MAZZOLANI, B.C., PERIM, P., SMAIRA, F.I., REZENDE, N.S., BESTETTI, G.C., DUMAS, A., DE OLIVEIRA, L.F., SWINTON, P., DOLAN, E. and SAUNDERS, B. 2021. Self-reported training variables are poor predictors of laboratory measures in cyclists. *The journal of sport and exercise science* [online], 5(2), pages 139-148. Available from: https://doi.org/https://doi.org/10.36905/jses.2021.02.07

Self-reported training variables are poor predictors of laboratory measures in cyclists.

MAZZOLANI, B.C., PERIM, P., SMAIRA, F.I., REZENDE, N.S., BESTETTI, G.C., DUMAS, A., DE OLIVEIRA, L.F., SWINTON, P., DOLAN, E. and SAUNDERS, B.

2021

SESNZ
SPORT & EXERCISE SCIENCE
NEW ZEALAND

The Journal of Sport and Exercise Science, Vol. 5, Issue 2, 139-148 (2021)

www.sesnz.org.nz

JSES
ISSN: 2703-240X

Self-reported training variables are poor predictors of laboratory measures in cyclists

Bruna C. Mazzolani[1], Pedro Perim[1], Fabiana I. Smaira[1], Nathalia S. Rezende[1], Giulia C. Bestetti[1], Alina Dumas[1], Luana F. de Oliveira[1], Paul Swinton[2], Eimear Dolan[1], Bryan Saunders[1, 3 *]

[1]*Applied Physiology and Nutrition Research Group, School of Physical Education and Sport; Rheumatology Division; Faculdade de Medicina FMUSP, Universidade de Sao Paulo, Sao Paulo, SP, BR, University of São Paulo, Brazil*
[2]*School of Health Sciences, Robert Gordon University, Aberdeen, United Kingdom*
[3]*Institute of Orthopaedics and Traumatology, Faculty of Medicine FMUSP, University of São Paulo, Brazil*

A R T I C L E I N F O

Received: 02.09.2020
Accepted: 03.02.2021
Online: 08.03.2021

Keywords:
Training predictors
Cycling
VO_{2max}
Peak power output
Wingate
Time-trial
Intensity
Laboratory measures

A B S T R A C T

Cycling is an activity that depends on a range of physiological attributes, as well as genetic, dietary, lifestyle and training factors. The aim of this study was to determine what self-reported training-related factors might predict laboratory-measured physiological and performance characteristics of a heterogeneous group of male and female self-classified cyclists. Forty-eight male and fourteen female cyclists completed all aspects of the study including a training questionnaire, incremental cycling test to determine maximal oxygen uptake (VO_{2max}), 30-s Wingate test and a 4-km cycling time-trial. Principle component analysis and LASSO regression modelling were used to analyse laboratory-measures and training variables and the predictive capacity of the latter. Total distance covered across all intensities was the only training variable included in most bootstrap models (63.8%), although the actual contribution was very low with a median f^2 effect size equal to 0.01. Self-reported training variables were poor predictors of laboratory-based physiological and performance variables in this heterogeneous group of cyclists. Total distance covered was the only training variable included in most regression models, but the predictive capability of outcomes was low. Researchers and coaches should be wary that self-reported classification may not directly reflect the level of the cyclist.

1. Introduction

Endurance cycling is a predominantly aerobic activity that requires a high turnover of energy to produce mechanical power (Jeukendrup, Craig, & Hawley, 2000). Studies have demonstrated that laboratory measures such as maximal oxygen uptake (VO_{2max}), peak power output and power at the lactate or ventilatory thresholds are strong predictors of cycling performance (Bentley, McNaughton, Thompson, Vleck, & Batterham, 2001; Borszcz, Tramontin, de Souza, Carminatti, & Costa, 2018; Hawley & Noakes, 1992; Pfeiffer, Harder, Landis, Barber, & Harper, 1993). Although these laboratory variables are considered good predictors of cycling performance, less is known about the contributing factors underlying these measured variables, which are likely reflective of any number of genetic, dietary, and lifestyle influences. While these factors undoubtedly play a role, laboratory variables are also likely reflective of training habits.

Exercise intensity varies across training sessions and for convenience is often grouped into three categories, namely low intensity training (i.e., high volume, low intensity training), lactate threshold training (i.e., involves primarily continuous or intervals of moderate-intensity exercise) and high-intensity interval training (i.e., HIIT; mainly interval training, intermittent intervals, or short, high-intensity sprints) (Seiler, 2010; Stoggl & Sperlich, 2015). There is likely to be overlap in some physiological adaptations (e.g., maximal oxygen uptake [VO_{2max}], capillary density, mitochondrial biogenesis, stroke volume, etc) to these different training stimuli, but the physiological and performance adaptations that occur with HIIT are often superior to those that occur with continuous endurance training (Helgerud et al., 2007; Ni Cheilleachair, Harrison, & Warrington, 2017). Thus, the proportion of weekly training at different intensities is likely to be an important factor contributing to an individual's performance during laboratory tests, although the extent of this relationship is not well-established.

*Corresponding Author: Bryan Saunders, University of São Paulo, drbryansaunders@outlook.com

There is a large discrepancy in the scientific literature regarding how cyclists are classified (i.e., "trained", "well-trained", "professional", etc) between studies. Some authors have attempted to address this issue and provide a framework by which to classify male and female volunteers according to physiological parameters measured in the laboratory as well as weekly cycling training distances (De Pauw et al., 2013; Decroix, De Pauw, Foster, & Meeusen, 2016). However, we have previously shown that competitive (Brazilian state, national and international level) male cyclists had average VO_{2max} values of ~53 $ml \cdot kg^{-1} \cdot min^{-1}$ (Farias de Oliveira, Pires da Silva, de Salles Painelli, Gualano, & Saunders, 2016), considerably below well-trained (>60 $ml \cdot kg \cdot min^{-1}$; (Jeukendrup, Hopkins, Aragon-Vargas, & Hulston, 2008) and professional cyclists (Mujika & Padilla, 2001) despite a similar reported training volume. It is currently unknown why such large discrepancies between cycling populations exist, but it could be due to additional training factors that are not considered, such as intensity, frequency and primary mode (e.g., road or mountain bike). It would be of interest, therefore, to determine whether these self-reported training factors relate to commonly evaluated laboratory measures of cycling capacity.

