, and age are added to the plot. MaxHR = maximal HR; HR = heart rate.

GraphPad Prism (GraphPad Software; Motulsky & Brown, 2006) One outlier, an endurance athlete of the Master@Heart trial with an extreme TL, was identified and removed from the analyses. Differences between Pro@Heart and Master@Heart athletes were evaluated using unpaired Student's $t$ tests for continuous variables and chi-square tests for categorical data. A two-tailed $p$ value <.05 was considered statistically significant.

# Results

## Demographics

Out of 152 athletes that provided their training data by the end of December 2021, 43 met the inclusion criteria (Leuven $n = 27$, Hasselt $n = 9$, and Australia $n = 7$) of which in 27 an incremental exercise test including lactate measurements was available (see flowchart in Supplementary Material S7 [available online]).

Twenty-one Pro@Heart male athletes (age 21 ± 4 years) and 22 male Master@Heart athletes (age 54 ± 5 years) were included. The athletes were engaged in cycling, running, duathlon, and triathlon. Participants recorded 10.2 ± 4.1 hr per week over 258.6 ± 87.4 sessions per year. The average number of recorded training sessions was higher in Pro@Heart than Master@Heart (6.0 ± 1.6 vs. 4.0 ± 1.0 sessions per week, $p < .001$, respectively; Table 2). Similarly, Pro@Heart athletes trained more hours per week than Master@Heart athletes (12.6 ± 4.3 hr per week vs. 7.9 ± 2.4; $p < .001$; Table 2). Peak oxygen consumption was 50.6 ± 6.5 ml·kg$^{-1}$·min$^{-1}$ in the Master@Heart athletes and 66 ± 5.9 ml·kg$^{-1}$·min$^{-1}$ in the Pro@Heart athletes ($p < .0001$).

## Maximal Heart Rate

Lab MaxHR (183 ± 12 bpm) was lower compared with the Tangent MaxHR estimated by the software (188 ± 13 bpm, $p < .0001$; Figure 2b), irrespective of the study population (Pro@Heart 192 ± 9 bpm vs. 197 ± 6 bpm, $p < .0001$; Figure 2c; Master@Heart 175 ± 9 bpm vs. 179 ± 12 bpm, $p = .03$; Figure 2d). The mean bias was −5.1 bpm and limits of agreement 15 bpm (Figure 2e). A strong correlation was found between both measures of MaxHR ($r = .81$, $p < .05$; Figure 2a). Two participants in the Pro@Heart study showed unexpectedly lower Lab MaxHR compared with Tangent MaxHR (Figure 2c, red triangles). Careful examination of the source data from these athletes revealed that maximal effort was achieved (respiratory exchange ratio > 1.1). As expected, Tangent MaxHR was higher in Pro@Heart compared with Master@Heart (197 ± 6 bpm vs. 179 ± 12 bpm, respectively; $p < .0001$).

## Training Characteristics

In the subset of participants ($n = 27$) who underwent a maximal incremental exercise test, LuTRIMP was 551 ± 163 AU and eTRIMP 1254 ± 366 AU. LuTRIMP correlated strongly with eTRIMP ($r = .92$, $n = 27$, $p < .0001$, Figure 3). TL determined by eTRIMP was higher in Pro@Heart than in Master@Heart (1788 ± 597 AU vs. 1190 ± 314 AU; $p < .001$, $n = 43$; Table 2).

The fraction of total training time spent in the five predefined HR zones based on Tangent MaxHR was 19% ± 14% in Zone 1, 28% ± 8% in Zone 2, 31% ± 11% in Zone 3, 17% ± 8% in Zone 4, and 4% ± 3% in Zone 5. There was no difference between the groups for relative time spent in the predefined HR zones (Supplementary Material S8 [available online]).

