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Validity of detrended fluctuation analysis of heart rate variability to determine intensity thresholds in elite cyclists

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ABSTRACT

Background: The evaluation of performance in endurance athletes and the subsequent individualisation of training is based on the determination of individual physiological thresholds during incremental tests. Gas exchange or blood lactate analysis are usually implemented for this purpose, but these methodologies are expensive and invasive. The short-term scaling exponent alpha 1 of detrended Fluctuation Analysis (DFA-α1) of the Heart Rate Variability (HRV) has been proposed as a non-invasive methodology to detect intensity thresholds. **Purpose:** The aim of this study is to analyse the validity of DFA-α1 HRV analysis to determine the individual training thresholds in elite cyclists and to compare them against the lactate thresholds. **Methodology:** 38 male elite cyclists performed a graded exercise test to determine their individual thresholds. HRV and blood lactate were monitored during the test. The first (LT1 and DFA-α1-0.75, for lactate and HRV, respectively) and second (LT2 and DFA-α1-0.5, for lactate and HRV, respectively) training intensity thresholds were calculated. Then, these points were matched to their respective power output (PO) and heart rate (HR). **Results:** There were no significant differences ($p > 0.05$) between the DFA-α1-0.75 and LT1 with significant positive correlations in PO ($r = 0.85$) and HR ($r = 0.66$). The DFA-α1-0.5 was different against LT2 in PO ($p = 0.04$) and HR ($p = 0.02$), but it showed significant positive correlation in PO ($r = 0.93$) and HR ($r = 0.71$). **Conclusions:** The DFA1-a-0.75 can be used to estimate LT1 non-invasively in elite cyclists. Further research should explore the validity of DFA-α1-0.5.

KEYWORDS
Thresholds; heart rate variability; elite cyclists; non-linear analysis

Highlights

- The power and heart rate values derived from the DFA-α1-0.75 threshold showed high levels of validity and agreement when they were compared against the first lactate threshold.
- The second lactate threshold and the DFA-α1-0.5 were different ($p < 0.05$) but showed high levels of correlation.
- The detrended fluctuation analysis is a valid method to estimate the first lactate threshold and more studies are needed to verify its validity with the second lactate threshold.

Introduction

Endurance cycling in its different varieties (professional road cycling, cyclocross, mountain biking) is among the most demanding endurance sports owing to the high physiological loads imposed on riders during training and competitions (Lucía, Hoyos, Santalla, Earnest, & Chicharro, 2003). Adequate fitness evaluation and subsequent individualisation of training programmes are needed to optimise performance while at the same time prevent overreaching and especially, overtraining (Wyatt, Donaldson, & Brown, 2013). Training prescription is typically based on training zones delimited by previously identified individual physiological "thresholds' during incremental tests (Samuel, Lindsay, & Muniz-Pumares, 2021). These thresholds are determined by the assessment of blood lactate concentration (lactate threshold/s) or gas-exchange parameters (ventilatory threshold/s) while workload progressively increases (Pallarés, Morán-Navarro, Ortega, Fernández-Elías, & Mora-Rodriguez, 2016). Other methods such as the assessment of heart rate variability (HRV) have also been proposed for evaluation of intensity thresholds and training zones in several populations, ranging from patients (Rogers, Mourot, & Gronwald, 2021c) to