Performance tests tax different energy contribution systems, with the energy supply during any given exercise protocol dependant on its intensity and duration. Maximal oxygen uptake (VO_{2max}) is the maximum capacity of an individual to transport and use oxygen during high intensity exercise (Bassett & Howley, 2000), and is one of the most frequently used physiological variables to determine aerobic power and training effects. The 30-s Wingate is a short-duration high-intensity exercise protocol predominantly supplied by anaerobic energy sources (Beneke, Pollmann, Bleif, Leithauser, & Hutler, 2002; Smith & Hill, 1991) and used to determine anaerobic performance. Middle distance time-trials (i.e., 4-km), although predominantly supplied by aerobic sources, require a substantial contribution from anaerobic sources (Craig et al., 1993) while an incremental cycling test to exhaustion is predominantly aerobic. Thus, these three protocols comprise a comprehensive battery that can determine the various physiological and performance measures essential for cycling performance, though no data exists relating training frequencies across intensity domains on these laboratory parameters.

The aim of this study was to determine whether self-reported training-related factors (e.g., intensity, frequency, supervision) might predict laboratory-measured physiological and performance characteristics of a heterogeneous group of male and female self-classified cyclists.

2. Methods

2.1. Participants

Cyclists were recruited via social media channels, with 144 cyclists (107 male, 37 female) registering initial interest. This number was further reduced to 52 male and 18 female cyclists, however, not all completed the full battery of exercise protocols due to time commitments and full exercise data is available as follows: Incremental cycling test, men = 52, women = 18; 30-s Wingate test, men = 50, women = 14; 4-km time-trial, men = 48, women = 14. Inclusion criteria included, i) aged 18-60 y; ii) minimum one-year of structured cycling training (>60 km/week (De Pauw et al., 2013). Exclusion criteria included any chronic health issue that would impede performing the exercise tests. The study was approved by the institution's Ethical Advisory Committee. Participants were informed of all protocols and risks associated with the study and provided written informed consent prior to participating.

2.2. Experimental design

The participants attended the laboratory on three separate occasions. The first visit involved anthropometric measurements and completion of the questionnaires. The next visit was for the determination of maximal cycling power output (W_{max}) and VO_{2max}; following 15 min rest, a familiarisation of the 30-s Wingate test was performed. On the last visit, participants performed the 30-s Wingate followed by a 4-km cycling time-trial (TT), separated by 20 min rest to allow recovery of muscle lactate and pH (Bangsbo, Johansen, Graham, & Saltin, 1993; Zinner et al., 2016). Participants abstained from alcohol, caffeine and strenuous exercise and completed a food record for the 24 h period prior to the initial main trial and adopted the same routine prior to the next session. Participants arrived at the laboratory a minimum of 2 h following their last food consumption.

2.3. Experimental Procedures

2.3.1. VO_{2max} test

The test was performed on a cycle ergometer (Lode Excalibur, Lode B.V., The Netherlands) and began at 100 W for men and 50 W for women, increasing 25 W every 3 min until exhaustion. Ventilatory and gas exchange measurements were recorded using a breath-by-breath system (Quark, Cosmed, Italy); the highest value averaged over 15-s was defined as VO2max. Maximal power output was calculated as the last completed stage plus the fraction of time spent in the final non-completed stage multiplied by 25 W. Outcome measures included absolute (aVO_{2max}) and relative (rVO_{2max}) VO_{2max}, absolute (aW_{max}) and relative (rW_{max}) W_{max}, and ventilatory thresholds 1 (VT1) and 2 (VT2) (Pallares, Moran-Navarro, Ortega, Fernandez-Elias, & Mora-Rodriguez, 2016).

2.3.2. 30-s Wingate

The test was performed on a cycle ergometer (Lode Excalibur, Lode B.V., The Netherlands). Following a 10-min warm-up (1.5 $W \cdot kg^{-1}$) and 1-min at 75 W, participants pedalled maximally for 30 s against a resistance of 0.7 $Nm \cdot kg^{-1}$BM for men and 0.6 $Nm \cdot kg^{-1}$BM for women. Participants could choose their preferred cadence during the warm-up but were required to maintain 60 $rev \cdot min^{-1}$ during the final 15 s prior to the Wingate to standardise the starting cadence (Kohler, Rundell, Evans, & Levine, 2010). Participants' remained seated throughout the sprint and received strong standardised verbal encouragement throughout. Data was sampled at 5 Hz. Absolute (aPPO; W) and relative (rPPO; $W \cdot kg^{-1}$) peak power output and absolute (aMPO; W) and relative (rMPO; $W \cdot kg^{-1}$) mean power output were determined.

2.3.3. 4-km cycling time-trial

The 4-km time-trial was performed on a road bicycle (Caloi, size medium) and attached to a roller connected to software (CompuTrainer, RacerMate Inc, USA), with the position of the handlebar and seat setup modified according to each participant's preference. The bicycle was calibrated (2 - 2.5 lbs resistance; chain ratio 3:1) before participants performed a 10-min warm-up at 100 W, followed by 2 min rest (on the bike). A further calibration (2.5 – 2.75 lbs; chain ratio 3:1) was performed prior to performance of the 4-km TT. Participants were instructed to complete the exercise in the fastest possible time and could change gearing throughout. Time-to-complete the time-trial (TTC; s) and mean power output (MPO; W) were recorded.