## Data Collection Period

To evaluate the influence of the duration of the data collection period, we calculated the weekly TL using eTRIMP for different time windows (1, 3, 6, 9, and 12 months). Correlations with the 12-month eTRIMP were .55, .78, .92, and .97 for the 1-, 3-, 6-, and 9-month time windows, respectively (all correlations $p < .0001$). Bland–Altman analyses revealed a bias of −92 AU, −9 AU, 53 AU, and 36 AU for 1-, 3-, 6-, and 9-month windows, respectively (Supplementary Material S9 [available online]).

## Questionnaires

In Master@Heart athletes ($n = 22$), quantitative TL assessment derived from HR training logs was compared with the TL evaluation as reported by standard exercise questionnaires at the time of cardiac preparticipation evaluation (de Bosscher et al., 2021).

**Table 2 General Characteristics of the Study Population**

| Variable | Total | Master@Heart | Pro@Heart |
|---|---|---|---|
| Men, $n$ (%) | 43 (100) | 22 (100) | 21 (100) |
| Clinical data | | | |
| Age (years) | 38 ± 17 | 54 ± 5 | 21 ± 4* |
| Weight (kg) | 72 ± 5.8 | 74.7 ± 5.7 | 69.7 ± 6.9* |
| Height (cm) | 178 ± 6 | 179 ± 6 | 178 ± 5 |
| $VO_2$peak (ml·kg$^{-1}$·min$^{-1}$) | 58.5 ± 10.0 | 50.6 ± 6.5 | 66 ± 5.9* |
| Training load by heart rate monitor | | | |
| Recorded training sessions | 259 ± 87 | 208 ± 51 | 313 ± 85* |
| Sessions per week | 5.0 ± 1.7 | 4.0 ± 1.0 | 6.0 ± 1.6* |
| Hours per week | 10.2 ± 4.1 | 7.9 ± 2.4 | 12.6 ± 4.3* |
| Recorded training sessions with chest heart rate (%) | 97.9 ± 4.3 | 97.1 ± 5.1 | 98.2 ± 3.6 |
| eTRIMP (AU) | 1,481 ± 557 | 1,190 ± 314 | 1,788 ± 597* |

*Note*. Data are mean ± *SD*. AU = arbitrary units; eTRIMP = Edwards training impulse; Pro@Heart = Prospective Athlete Heart study; Master@Heart = Master Athlete's Heart study.
*$p < .05$.