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physically trained individuals (Gronwald et al., 2021; Rogers, Giles, Draper, Hoos, & Gronwald, 2021a; Rogers, Giles, Draper, Mourot, & Gronwald, 2021b) based on the relationship between exercise intensity and autonomous nervous system regulation. Through HRV it is possible to carry out a non-invasive assessment of the autonomous nervous system balance (Heart rate variability, 1996) with the heart rate (HR) response mostly subjected to parasympathetic (vagal) modulation during resting conditions and low-intensity exercise (Karemaker & Lie, 2000) but with a raise in sympathetic drive and a subsequent decrease in vagal activity with increasing workloads. Therefore, HRV would be a variable that could assess exercise intensity accurately through low-cost wearables like a validated heart rate monitor. In this regard, the use of linear measures of HRV (time- and frequency-domain indexes) have been implemented to determine the anaerobic threshold (Noeman, Hamooda, & Baalash, 2011). However, it has been suggested these indexes of HRV show reductions even at low exercise intensity and therefore, these measures are not able to discriminate between different training intensities (Casadei, Cochrane, Johnsoton, Conway, & Sleight, 1995; Hautala, Mäkikallio, Seppänen, Huikuri, & Tulppo, 2003; Tulppo, Makikallio, Takala, Seppanen, & Huikuri, 1996).

Despite the aforementioned disagreement on the physiological information provided by the linear parameters of HRV, these tools have shown unique spectral signatures corresponding to the autonomic control dynamics (Malpas, 2002). Several approaches have been used showing different sensibility to detect autonomic modulation in various types of populations (Aguilera, Elias, & Clemente-Suárez, 2021; Clemente-Suárez, 2018; Clemente-Suárez et al., 2015; Mendoza-Castejón & Clemente-Suárez, 2020; Sánchez-Conde & Clemente-Suárez, 2021), including a fractal approach to identify the existence of persistent correlations over a wide range of time scales (Echeverrıa et al., 2003). Specifically, the short term scaling exponent alpha 1 of detrended Fluctuation Analysis (DFA-α1) has proven to be suitable for the analysis of nonstationary data of time series such as heart beat (Platisa & Gal, 2008). In this regard, DFA-α1 is appropriate to differentiate among different physiological demands during endurance exercise (Gronwald & Hoos, 2020). The DFA-α1 shows some advantages over other "more conventional" fractal methods because it allows the detection of long-range correlations embedded in nonstationary time series while avoiding spurious detection of apparent long-range correlations that are artefacts of nonstationary behaviour (Ivanov et al., 2001).

Despite the promising results for the determination of training intensity domains in different populations with DFA-α1 (Naranjo-Orellana, Nieto-Jimenez, & Ruso-Alvarez, 2020; Rogers et al., 2021b; Rogers et al., 2021a), the usefulness of this method has not been evaluated in elite endurance athletes. This is of importance because this non-invasive methodology would allow a more continuous evaluation throughout the training process. Therefore, it could result in a constant update of the intensity zones and lead to a more precise training process. Therefore, the purpose of this study was to assess the validity of DFA-α1 of HRV to determine individual intensity thresholds in elite endurance cyclists when the power and heart rate values derived from this analysis are compared against the lactate thresholds.

Methods

Participants

Thirty-eight ($N = 38$; weekly training volume = 22.5 ± 4.6 h; 22.5 ± 7.2 years [range 17–41 years]) male elite endurance cyclists (category 4 McKay et al., 2022) volunteered to participate in this investigation. Their estimated VO_2max was 70.5 ± 4.6 $ml \cdot kg^{-1} \cdot min^{-1}$ (Cisternas, 2019). This study followed the principles of the Declaration of Helsinki and was approved by the Universidad Miguel Hernández Ethics Committee. Written informed consent was obtained from all the participants.

Experimental design

The subjects performed a graded exercise test (GXT) following a standardised protocol (Pallarés et al., 2016). After a 5-min warm-up at 50 W, the workload increased by 25 $W \cdot min^{-1}$ until volitional exhaustion (or until the cyclists were not able to maintain the set workload). The cyclists completed the tests using their own bicycles attached to a Cycleops Hammer Cycle Ergometer (CycleOps, Madison, WI, United States of America) (Lillo-Bevia & Pallarés, 2018), in a seated position. The cyclists were instructed to select and maintain their preferred cadence during all the GXT (the mean cadence was 84.23 ± 7.43 rpm). The power output (PO) was continuously monitored using a unit display (Garmin Edge 1000, Garmin International Inc.; Olathe, KS, United States of America) fixed on the bicycle's handlebars, and peak PO (PPO) was calculated as follows: $PPO = PO_f + [(t/60 \times 25)]$, in which PO_f is the power output (watts) of the last completed workload, t is the time (in seconds) the last uncompleted workload was maintained for, 60 is the

duration (in seconds) of each completed workload, and 25 is the PO difference (in watts) between two consecutive workloads.