2.3.4. Questionnaires

Participants completed a training questionnaire relating to their current training routines, including information on weekly frequency (0 – 7 days) in each intensity domain (low intensity, long distance; medium distance, medium intensity; short distance, high intensity), average duration (<1 h; 1-2 h; 2-3 h; 3-4 h; 4-5 h; >5 h) of a ride in each intensity, average distance covered (<50 km; 50-100 km; 100-150 km; 150-200 km; 200-250 km; >250 km) during a ride in each intensity. Descriptors of low intensity, long distance (e.g., long duration and distance, steady pace), medium distance, medium intensity (e.g., training with intermediate sprints, escape and attacks simulations, short and active recovery intervals) and short distance, high intensity (e.g., training with many sprints, simulated starts and jumps, rest intervals) were provided and discussed with the participants to ensure understanding of the zones and accuracy of reported variables. Primary cycling mode (road cycling; mountain biking; BMX; velodrome; triathlon) and highest level of competition at which any individual was competing at (regional; state-level; national; continental/Pan-American; International/Olympic; do not compete) was extracted, as was whether the individual had a coach or not. They were also required to self-classify themselves as professional (i.e., engaged in cycling as a main paid occupation with structured training as part of a professional cycling team), amateur (i.e., engaged in cycling with structured training but not as a paid occupation but occasional to frequent involvement in competitions) or recreational (i.e., engaged in cycling without a specifically structured training program, not competing in any competitions), categories that were explained to the volunteers by an investigator. Various iterations were developed based on feedback attained during pilot testing, whereby members of the research team, and specifically those with extensive cycling experience, completed and fed-back on the questionnaire. Completion of questionnaires was performed under the supervision of an investigator who clarified any issues or confusion regarding questions.

2.3.5. Anthropometry and body composition

Measurements of weight, height and eight skinfolds (biceps, subscapular, triceps, supra spinal, abdominal, iliac crest, medial thigh and calf) were performed to estimate %body fat for men (Withers, Craig, Bourdon, & Norton, 1987) and women (Jackson & Pollock, 1985). Measurements were performed by a trained individual according to the recommendations of the International Society for the Advancement of Kinanthropometry and body composition is reported as the sum of skinfolds.

2.4. Data Analysis

Independent-samples t-tests were used to determine differences between the means of men and women for all measured continuous variables and a one-way mixed-model was used to determine differences between self-categorisation groups (recreational, amateur, professional) for men, but not women due to a lack of different groups. Welch's correction was used to account for groups heterogeneity between self-categorisation groups. To identify differences between specific groups when a significant value was shown, a Games-Howell post hoc test was performed. Statistical significance was set at $p < 0.05$.

To assess the predictive capability of training-related factors (16 variables: frequency and distance covered at low, medium and high intensity; self-reported classification; modality; coached; competition level) whilst controlling for participant demographics (5 variables: sex; age; height; weight; BMI) across a range of laboratory-measured outcomes (14 variables), a multivariable method was required that avoided problems with overfitting. Therefore, LASSO (least absolute shrinkage and selection operator) regression models were conducted as a penalised regression method. Models were generated using the glmnet package (Friedman, Hastie, & Tibshirani, 2010) in R with statistical properties of estimates based on 10,000 bootstrap samples.

To summarise the predictive capability of training-related factors, a collective laboratory-based measure representing "average" performance across tests was created. The dependent variable was achieved by conducting a principal component analysis (PCA) and using the weights obtained from the first principal component. PCA was conducted with imputation of missing data using the imputePCA function from the missMDA package in R (Josse & Husson, 2016). LASSO regression was then conducted with model inputs and the PCA derived measure. Importance of model inputs were described by the percentage inclusion in models, the size of the regression coefficient and Cohen's f^2 effect size which was calculated using standard formula (Cohen, 1988). Outcomes are reported as mean ± 1SD unless otherwise stated.

3. Results

3.1. Demographic, training, physiological and performance characteristics

The sample consisted of five professional male cyclists, 45 men and 16 women self-reported as amateur while the remaining two men and one woman considered themselves recreational. One woman did not classify herself in any category. According to VO_{2max} classifications (De Pauw et al., 2013; Decroix et al., 2016), twelve men and four women were classified as untrained, 24 men and ten women as recreationally trained, 15 men and three women as trained and one man and one woman as well-trained (Figure 1). The primary cycling modes of the sample of cyclists consisted of road cycling (N = 42), mountain biking (N = 21) and triathlon (N = 6); one individual did not choose a primary modality. Twenty-one men and eight women were supervised by a coach.

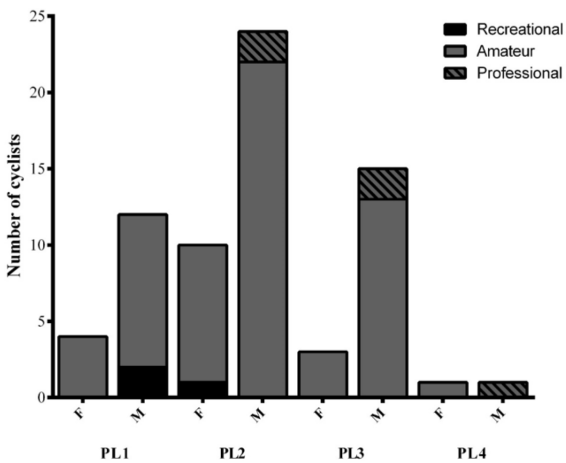

Figure 1: Number of cyclists in each category according to recommendations (De Pauw et al., 2013; Decroix et al., 2016) (x-axis) and self-reported classification (within columns). F = Female, M = Male, PL1 = untrained, PL2 = active (Females) or recreationally trained (Males), PL3 = trained, PL4 = well-trained. Twelve men and 4 women were classified as untrained (PL1), 24 men and 10 women as recreationally trained (PL2), 15 men and 3 women as trained (PL3) and 1 man and 1 woman as well-trained (PL4). Five men self-reported as professional cyclists, 45 men and 16 women self-reported as amateur while the remaining 2 men and 1 woman considered themselves recreational. One woman didn't classify herself in any category.