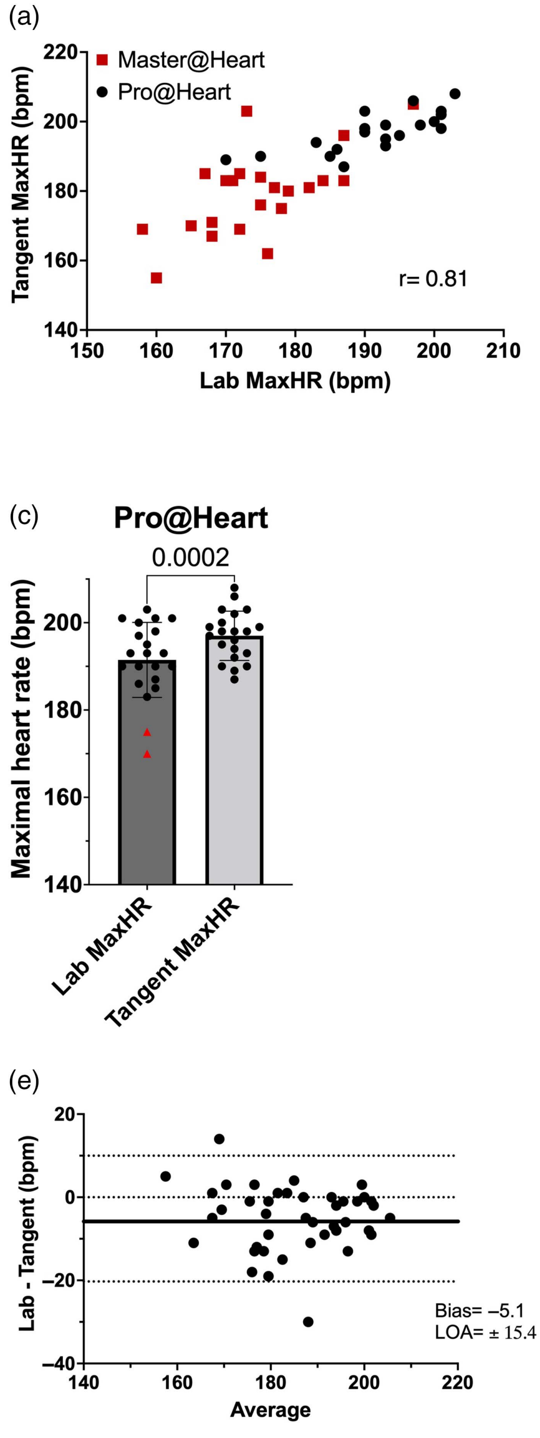


**Figure 2** — (a) Correlation between Lab MaxHR and Tangent MaxHR (Master@Heart in square red and Pro@Heart in round black). (b) Comparison of Lab MaxHR and Tangent MaxHR. Data are mean ± *SD*. (c) Subanalyses comparing Lab MaxHR and Tangent MaxHR in Pro@Heart. In red triangle, two participants with much lower Lab MaxHR compared to Tangent MaxHR. Data are mean ± *SD*. (d) Subanalyses comparing Lab MaxHR and Tangent MaxHR in Master@Heart participants. In red, two participants with much lower Lab MaxHR compared with Tangent MaxHR. Data are mean ± *SD*. (e) Bland–Altman analyses with mean bias (black full line) and boundaries of 95% limits of agreement (dotted lines). MaxHR = maximal heart rate; Lab MaxHR = MaxHR determined in the lab; Tangent MaxHR = MaxHR determined using training files; Pro@Heart = Prospective Athlete Heart study; Master@Heart = Master Athlete's Heart study.

Measured training hours (7.9 ± 2.4 hr per week) were ~30% lower than training hours reported via the questionnaires (12.3 ± 3.8 hr per week, $p = .0004$). The number of registered weekly training sessions was lower than the reported values (4.0 ± 1.0 vs. 4.8 ± 1.4; $p = .019$). There was no significant correlation between the reported and measured number of training sessions per week ($r = .20$, $p = .37$; Figure 4), nor between the reported and measured number of training hours per week ($r = −.12$, $p = .59$; Figure 4).