Threshold determination

The peripheral (capillary) blood lactate concentration [La^-] was assessed from the participant's right earlobe using a portable analyzer (Lactate Pro 2, Arkray; Kyoto, Japan) (Baldari et al., 2009) at baseline (before the warm-up) and at the end of each 1-minute workload of the GXT. The "lactate thresholds' were estimated from [La^-] measures, as explained elsewhere (Pallarés et al., 2016). Thus, the "first lactate threshold" (LT1) was considered as the workload (watts) at which [La^-] started to rise above baseline values whereas the LT2 was set at the workload eliciting an increase in [La^-] $\geq$2 mmol·L^{-1} with regard to baseline values. Both lactate thresholds were individually checked through a visual interpretation by two experienced researchers (DBG, MMM). If there was any disagreement, a consensus was met by all the authors.

As for HRV, R-R intervals (RRi) were continuously recorded (Garmin Edge 1000) for HR and HRV analyses with a transmitter belt (Polar Bluetooth H10, Oy, Finland). The transmitter belt was connected to the Garmin head unit via Bluetooth. "FIT" files for each subject were imported into Kubios 3.3.2 (Biosignal Analysis and Medical Imaging Group, Department of Physics, University of Kuopio, Kuopio, Finland) (Tarvainen, Niskanen, Lipponen, Ranta-Aho, & Karjalainen, 2014). Kubios preprocessing settings were set at the default values including the RR detrending method, which was kept at "Smoothen priors" (Lambda = 500) (Niskanen, Tarvainen, Ranta-Aho, & Karjalainen, 2004). The analysis and processing of the data were performed according to the standard criteria (Heart rate variability, 1996; Peltola, 2012). The files were corrected for ectopic beats and artifacts before the analysis using a medium level of artifact correction (Alcantara et al., 2020). The interpolation of the series was performed by a piecewise cubic spline interpolation method provided by Kubios' software. A full description of the algorithm can be found elsewhere (Lipponen & Tarvainen, 2019). This is the recommended technique by the literature for artifact and ectopic beat corrections when examining R-R intervals (Peltola, 2012; Perrotta, Jeklin, Hives, Meanwell, & Warburton, 2017). The literature also suggests holding the 80% of normal R-R intervals for further analysis, and for the present study, only the signals with less than 20% of corrected beats were included in the analyses. For DFA-α1 estimation, the root mean square fluctuation of the integrated and detrended data was measured in 2-minute windows (Chen, Ivanov, Hu, & Stanley, 2002). The data were then plotted against the size as reported previously (Rogers et al., 2021a). DFA-α1 window width was set to $4 \leq N \leq 16$ beats. The specific methodology for thresholds determination using DFA-α1 is detailed elsewhere (Gronwald et al., 2021; Rogers et al., 2021a; Rogers et al., 2021b). Briefly, for the detection of the "first HRV threshold", a DFA-α1 value of 0.75 ("DFA-α1–0.75") was chosen based on this being the midpoint between a fractal behaviour of the HR time series of 1.0 (observed in low-intensity exercise) and an uncorrelated value of 0.5 with a random behaviour of the HR time series (corresponding to high-intensity exercise) (Platisa & Gal, 2008). For the detection of the "second HRV threshold", a DFA-α1 value of 0.5 ("DFA-α1–0.5") was chosen (Rogers et al., 2021b). Thereafter, these breakpoints (DFA-α1 values of 0.5 and 0.75) were matched to the HR and PO value obtained during the GXT.