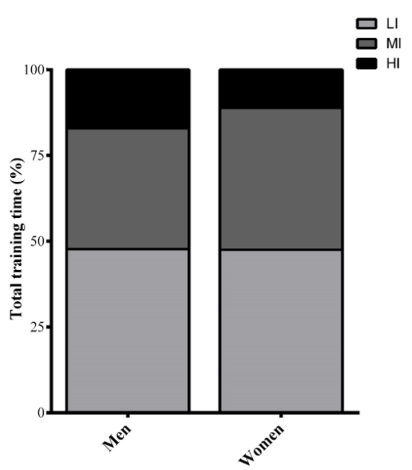

Figure 2: Relative training distribution across low (LI), medium (MI) and high (HI) intensity zones in men and women as a percentage of total weekly training volume.

All laboratory measured variables showed a sex difference (all $p \leq 0.05$), except relative power output at the ventilatory thresholds. Weight, aVO_{2max}, rVO_{2max}, VT2 W_{max}, weekly training distance covered, and duration was different between men's self-classification groups (all $p < 0.05$), with greater values in professionals > amateur > recreational (Table 1). Similarly, rPPO, aMPO and rMPO were greater for professionals compared to the recreational group (all $p < 0.01$) (Table 1). rW_{max} was different between recreational and professional groups with greater values for professional, with no differences between amateur and recreational or professional and amateur. Average weekly distance and training duration across all intensities was 307 ± 140 km and 10.3 ± 3.6 hours for men, 278 ± 107 km and 8.8 ± 4.5 hours for women. The distribution per training intensity was as follows: Low intensity: 47.7% (Men: 47.7%; Women: 47.5%); Moderate intensity: 36.7% (Men: 35.2%; Women: 41.4%) and High intensity: 15.7% (Men: 17.1%; Women: 11.1%) (Figure 2).

3.2. LASSO Regression

The importance of each predictor was initially assessed by quantifying percentage inclusion in LASSO bootstrap samples across the laboratory-based measurements (Figure 3). The median value was largest for sex (98.8%), followed by weekly cycling distance across all intensities (63.8%) and age (57.0%). In general, the remaining predictor variables did not feature frequently in LASSO models (e.g., median < 25% inclusion).

PCA on the laboratory-based measurements identified that the initial principal component accounted for 53.1% of the total variance and represented a collective "average" performance. The results of the LASSO regression with the PCA derived measure showed that only a small number of predictors were relevant with sex (100%), height (97.7%), age (93.1%) and all intensity distance (91.1%) featuring in most bootstrap samples (Figure 4). Cohen's f^2 effect size was very small for all training related factors with the largest median value obtained for all intensity distance (f^2 = 0.01).

4. Discussion

We aimed to determine whether self-reported training variables were effective predictors across a range of laboratory-based measures in a heterogenous group of male and female self-classified cyclists. LASSO regression was used to mitigate against overfitting and generation of spurious results. The analyses showed that of all the training variables considered, only total distance covered summing all intensities tended to feature as a predictor; however, the actual predictive contribution to the outcome measures was very small with Cohen's f^2 equal to 0.01. Training intensity, years of experience, level of competition and having a coach were not predictive of any of the performance outcomes measured in this study. Principal component analysis demonstrated that all laboratory-based measures were strongly associated with each other.

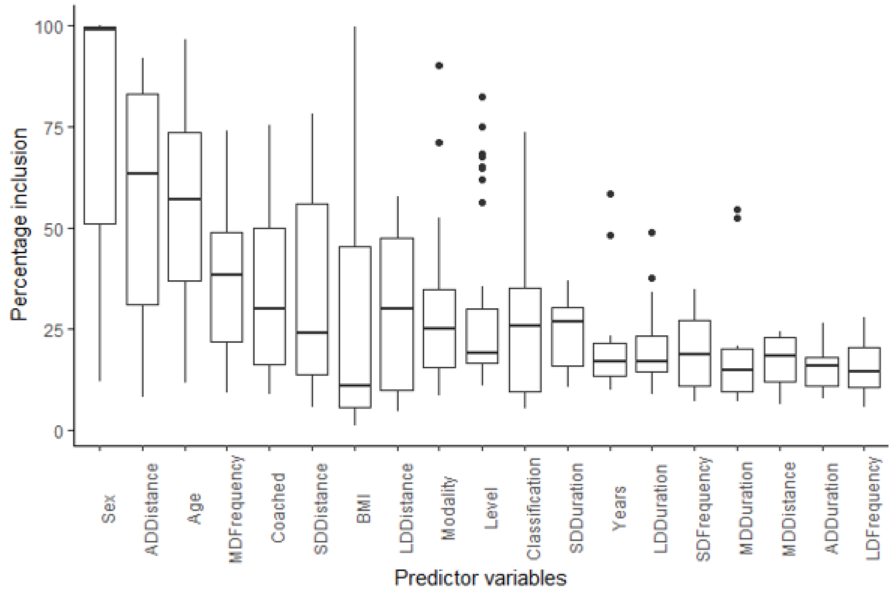

Figure 3: Boxplots illustrating distribution of percentage inclusion in LASSO bootstrap models across all dependent variables. The black line represents the median value, with higher values representing greater percentage inclusion and therefore greater importance in prediction. Legend: ADDistance = all training distance covered, MDFrequency = medium-intensity training frequency, LDDistance = low-intensity training distance covered, SDDuration = high-intensity training duration, SDFrequency = high-intensity training frequency , MDDistance = medium-intensity training distance covered , LDDuration = low-intensity training duration, ADDuration = all training duration , MDDuration = medium-intensity training duration, LDFrequency = low-intensity training frequency, Level = level of competition, BMI = body mass index.