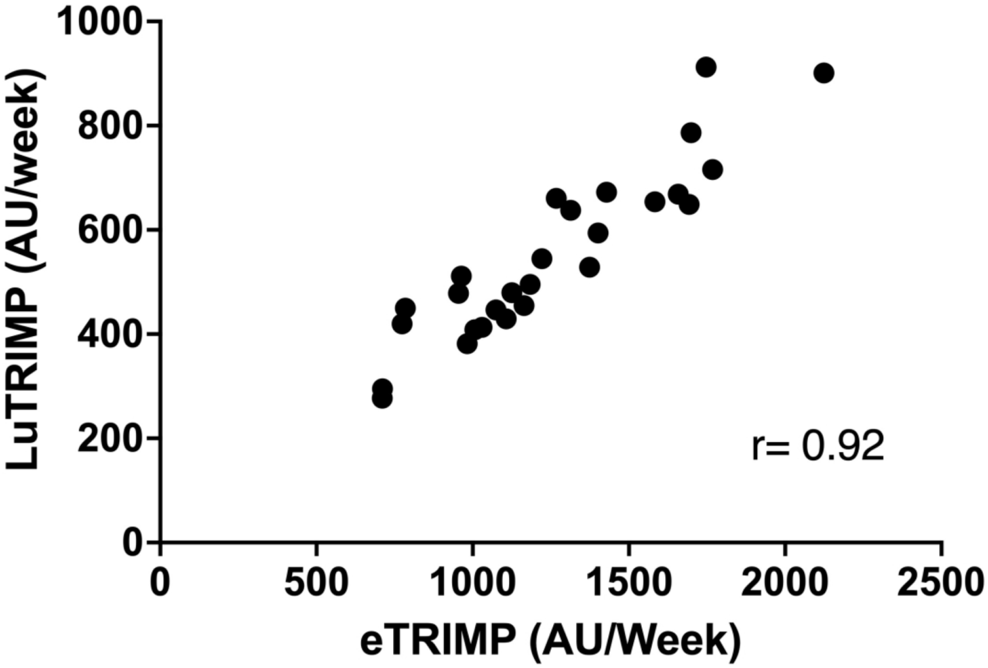


**Figure 3** — Correlation between LuTRIMP and eTRIMP average per week for a year of training. LuTRIMP = Lucia training impulse score; eTRIMP = Edwards training impulse.

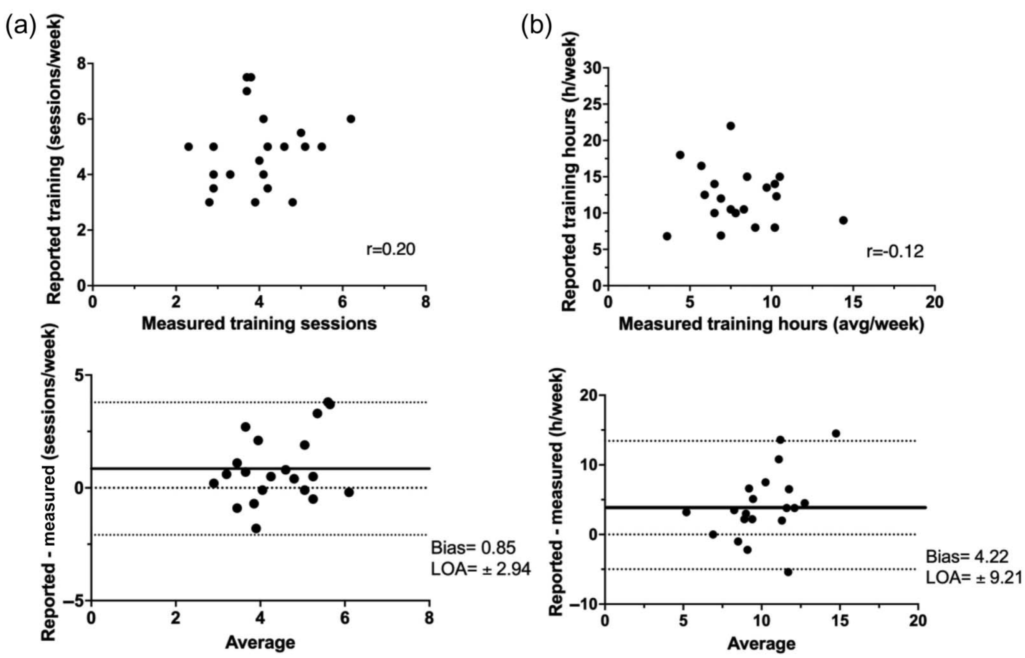


**Figure 4** — (a) Correlation and Bland–Altman analysis of reported versus measured number of training sessions per week with bias (black full line) and 95% LOA (gray dotted line). (b) Correlation and Bland–Altman analysis of reported versus measured average training hours per week with bias (black full line) and 95% LOA (gray dotted line).

## Discussion

We demonstrate that it is feasible to semiautomatically characterize and track TL over time. Our data demonstrate that a TL quantification only relying on HR monitoring is equally valid compared with a method that integrates individual lactate thresholds and training data. Finally, we show that self-reported TL assessed by questionnaires does not accurately reflect objective metrics as documented by wearables. This methodology can easily be implemented in a larger number of individuals. Future studies should incorporate more objective TL metrics to improve our understanding of the interaction between sports and the cardiovascular system.