Statistical analysis

Normal distributions of the data were confirmed by Kolmogorov–Smirnov tests ($p > 0.05$). Paired Student's *t*-tests were used to compare the PO and HR values at DFA-α1 breakpoints and at LT1 and LT2 thresholds, respectively. Pearson's product-moment correlation (r) was used to assess the relationship between both DFA-α1 and lactate methods. Besides, the standardised differences or effect sizes (ES) at 95% CI between groups were expressed in Cohen's *d* units and interpreted as trivial (<0.19), small (0.20–0.49), moderate (0.50–0.79), and large (>0.80) (Cohen & Maydeu-Olivares, 1992). Pearson's correlation coefficients (r) were interpreted as trivial (< 0.09), small (0.10–0.29), moderate (0.30–0.49), high (0.50–0.69), very high (0.70–0.89) and almost perfect (> 0.90) (Hopkins, Marshall, Batterham, & Hanin, 2009). Bland and Altman's analysis was also used to assess the agreement between the workload eliciting the different types of thresholds. Additionally, intra-class correlation coefficients (ICC) (Shrout & Fleiss, 1979), coefficients of variation (CV), and standard error of measurement (SEM) (Lexell & Downham, 2005), estimate (SEE) (Smith, 2015) and prediction (SEP) (Caldwell, 2021) were calculated to assess the inter-methods agreement. ICC values were interpreted as: excellent (> .90), good (.75 to .90) and poor to moderate (<.75). All statistical analyses were performed using the open-source project JASP statistical package (V. 0.15, JASP Team, 2021) and JAMOVI (Version 2.0, Jamovie, Sydney, Australia), with statistical significance accepted when $p \leq 0.05$.

Results

The main characteristics of the participants are shown in Table 1. Time series contained 2.04 ± 0.95% of artefacts during each 2-minute measurement window. There were no significant differences ($p > 0.05$) between the external (*i.e.* PO) or the internal (*i.e.* HR) workload eliciting the LT1 or the DFA-α1 1–0.75, whereas DFA-α1 1–0.5 corresponded to significantly lower values of PO and HR than LT2. On the other hand, a significant correlation was found between PO/HR at LT1 and PO/HR at DFA-α1–0.75, and between PO/HR at LT2 and PO/HR at DFA-α1– 0.5, but not between HR at LT1 and HR at DFA-α1–0.75 (Table 2).

ICC showed good and excellent levels of inter-method agreement for PO in the DFA-α1-0.75 and DFA-α1-0.5, and poor to moderate in heart rate (Table 3). In addition, CV remained below 8% in all the variables. Finally, Bland–Altman analysis showed overall good agreement between LT and DFA-α1 methods (Figure 1).

Discussion

The main purpose of this study was to test the validity of the DFA-α1 to determine individual training intensity thresholds against the traditional methodology using the blood lactate concentration in professional cyclists. The main finding was that the power and heart rate values derived from the DFA-α1 thresholds showed high levels of validity and agreement when they were compared against the LT1. Therefore, the use of DFA-α1 can be implemented to non-invasively evaluate this threshold in this population.

Table 1. Descriptive characteristics of the participants.

	Mean	SD
Age (years)	22	7
Height (cm)	170.8	8.5
Weight (kg)	61.0	7.1
PPO (watts)	353	65
PPO (watts/kg)	5.8	0.6
HRmax (beats/min)	191	10

Abbreviations: PPO, peak power output; SD, standard deviation; HRmax, maximum heart rate.