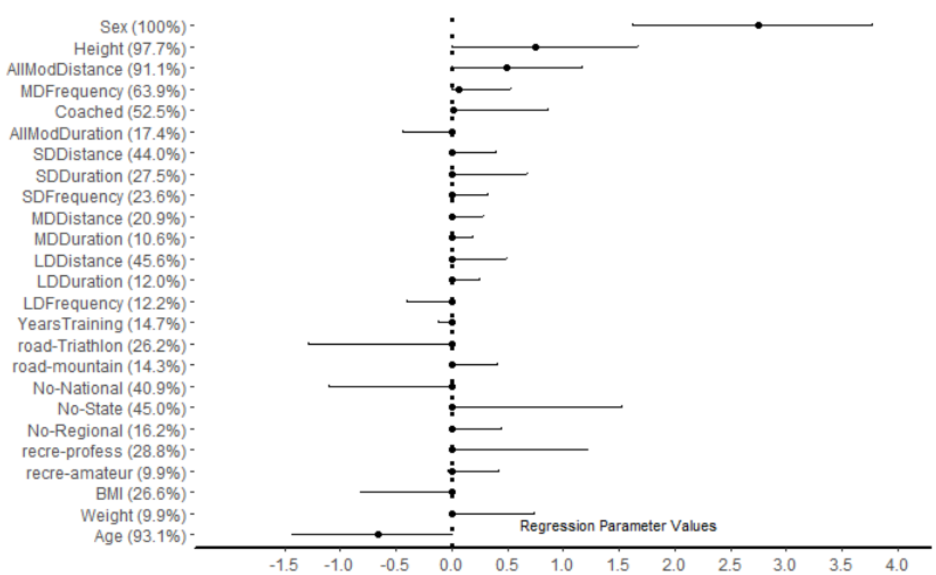

Figure 4: LASSO regression for single dependent variable representing all laboratory-based performance measures according to the PCA analysis weights. Intervals represent 95% confidence intervals for the regression coefficient. Larger regression coefficients and greater percentage inclusion indicates greater importance in prediction. Legend: AllModDistance = all training distance covered, AllModDuration = all training duration , MDDistance = medium-intensity training distance covered, MDDuration = medium-intensity training duration, MDFrequency = medium-intensity training frequency, LDDistance = low-intensity training distance covered, LDDuration = low-intensity training duration, LDFrequency = low-intensity training frequency, SDDistance = high-intensity training distance, SDDuration = high-intensity training duration, SDFrequency = high-intensity training frequency , Level = level of competition, BMI = body mass index, road-triathlon = triathlon modality, road-mountain = mountain bike modality, recre-profess = self-classification as recreational or professional, recre-amateur = self-classification as recreational or amateur , No-National = non-national competitors, No-State = non-state competitors, No-Regional = non-regional competitors.

Table 1: Physical, maximal and submaximal physiological characteristics of male cyclists according to self-reported classification

	Characteristic	Total		Recreational		Amateur		Professional	
		n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)
	Age (y)	52	36 (10)	2	42 (0)	45	37 (10)	5	28 (8)
	Height (cm)	52	1.78 (0.06)	2	1.81 (0.01)	45	1.78 (0.07)	5	1.75 (0.03)
	Weight (kg)	52	78.0 (11.1)	2	84.5 (0.07)	45	78.3 (11.5) [a]	5	72.0 (7.5) [a,b]
	BMI (kg·m²)	52	24.6 (3.1)	2	25.8 (0.4)	45	24.7 (3.3)	5	23.4 (2.0)
	Body fat (%)	49	(13.7) (5.2)	0	-	44	13.9 (5.2)	5	11.3 (4.7)
	Weekly training distance (km)	51	307 (140)	2	75 (35)	44	298 (105) [a]	5	488 (244) [a,b]
	Weekly training duration (hours)	51	10.3 (3.6)	2	7.5 (0.0)	44	10.0 (3.5) [a]	5	14.5 (2.7) [a,b]
Incremental test	VO_{2max} Absolute ($L \cdot min^{-1}$)	52	3.9 (0.5)	2	2.8 (0.2)	45	3.9 (0.5) [a]	5	4.1 (0.3) [a,b]
	VO_{2max} Relative ($ml \cdot kg \cdot min^{-1}$)	52	50.2 (7.9)	2	32.6 (1.8)	45	50.1 (6.7) [a]	5	57.4 (8.9) [a,b]
	W_{max} Absolute (W)	52	291 (38)	2	223.5 (20.5)	45	292.6 (36.8)	5	306.2 (27.9)
	W_{max} Relative (W)	52	3.8 (0.6)	2	2.6 (0.2)	45	3.8 (0.6)	5	4.3 (0.5) [a]
	VT1 (W)	52	187 (41)	2	156.0 (32.5)	45	187.1 (42.3)	5	196.8 (34.6)
	VT2 (W)	52	226 (39)	2	194 (2.8)	45	226.6 (40.8) [a]	5	236.8 (21.3) [a,b]
	VT1 (%aW_{max})	52	64.3 (11.9)	2	71.0 (21.2)	45	63.9 (11.5)	5	65.4 (15.0)
	VT2 (%aW_{max})	52	77.7 (9.4)	2	87.5 (9.2)	45	77.2 (9.4)	5	78.0 (9.8)
Wingate	PPO Absolute (W)	50	1040 (209)	0	-	45	1022 (206)	5	1201 (187)
	PPO Relative ($W \cdot kg^{-1}$)	50	13.6 (2.8)	0	-	45	13.2 (2.6)	5	16.8 (1.5) [b]
	MPO Absolute (W)	49	539.8 (190.3)	0	-	44	520.7 (191.3)	5	708.5 (39.9) [b]
	MPO Relative ($W \cdot kg^{-1}$)	49	7.1 (2.5)	0	-	44	6.7 (2.4)	5	10.0 (1.0) [b]
4-km time-trial	MPO (W)	48	262.8 (44.3)	0	-	43	258.4 (44.5)	5	300.8 (17.0) [b]
	Time-to-complete (s)	48	397.7 (24.8)	0	-	43	400.0 (25.0)	5	377.8 (10.7) [b]