In the majority of sports cardiology studies, TL is reported as the number of sports hours per week or as total training volume (i.e., TRIMP scores). The most recent sports cardiology guidelines advice to describe sports participation in its four different components using the FITT principle (i.e., frequency, intensity, time, and type of sports). This distinction is clinically important as exercise intensity is a stronger predictor of adverse outcomes than exercise duration in patients at risk of arrhythmias (Lie et al., 2018). Accurate quantification of these variables over time is challenging using questionnaires because individuals cannot accurately recall the amount, type, and intensity of physical activity, particularly over long periods (Helmerhorst et al., 2012; Tran et al., 2020; van Poppel et al., 2010). We provide a semiautomatic approach that allows quantifying these different aspects of training characteristics in a large population. Frequency, duration (time), and type of each training activity are easily obtained from wearables. The most challenging aspect relates to the appraisal of exercise intensity, which is required to calculate the overall training volume.

A critical first step in the determination of exercise intensity is the need for accurate and automatic estimation of MaxHR (Fletcher, 1997). Automatic determination of MaxHR requires verification for possible outliers in data collection to prevent overestimation due to artifacts (Pasadyn et al., 2019). To facilitate this process, we developed an automatic correction step, the so-called "tangent method," to accurately determine the MaxHR. In keeping with previous studies (Abad et al., 2016; Semin et al., 2008), we demonstrate that MaxHR in the field, determined by this tangent method, slightly exceeds MaxHR in the lab, both in junior and senior athletes. The higher MaxHR in the field has been described and can be explained by motivational factors (e.g., increased state of arousal during exciting and competitive training sessions), differences in exercise duration, and environmental conditions (Semin et al., 2008).

Accurate determination of MaxHR enabled subsequent characterization of each training session into training zones which, in combination with exercise duration and frequency, yields TL. Depending on differences in weighting factors, several methods are available to calculate total TL, for example, LuTRIMP and eTRIMP (Sanders et al., 2017; van Erp et al., 2020). In large-scale clinical studies, the use of LuTRIMP introduces both economical and practical limitations because of the need to incorporate data from a maximal cardiopulmonary exercise test. By contrast, the eTRIMP has some significant advantages because it can be calculated based on HR derived by HR monitors. We showed an excellent correlation, which indicates the interchangeable use of these methods to determine TL.

Our data, using this novel method to automatically calculate eTRIMP from wearable data, seem to demonstrate that the use of sports questionnaires lacked validity and reliability to evaluate long-term training schedules. Reported training hours were consistently higher than the measured training hours without any correlation between both. Similarly, no significant relationship was observed between the number of training sessions reported by questionnaire and that measured by wearable data. It should however be kept in mind that a gold standard is lacking.

We believe that the method described in this study holds great promise for the characterization of TL in sports cardiology studies and its association with exercise-induced cardiac remodeling. The importance of this aspect cannot be overestimated as the distinction between physiological adaptation to regular exercise, and the presence of subtle structural heart disease can be challenging in some cases (Pelliccia et al., 2002). Within the athlete population, substantial variability exists in the extent of cardiac remodeling, even among elite athletes (Abergel et al., 2004). The potential mechanisms explaining these interindividual differences in exercise-induced cardiac adaptations may include differences in underlying genetics, differences in training behavior, and the interaction between both (de Bosscher, Heidbuchel, et al., 2022).

From our data, we would advise to collect at least 3 months and optimally 6 months of training history to have an accurate estimation of TL in athletes with low variability. Due to different training periodization, injuries, and competition seasons, shorter intervals are prone to excessive variability. A monitoring period of 3–6 months provides an accurate indication of the actual average TL and may help to unravel the relationship with exercise-induced cardiac adaptation.

### Limitations

Although we know that competitive athletes typically wear HR monitors for use in their daily training periodization, we cannot exclude that a number of sessions were not recorded (Sanders et al., 2019; Solli et al., 2017; van Erp et al., 2020). The lack of gold standard to compare our results with is a limitation of our paper. When the wearable is worn in every training session, this should give an excellent idea of the TL, but ensuring this would require continuous supervision of the athlete and would be feasible only in small studies. We did not ask our participants to self-evaluate the use of their wearable in time. We also only measured training sessions and not activity during daily living. Hence, we cannot exclude that TL may have been underestimated in some individuals. Similarly, strength sessions are less often registered, thereby inducing the risk of underestimating the amount of strength training.