The first lactate threshold has been deemed as the limit between the moderate and the heavy intensity domains (Burnley & Jones, 2007). An accurate determination of this threshold has a meaningful impact on the success of an individualised training programme because larger proportions of training below LT1 are observed in successful endurance athletes (Casado, Hanley, Santos-Concejero, & Ruiz-Pérez, 2021). Furthermore, the LT1 determination is important for training optimisation because this point represents the intensity in which [La^-] production is higher than its clearance, being lactate a major energetic substrate (Poole, Rossiter, Brooks, & Gladden, 2021; San-Millán & Brooks, 2018). In this study, DFA-α1-0.75 showed no differences and trivial effect sizes when the values of power and heart rate are compared to those obtained in the LT1 (Table 2). Regarding power output, the average differences remained low (0.66 and 0.01 for absolute and relative power, respectively) and displayed significant positive correlations (r values of 0.77 and 0.55 for absolute and relative power, respectively). In contrast, although the heart rate values were similar between DFA- α1-0.75 and LT1 ($p > 0.05$), no correlation was found between them ($r = -0.23$). Previous researchers have identified DFA-α1-0.75 as a valid measurement in recreational runners when this point is compared against the first ventilatory threshold (Rogers et al., 2021c; Rogers et al., 2021a). The rationale behind the mentioned research is that VT1 is usually located at a point of significant parasympathetic withdrawal (Tulppo et al., 1996), and a DFA-α1 value of 0.75 is chosen because this is the midpoint between a fractal and a random dynamic in the heart rate time series (Gronwald, Hoos, & Hottenrott, 2019). In line with this, previous research has identified that VT1 has a temporal appearance similar to that of LT1 (Echeverria et al., 2003). Furthermore, the Bland Altman plots (Figure 1) and the inter-method agreement showed good levels of similarity between the two measurements (see Table 3 for further details).

Table 2. Comparison of lactate thresholds (LT) and Detrend Fluctuation Analysis (DFA) α1 thresholds obtained with heart variability analysis.

						95% CI			95% CI	
	LT	DFA α1	Average difference	p	Cohen's d	Lower	Upper	r	Lower	Upper
PO (watts) at LT1 vs DFA α1–0.75	201± 56	200 ± 57	1	0.90	0.02	−0.30	0.34	0.85*	0.74	0.92
HR (beats/min) at LT1 vs DFA α1–0.75	153 ± 14	150 ± 17	3	0.22	0.21	−0.12	0.53	0.66*	−0.43	0.81
PO (watts) at LT2 vs DFA α1– 0.5	284 ± 61	276 ± 58	8	0.04	0.35	0.02	0.68	0.93*	0.87	0.96
HR (beats/min) at LT2 vs DFA α1– 0.5	176.84 ± 11.35	173.18 ± 12.32	3.66	0.02	0.41	0.07	0.74	0.71*	0.51	0.84

Abbreviations: CI, confidence interval; HR, heart rate; LT1, first lactate threshold: LT2, second lactate threshold; PO, power output. Symbol; *significant correlation ($p < 0.001$).

Table 3. Inter-method agreement between lactate thresholds and detrend functional analysis (DFA) α1 thresholds obtained with heart rate variability analysis.

		95% CI					
	ICC	Lower	Upper	CV (%)	SEM (watts or beats/min)	SEE (watts or beats/min)	SEP (watts or beats/min)
PO (watts) at LT1 vs DFA α1–0.75	0.86	0.77	0.92	7.8	21	29	41
HR (beats/min) at LT1 vs DFA α1– 0.75	0.64	0.45	0.78	4.7	9	11	17
PO (watts) at LT2 vs DFA α1– 0.5	0.92	0.87	0.95	4.01	16	22	31
HR (beats/min) at LT2 s DFA α1– 0.5	0.67	0.50	0.80	2.8	6	8	12

Abbreviations: ICC, intraclass correlation coefficient; CI, confidence interval; CV, coefficient of variation; HR, heart rate; LT1, first lactate threshold: LT2, second lactate threshold; PO, power output; SEE, standard error of estimate; SEM, standard error of measurement; SEP, standard error of prediction.