[a] $p < 0.05$ when compared to Recreational group; [b] $p < 0.05$ when compared to Amateur group

Table 2: Physical, maximal and submaximal physiological characteristics of female cyclists according to self-reported classification

	Characteristic	Total		Recreational		Amateur	
		n	Mean (SD)	n	Mean	n	Mean (SD)
	Age (y)	17	43 (9)	1	41	16	44 (9)
	Height (cm)	17	1.63 (0.06)	1	1.60	16	1.63 (0.06)
	Weight (kg)	16	60.3 (16.1)	1	59.9	15	60.1 (8.6)
	BMI (kg·m²)	16	22.5 (2.3)	1	23.4	15	22.5 (2.5)
	Body fat (%)	16	18.1 (5.3)	1	21.5	15	18.3 (5.1)
	Weekly training distance (km)	16	281 (109)	1	300	15	281 (112)
	Weekly training duration (hours)	16	8.8 (4.5)	1	8	15	9.2 (4.4)
Incremental test	VO_{2max} Absolute ($L \cdot min^{-1}$)	17	2.6 (0.5)	1	2.6	16	2.5 (0.5)
	VO_{2max} Relative ($ml \cdot kg \cdot min^{-1}$)	17	42.6 (6.8)	1	43.3	16	42.6 (7.0)
	W_{max} Absolute (W)	17	200 (31)	1	217	16	198 (32)
	W_{max} Relative (W)	17	3.3 (0.5)	1	3.6	16	3.3 (0.5)
	VT1 (W)	17	122 (21)	1	135	16	122 (22)
	VT2 (W)	17	144 (21)	1	156	16	143 (21)
	VT1 (%aW_{max})	17	61.6 (6.8)	1	62.0	16	61.6 (7.0)
	VT2 (%aW_{max})	17	73.0 (6.6)	1	72.0	16	72.8 (6.9)
Wingate	PPO Absolute (W)	14	547.5 (249.8)	1	596.1	13	543.7 (102.5)
	PPO Relative ($W \cdot kg^{-1}$)	14	9.3 (1.4)	1	10.0	13	9.2 (1.5)
	MPO Absolute (W)	14	394.6 (73.0)	1	426.2	13	392.1 (75.4)
	MPO Relative ($W \cdot kg^{-1}$)	14	5.5 (2.8)	1	7.1	13	5.8 (2.6)
4-km time-trial	MPO (W)	16	172.8 (31.7)	1	197.0	15	168.5 (27.3)
	Time-to-complete (s)	16	460.8 (38.5)	1	431.0	15	466.7 (36.7)

Self-reported total weekly distance (km) was the primary training variable included in most of the LASSO models suggesting that cumulative weekly distance covered may be the most important training variable for any individual to consider. A large training volume is considered critical for endurance performance (Laursen, 2010) making it logical that the more cycling performed, the better the physiological and performance measures, although the actual prediction contribution here was low. No men reported cycling less than 50 km per week, which would categorise them as untrained according to distance-based classification (<60 km) (De Pauw et al., 2013), however, 12 men were classified as untrained according to their VO_{2max}. Of these, almost 60% reported covering more than 150 km per week (which would classify them at least as "trained" according to distance), which appears to somewhat contrast our finding that distance covered per week is a predictor of VO_{2max}. This may be due to an absence of a properly implemented training regime, meaning that, while more distance led to greater increases in maximal oxygen uptake, the absolute benefits were less than with a well-structured program. Increases in total training volume correlate well with improvements in physiological and performance variables (Seiler, 2010) and, although the data suggest low predictive ability here in our heterogenous group of cyclists, our results support the notion that athletes might look to increase their total training volume to improve these measured parameters. These data should be confirmed by further studies using objective training metrics obtained from GPS systems.

Aside from total distance covered per week, the predictive power of which was weak, no other training variable assessed here predicted performance. Approximately 50% of weekly training was reported to be at low intensity, a substantial proportion at moderate intensity (~37%) and the remaining at high intensity (~17% for men and ~11% for women). However, training volume at the different intensities were not found to be predictors of these laboratory measures, suggesting that more intense work does not necessarily return greater laboratory-performance parameters herein. The importance of high-intensity training for adaptation and performance is well-known (Laursen & Jenkins, 2002), and thus it could be speculated that the results here may be due, at least in part, to inaccuracies in self-reporting training variables. Any confusion about the questionnaire was resolved via discussion with the researchers, and we attempted to educate the volunteers on the different training intensities to minimise any possible errors. Nonetheless, studies have shown that most individuals tend to overestimate the amount of physical activity they actually perform (Downs, Van Hoomissen, Lafrenz, & Julka, 2014) while the quantification of intensity distribution assessed herein likely adds another level of complexity. Individuals might differ in their interpretation of their own intensity zones, meaning they may not accurately categorise their own habitual training intensities, over- or underestimating the true intensity (and subsequently time spent within these zones, distance covered, etc) of their training. Our data raise the potential that athletes cannot accurately quantify their own training intensities, something that coaches should contemplate when prescribing training and may wish to consider educating their athlete. Future studies should objectively measure training characteristics using electronic devices that measure distance, power output and/or heart rate, and determine how well they agree with subjective evaluation of training, as well as their relationship to these measure laboratory variables.

All volunteers self-identified as cyclists, and we further asked them to classify themselves as professional, amateur or recreational. There appears to be a large discrepancy between how studies classify cyclists (i.e., “trained”, “well-trained”, “professional”, etc), since classification of training status of volunteers is not usually performed using an objective and/or universal system. This has led to the creation of a framework based upon available literature to classify volunteers according to several parameters, the most appropriate of which was deeme

rVO_{2max} (De Pauw et al., 2013; Decroix et al., 2016). Although self-classification here showed differences between recreational, amateur and professional groups for many laboratory parameters, classification according to rVO_{2max} recommendations (De Pauw et al., 2013; Decroix et al., 2016) showed our population was classified from untrained to well-trained cyclists, with none categorised as professional despite having five professional cyclists. In fact, two of those were only classified as “recreationally trained”. Thus, self-reported classification as a professional cyclist was not a predictor of better performance scores, although this may have been due to the low number of professionals that participated in the study. This could either reflect the limitations of the categorisation method according to recommendations or represent a lower standard among these professionals. Since there are limited number of world-class or elite athletes available for research (Burke, 2017), this provides important information that self-reported classification may not directly reflect the level of the cyclist.