At this moment, we did not incorporate the session rating of perceived exertion method. The session rating of perceived exertion has been shown to be a valid and reliable method of measuring TL (Foster et al., 2001; Haddad et al., 2017). However, its measurement requires daily discipline of the athlete to manually record this measure.

## Conclusions

Semiautomatic quantification of TL from big data sets of training files is feasible in a time-efficient manner. LuTRIMP and eTRIMP can be used interchangeably for the purpose of TL quantification. Questionnaires to self-report training activity lack the necessary granularity to accurately identify an athletes' TL in these prospective studies.

### Acknowledgments

Dausin and Ruiz-Carmona are joint first authors. La Gerche and Claessen are shared senior authors. Pro@Heart Consortium includes the following author groups: *Department of Cardiology, Baker Heart and Diabetes Institute, Melbourne, Australia:* Amy Mitchell, Maria Brosnan, and David Prior. *Department of Cardiovascular Sciences, KU Leuven, Leuven, Belgium:* Piet Claus, Kaatje Goetschalckx, Sofie Van Soest, and Mathias Claeys. *Department of Cardiology, University Hospitals Leuven, Leuven, Belgium:* Sofie Van Soest and Mathias Claeys. *Department of Cardiology, Hartcentrum, Jessa Ziekenhuis, Hasselt, Belgium:* Olivier Ghekiere, Daisy Thijs, and Peter Vanvoorden and Dominique Hansen. *REVAL/BIOMED, Hasselt University, Diepenbeek, Belgium:* Bert Op't Eijnde. *Department of Cardiovascular Sciences, University of Antwerp, Antwerp, Belgium:* Caroline M. Van De Heyning, Paul Van Herck, Bernard Paelinck, Haroun

El Addouli, Hielko Miljoen, Kasper Favere, Dorien Vermeulen, and Isabel Witvrouwen. *Department of Cardiology, University Hospital Antwerp, Antwerp, Belgium:* Caroline M. Van De Heyning, Bernard Paelinck, Hielko Miljoen, Kasper Favere, Dorien Vermeulen, and Isabel Witvrouwen. *Department of Radiology, University Hospitals Leuven, Leuven, Belgium:* Steven Dymarkowski, Tom Dresselaers, and Jan Bogaert. *Faculty of Medicine and Life Sciences, Cardiology and Organ Systems, Hasselt University, Diepenbeek, Belgium:* Dominique Hansen. *Department of Cardiology, Algemeen Ziekenhuis Nikolaas, Sint-Niklaas, Belgium:* Kristof Lefebvre. *Centre for Heart Rhythm Disorders, University of Adelaide and Royal Adelaide Hospital, Adelaide, Australia:* Adrian Elliott and Prashanthan Sanders. *Department of Cardiology, Royal Melbourne Hospital, Melbourne, Australia*: Jonathan Kalman. *Victor Chang Cardiac Research Institute, Darlinghurst, New South Wales, Australia:* Diane Fatkin. *Energy lab, Paal, Belgium:* Wim Van Hoolst. During the start-up and execution of the Master@Heart trial, a project advisory committee was created with yearly meetings on the development and progress of the study. The committee included the following public partners: Cycling Vlaanderen, Sport en Keuringsartsen, Triathlon Vlaanderen, and Sport Vlaanderen. The authors would like to thank the staff members of all sites for helping conduct the Pro@Heart and Master@Heart studies. The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The Master@Heart trial is supported by a research grant by the Fund for Scientific Research Flanders (FWO-TBM [T003717N]). The Pro@Heart is supported by an unrestricted research grant from Boston Scientific Belgium and Abbott Belgium and a research grant by KOOR from UZ Leuven and the National Health and Medical Research Council of Australia (APP1130353). Willems is supported as postdoctoral clinical researcher by the Fund for Scientific Research Flanders. Willems reports research funding from Abbott, Biotronik, Boston Scientific, and Medtronic; speakers and consultancy fees from Medtronic, Boston Scientific, Biotronik, and Abbott.