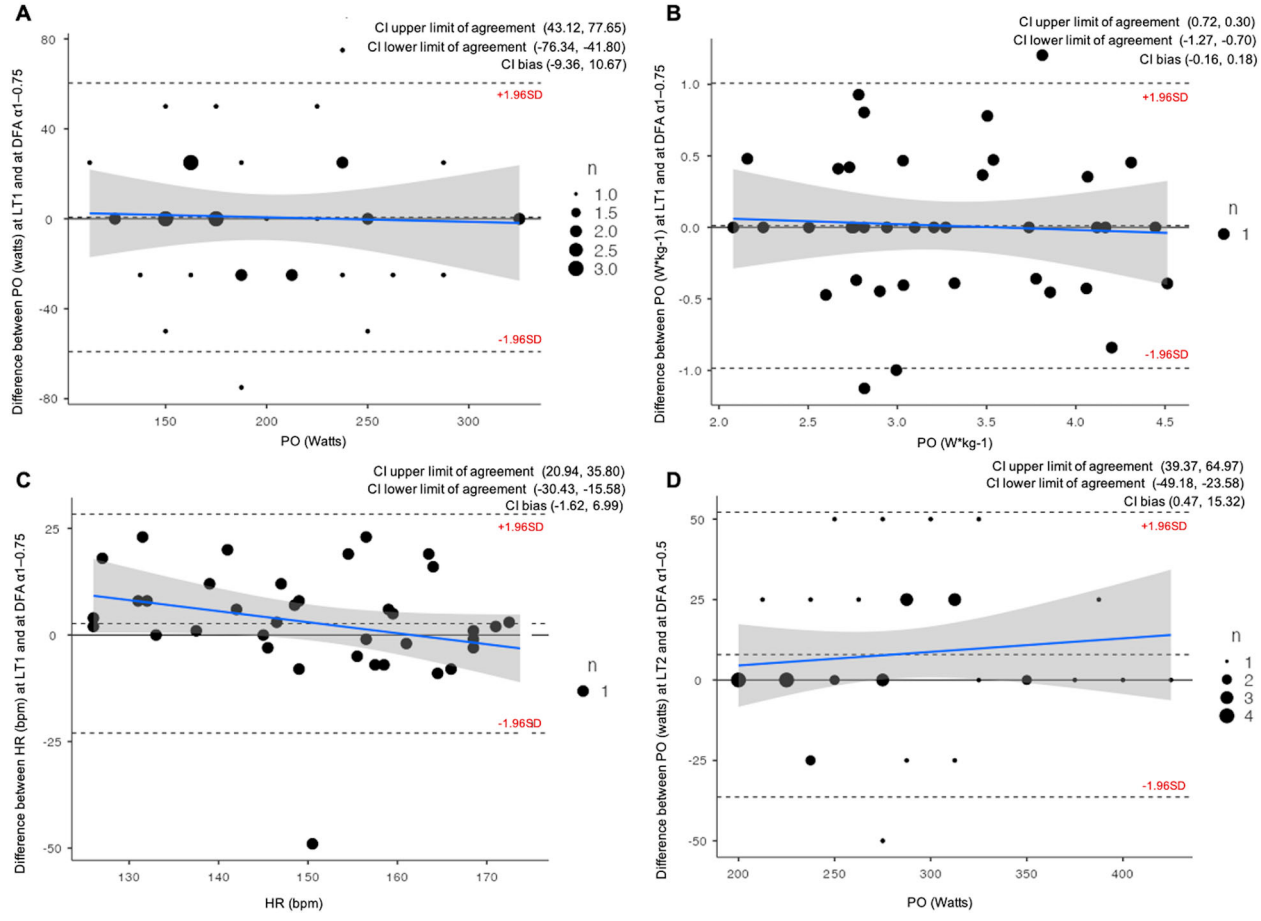

Figure 1. a. Agreement between Lactate thresholds versus DFA α1 thresholds b. Agreement between Lactate thresholds versus DFA α1 thresholds.