All performance variables across the three tests were strongly associated with each other, suggesting that the physiological components required for each overlap. Physiological and performance gains following either isolated sprint or endurance training are specific to the mode employed; combined sprint (i.e., high-intensity) and endurance (i.e., low-intensity) training leads to sub-optimal performance improvements compared to isolated gains with either training mode (Callister, Shealy, Fleck, & Dudley, 1988). Since the chosen tests have different energy contribution requirements, it could be speculated that strong performance in one test (e.g., endurance test) might not be associated with optimal performance in another (e.g., sprint test) due to specific training adaptations. Nonetheless, our data showed that performance between all tests were positively associated, meaning those individuals that performed better in the aerobic test were also those who performed better in the anaerobic Wingate sprint. It is possible that interference from concurrent sprint and endurance exercise is only important at the highest (elite) level where maximal gains are desired while crossover in the gains obtained from isolated high-intensity or low-intensity training does occur (Gillen et al., 2016).

There are some limitations of this study. Firstly, the questionnaire has not previously been validated and thus, it cannot be ruled out that self-reported training variables obtained via a different question would not yield different results. Various iterations of the questionnaire were developed based on feedback attained during pilot testing, whereby members of the research team, and specifically those with extensive cycling experience, completed and fed-back on the questionnaire. Further work should determine whether individuals can accurately quantify their training intensities/volumes. Participants were not familiarised to the 4-km time-trial prior to completing it and had also performed a 30-s Wingate test 20 min previously. Previous work has shown good reliability between two 4-km time-trial sessions without a familiarisation (Azevedo et al., 2019) while we (Oliveira et al., 2017) and others (Borg et al., 2018) have shown that cyclists may not require a familiarisation to produce reliable results, although we acknowledge this would have strengthened our data.

In conclusion, self-reported training variables were poor predictors of laboratory-based physiological and performance variables in this heterogenous group of cyclists, suggesting that most of the self-reported variables acquired via the questionnaire in this study are not useful pre-screening tools when recruiting volunteers for participation in studies requiring non-elite cyclists. It is acknowledged, however, that most studies will want to employ inclusion criteria prior to participant recruitment and these data suggest that total weekly distance covered is the only variable herein with some predictive power for this. Where objective data is available (e.g., exercise monitoring system), this would likely be preferable. The data do imply that total weekly distance may be an important variable to consider for non-elite cyclists attempting to improve their cycling capacity, and further work should objectively determine this.

Conflict of Interest

The authors declare no conflict of interests.

Acknowledgment

Bruna Caruso Mazzolani (2019/14820-6) and Pedro Perim (2018/01594-5), Eimear Dolan (2017/09635-0; 2019/05616-6) and Bryan Saunders (2016/50438-0) have been financially supported by Fundação de Amparo à Pesquisa do Estado de São Paulo. Nathalia Saffioti Rezende (2018-762) was financially supported by Conselho Nacional de Desenvolvimento Científico e Tecnológico. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001. Bryan Saunders has received a grant from Faculdade de Medicina da Universidade de São Paulo (2020.1.362.5.2).

The authors would like to acknowledge the participants who took part in the study for their time and dedication.

References

Azevedo, R. A., Cruz, R., Couto, P., Silva-Cavalcante, M. D., Boari, D., Lima-Silva, A. E., . . . Bertuzzi, R. (2019). Characterization of performance fatigability during a self-paced exercise. *Journal of Applied Physiology, 127*(3), 838-846. doi: 10.1152/japplphysiol.00090.2019

Bangsbo, J., Johansen, L., Graham, T., & Saltin, B. (1993). Lactate and H+ effluxes from human skeletal muscles during intense, dynamic exercise. *The Journal of Physiology, 462,* 115-133. doi: 10.1113/jphysiol.1993.sp019546

Bassett, D. R., Jr., & Howley, E. T. (2000). Limiting factors for maximum oxygen uptake and determinants of endurance performance. *Medicine & Science in Sports & Exercise, 32*(1), 70-84.

Beneke, R., Pollmann, C., Bleif, I., Leithauser, R. M., & Hutler, M. (2002). How anaerobic is the Wingate Anaerobic Test for humans? *European Journal of Applied Physiology, 87*(4-5), 388-392. doi: 10.1007/s00421-002-0622-4

Bentley, D. J., McNaughton, L. R., Thompson, D., Vleck, V. E., & Batterham, A. M. (2001). Peak power output, the lactate threshold, and time trial performance in cyclists. *Medicine & Science in Sports & Exercise, 33*(12), 2077-2081.

Borg, D. N., Osborne, J. O., Stewart, I. B., Costello, J. T., Sims, J. N. L., & Minett, G. M. (2018). The reproducibility of 10 and 20km time trial cycling performance in recreational cyclists, runners and team sport athletes. *Journal of Science and Medicine in Sport, 21*(8), 858-863. doi: 10.1016/j.jsams.2018.01.004

Borszcz, F. K., Tramontin, A. F., de Souza, K. M., Carminatti, L. J., & Costa, V. P. (2018). Physiological correlations with short, medium, and long cycling time-trial performance. *Research Quarterly for Exercise and Sport, 89*(1), 120-125. doi: 10.1080/02701367.2017.1411578

Burke, L. M. (2017). Practical issues in evidence-based use of performance supplements: Supplement interactions, repeated use and individual responses. *Sports Medicine, 47*(Suppl. 1), 79-100. doi: 10.1007/s40279-017-0687-1

Callister, R., Shealy, M. J., Fleck, S. J., & Dudley, G. A. (1988). Performance adaptations to sprint, endurance and both modes of training. *Journal of Strength & Conditioning Research, 2*(3), 46-51.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.): Lawrence Erlbaum Associates.