## References

Abad, C.C.C., Pereira, L.A., Kobal, R., Kitamura, K., Cruz, I.F., Loturco, I., & Nakamura, F.Y. (2016). Heart rate and heart rate variability of Yo-Yo IR1 and simulated match in young female basketball athletes: A comparative study. *International Journal of Performance Analysis in Sport, 16*(3), 776–791. https://doi.org/10.1080/24748668.2016.11868927

Abergel, E., Chatellier, G., Hagege, A.A., Oblak, A., Linhart, A., Ducardonnet, A., & Menard, J. (2004). Serial left ventricular adaptations in world-class professional cyclists: Implications for disease screening and follow-up. *Journal of the American College of Cardiology, 44*(1), 144–149. https://doi.org/10.1016/j.jacc.2004.02.057

Cardinale, M., & Varley, M.C. (2017). Wearable training-monitoring technology: Applications, challenges, and opportunities. *International Journal of Sports Physiology and Performance, 12*(7), 908–915. https://doi.org/10.1123/ijspp.2016-0314

de Bosscher, R., Dausin, C., Claus, P., Bogaert, J., Dymarkowski, S., Goetschalckx, K., Ghekiere, O., Belmans, A., van de Heyning, C.M., van Herck, P., Paelinck, B., el Addouli, H., la Gerche, A., Herbots, L., Heidbuchel, H., Willems, R., & Claessen, G. (2021). Endurance exercise and the risk of cardiovascular pathology in men: A comparison between lifelong and late-onset endurance training and a non-athletic lifestyle—Rationale and design of the Master@Heart study, a prospective cohort trial. *BMJ Open Sport & Exercise Medicine, 7*(2), Article e001048. https://doi.org/10.1136/bmjsem-2021-001048

de Bosscher, R., Dausin, C., Janssens, K., Bogaert, J., Elliott, A., Ghekiere, O., van de Heyning, C.M., Sanders, P., Kalman, J., Fatkin, D., Herbots, L., Willems, R., Heidbuchel, H., la Gerche, A., & Claessen, G. (2022). Rationale and design of the PROspective ATHletic Heart (Pro@Heart) study: Long-term assessment of the determinants of cardiac remodelling and its clinical consequences in endurance athletes. *BMJ Open Sport & Exercise Medicine, 8*(1), Article e001309. https://doi.org/10.1136/bmjsem-2022-001309

de Bosscher, R., Heidbuchel, H., Claessen, G., & la Gerche, A. (2022). Tackling an unmet need in sports cardiology: Understanding exercise-induced cardiac remodelling and its clinical consequences. *British Journal of Sports Medicine, 56*(14), 776–777. https://doi.org/10.1136/bjsports-2022-105440

Fletcher, G.F. (1997). How to implement physical activity in primary and secondary prevention. *Circulation, 96*(1), 355–357. https://doi.org/10.1161/01.CIR.96.1.355

Foster, C., Florhaug, J.A., Franklin, J., Gottschall, L., Hrovatin, L.A., Parker, S., Doleshal, P., & Dodge, C. (2001). A new approach to monitoring exercise training. *Journal of Strength and Conditioning Research, 15*(1), 109–115.