The second lactate threshold (LT2) has been proposed as a point to evaluate the limit between the high and the severe intensity domain. Above this intensity, the slow component of VO_2 increases and there is also an exponential increase in the blood [La^-]. Endurance athletes typically train above the LT2 using sets of intervals (high-intensity training; HIT) (Milanović, Sporiš, & Weston, 2015) because this has been proposed as a proper methodology to increase performance (Lindsay et al., 1996). In this study, a DFA-α1 level of 0.5 was chosen because it represents the limit at which the correlation properties of HR time series disappear (random behaviour) (Peng, Havlin, Stanley, & Goldberger, 1995). In our study, the LT2 and DFA-α1- 0.5 (Table 2) significantly differed in absolute ($p = 0.04$; $d = 0.35$) and relative ($p = 0.04$; $d = 0.34$) power as well as in heart rate ($p = 0.02$; d = 0.4). In addition to these significant differences, the DFA-α1- 0.5 showed a reduction of 8 W for absolute and 0.13 $W{\cdot}kg^{-1}$ for relative power, respectively and 3.66 bpm for heart rate. This fact could lead to a reduction in training intensity when the DFA-α1- 0.5 is applied to delimit training zones. In addition, the Bland Altman plots (Figure 1) and the inter-method agreement showed acceptable levels of

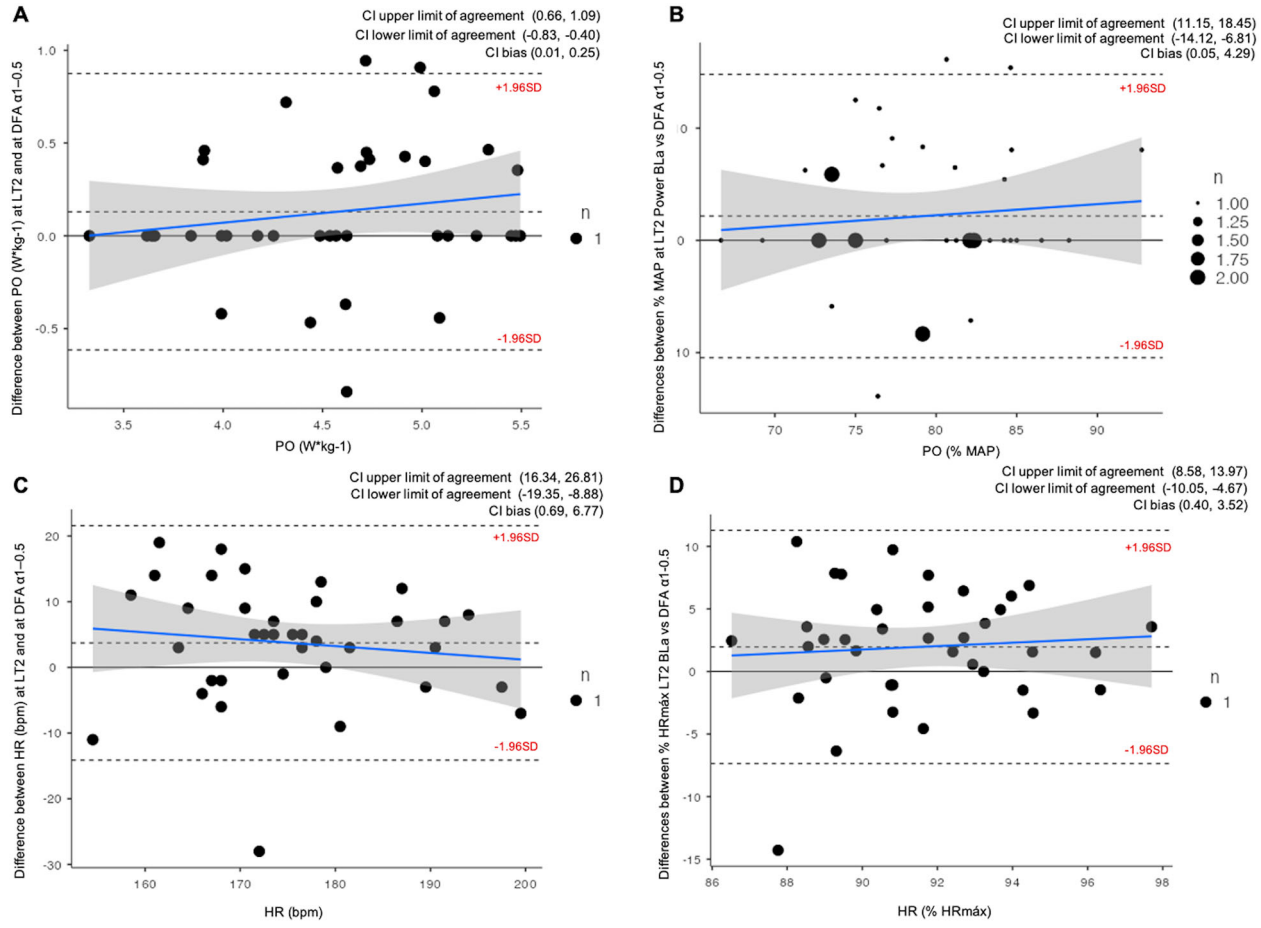

Figure 1 *Continued*

similarity between the two measurements (see Table 3 for further details). In contrast, significant positive correlations (*r* values of 0.93 and 0.71 for PO and HR respectively) were found between LT2 and DFA-α1-0.5, suggesting that both points are related and the changes appear in the same direction. Therefore, it is possible that both measures displayed a constant error. Further research may explore this relationship and its agreement. These correlations are in line with those reported previously in recreational runners (Rogers et al., 2021b); however, the mentioned study did not find differences between DFA-α1-0.5 and the second ventilatory threshold. This discrepancy could be due to the use of a different methodology between this study and ours. Nevertheless, regarding power output, the correlations coefficients and the inter-methodology agreement suggested that there is a strong relationship between the two methods. Thus, future research should explore this. One future research could be to compare the DFA-α1-0.5 against other blood lactate thresholds that have been tested in the literature because this could affect the intensity threshold determination (Jamnick, Botella, Pyne, & Bishop, 2018).

This study has different limitations that must be acknowledged. The calculation of the first threshold (DFA-α1-0.75) was using a fixed value of 0.75. The rationale behind this selection is that it represents a midpoint between a fractal (DFA-α1 = 1) and a random behaviour (DFA-α1 = 0.5) (Peng et al., 1995). Thus, further research should explore if there is an individualised point for each cyclist to estimate this threshold instead of selecting fixed points of the DFA-α. In this regard, different methodologies have also been proposed to evaluate different lactate thresholds (Jamnick et al., 2018). Therefore, other blood lactate indexes could also match with those derived from DFA-α1 measurements and future research should explore this. In line with this, previous research showed that the ramp slope affects lactate determination. In our study we selected 1-min step (Pallarés et al., 2016) but it remains unknown if longer steps will derive in different results when DFA-α1 and lactate thresholds are compared. Finally, the subjects in this study were only male and further investigations could explore the use of DFA-α1 to detect training intensity in female cyclists.

Although LT1 is considered the standard of measurement to evaluate the limit between the moderate and

the heavy intensity domains, its usefulness in repeated evaluation over time is limited because it is an invasive methodology. Due to these results, we can conclude that the DFA1-a-0.75 can be used to estimate LT non-invasively in professional cyclists. In addition, due to the aforementioned characteristics, DFA-α1 will allow its evaluation with greater repeatability and real-time thresholds assessment. This would be beneficial because it could result in a constant update of the intensity zones and lead to a more precise training process. Future research should evaluate the reliability of this methodology in highly trained endurance athletes.

Conclusions

The main conclusion of the present study is the power and heart rate values derived from the DFA-α1-0.75 thresholds showed high levels of validity and agreement when they were compared against the LT1. Therefore, detrended fluctuation analysis is a valid method to estimate the first lactate threshold. In contrast, the LT2 and the DFA-α1- 0.5 threshold were different but showed high levels of correlation and agreement.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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