Haddad, M., Stylianides, G., Djaoui, L., Dellal, A., & Chamari, K. (2017). Session-RPE method for training load monitoring: Validity, ecological usefulness, and influencing factors. *Frontiers in Neuroscience, 11*(NOV), Article 612. https://doi.org/10.3389/fnins.2017.00612

Helmerhorst, H.J.F., Brage, S., Warren, J., Besson, H., & Ekelund, U. (2012). A systematic review of reliability and objective criterion-related validity of physical activity questionnaires. *International Journal of Behavioral Nutrition and Physical Activity, 9*(1), Article 103. https://doi.org/10.1186/1479-5868-9-103

Lie, Ø.H., Dejgaard, L.A., Saberniak, J., Rootwelt, C., Stokke, M.K., Edvardsen, T., & Haugaa, K.H. (2018). Harmful effects of exercise intensity and exercise duration in patients with arrhythmogenic cardiomyopathy. *JACC: Clinical Electrophysiology, 4*(6), 744–753. https://doi.org/10.1016/j.jacep.2018.01.010

Lucía, A., Hoyos, J., Santalla, A., Earnest, C., & Chicharro, J.L. (2003). Tour de France versus Vuelta a España: Which is harder? *Medicine & Science in Sports & Exercise, 35*(5), 872–878. https://doi.org/10.1249/01.MSS.0000064999.82036.B4

Motulsky, H.J., & Brown, R.E. (2006). Detecting outliers when fitting data with nonlinear regression—A new method based on robust nonlinear regression and the false discovery rate. *BMC Bioinformatics, 7*(1), Article 123. https://doi.org/10.1186/1471-2105-7-123

Pasadyn, S.R., Soudan, M., Gillinov, M., Houghtaling, P., Phelan, D., Gillinov, N., Bittel, B., & Desai, M.Y. (2019). Accuracy of commercially available heart rate monitors in athletes: A prospective study. *Cardiovascular Diagnosis and Therapy, 9*(4), 379–385. https://doi.org/10.21037/cdt.2019.06.05

Pelliccia, A., di Paolo, F.M., & Maron, B.J. (2002). The athlete's heart: Remodeling, electrocardiogram and preparticipation screening. *Cardiology in Review, 10*(2), 85–90. https://doi.org/10.1097/00045415-200203000-00006

Sanders, D., Abt, G., Hesselink, M.K.C., Myers, T., & Akubat, I. (2017). Methods of monitoring training load and their relationships to changes in fitness and performance in competitive road cyclists. *International Journal of Sports Physiology and Performance, 12*(5), 668–675. https://doi.org/10.1123/ijspp.2016-0454

Sanders, D., van Erp, T., & de Koning, J.J. (2019). Intensity and load characteristics of professional road cycling: Differences between men's and women's races. *International Journal of Sports Physiology and Performance, 14*(3), 296–302. https://doi.org/10.1123/ijspp.2018-0190

Semin, K., Stahlnecker Iv, A.C., Heelan, K., Brown, G.A., Shaw, B.S., & Shaw, I. (2008). Discrepancy between training, competition and laboratory measures of maximum heart rate in NCAA division 2 distance runners. *Journal of Sports Science and Medicine, 7,* 455–460.

Solli, G.S., Tønnessen, E., & Sandbakk, Ø. (2017). The training characteristics of the world's most successful female cross-country skier. *Frontiers in Physiology, 8*(DEC), Article 1069. https://doi.org/10.3389/fphys.2017.01069

Tran, V.D., Do, V.V., Pham, N.M., Nguyen, C.T., Xuong, N.T., Jancey, J., & Lee, A.H. (2020). Validity of the international physical activity questionnaire–short form for application in asian countries: A study in Vietnam. *Evaluation & the Health Professions, 43*(2), 105–109. https://doi.org/10.1177/0163278718819708

van Erp, T., Sanders, D., & de Koning, J.J. (2020). Training characteristics of male and female professional road cyclists: A 4-year retrospective analysis. *International Journal of Sports Physiology and Performance, 15*(4), 534–540. https://doi.org/10.1123/ijspp.2019-0320

van Poppel, M.N.M., Chinapaw, M.J.M., Mokkink, L.B., van Mechelen, W., & Terwee, C.B. (2010). Physical activity questionnaires for adults a systematic review of measurement properties. *Sports Medicine, 40*(7), 565–600. https://doi.org/10.2165/11531930-000000000-00000