Craig, N. P., Norton, K. I., Bourdon, P. C., Woolford, S. M., Stanef, T., Squires, B., . . . Walsh, C. B. (1993). Aerobic and anaerobic indices contributing to track endurance cycling performance. *European Journal of Applied Physiology and Occupational Physiology, 67*(2), 150-158.

De Pauw, K., Roelands, B., Cheung, S. S., de Geus, B., Rietjens, G., & Meeusen, R. (2013). Guidelines to classify subject groups in sport-science research. *International Journal of Sports Physiology and Performance, 8*(2), 111-122.

Decroix, L., De Pauw, K., Foster, C., & Meeusen, R. (2016). Guidelines to classify female subject groups in sport-science research. *International Journal of Sports Physiology and Performance*, *11*(2), 204-213. doi: 10.1123/ijspp.2015-0153

Downs, A., Van Hoomissen, J., Lafrenz, A., & Julka, D. L. (2014). Accelerometer-measured versus self-reported physical activity in college students: implications for research and practice. *Journal of American College Health, 62*(3), 204-212. doi: 10.1080/07448481.2013.877018

Farias de Oliveira, L., Pires da Silva, R., de Salles Painelli, V., Gualano, B., & Saunders, B. (2016). Physiological characteristics of competitive Brazilian cyclists. *Journal of Science and Cycling*, 5(2). Retrieved from https://jsc-journal.com/index.php/JSC/article/view/263.

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software, 33*(1), 1-22.

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine, 27*(15), 2865-2873. doi: 10.1002/sim.3107

Gillen, J. B., Martin, B. J., MacInnis, M. J., Skelly, L. E., Tarnopolsky, M. A., & Gibala, M. J. (2016). Twelve weeks of sprint interval training improves indices of cardiometabolic health similar to traditional endurance training despite a five-fold lower exercise volume and time commitment. *PLoS One, 11*(4), e0154075. doi: 10.1371/journal.pone.0154075

Hawley, J. A., & Noakes, T. D. (1992). Peak power output predicts maximal oxygen uptake and performance time in trained cyclists. *European Journal of Applied Physiology and Occupational Physiology, 65*(1), 79-83.

Helgerud, J., Hoydal, K., Wang, E., Karlsen, T., Berg, P., Bjerkaas, M., . . . Hoff, J. (2007). Aerobic high-intensity intervals improve VO2max more than moderate training. *Medicine & Science in Sports & Exercise, 39*(4), 665-671. doi: 10.1249/mss.0b013c3180304570

Jackson, A. S., & Pollock, M. L. (1985). Practical assessment of body composition. *The Physician and Sportsmedicine, 13*(5), 76-90. doi: 10.1080/00913847.1985.11708790

Jeukendrup, A. E., Craig, N. P., & Hawley, J. A. (2000). The bioenergetics of world class cycling. *Journal of Science and Medicine in Sport, 3*(4), 414-433. doi: 10.1016/s1440-2440(00)80008-0

Jeukendrup, A. E., Hopkins, S., Aragon-Vargas, L. F., & Hulston, C. (2008). No effect of carbohydrate feeding on 16 km cycling time trial performance. *European Journal of Applied Physiology, 104*(5), 831-837. doi: 10.1007/s00421-008-0838-z

Josse, J., & Husson, F. (2016). missMDA: A package for handling missing values in multivariate data analysis. *Journal of Statistical Software, 70(1),* 31. doi: 10.18637/jss.v070.i01

Kohler, R. M., Rundell, K. W., Evans, T. M., & Levine, A. M. (2010). Peak power during repeated wingate trials: implications for testing. *Journal of Strength and Conditioning Research, 24*(2), 370-374. doi: 10.1519/JSC.0b013e3181b06f41

Laursen, P. B. (2010). Training for intense exercise performance: high-intensity or high-volume training? *Scandinavian Journal of Medicine and Science in Sports, 20* (Suppl. 2), 1-10. doi: 10.1111/j.1600-0838.2010.01184.x

Laursen, P. B., & Jenkins, D. G. (2002). The scientific basis for high-intensity interval training: optimising training programmes and maximising performance in highly trained endurance athletes. *Sports Medicine, 32*(1), 53-73. doi: 10.2165/00007256-200232010-00003

Mujika, I., & Padilla, S. (2001). Physiological and performance characteristics of male professional road cyclists. *Sports Medicine, 31*(7), 479-487.

Ni Cheilleachair, N. J., Harrison, A. J., & Warrington, G. D. (2017). HIIT enhances endurance performance and aerobic characteristics more than high-volume training in trained rowers. *Journal of Sports Sciences, 35*(11), 1052-1058. doi: 10.1080/02640414.2016.1209539

Oliveira, L. F., Yamaguchi, G., Painelli, V. S., Silva, R. P., Gonçalves, L. S., Gualano, B., & Saunders, B. (2017). Comprehensive reliability analysis of a 16 km simulated cycling time-trial in well-trained individuals. *Journal of Science and Cycling, 6*(1), 11-17.

Pallares, J. G., Moran-Navarro, R., Ortega, J. F., Fernandez-Elias, V. E., & Mora-Rodriguez, R. (2016). Validity and reliability of ventilatory and blood lactate thresholds in well-trained cyclists. *PLoS One, 11*(9), e0163389. doi: 10.1371/journal.pone.0163389

Pfeiffer, R. P., Harder, B. P., Landis, D., Barber, D., & Harper, K. (1993). Correlating indices of aerobic capacity with performance in elite women road cyclists. *The Journal of Strength & Conditioning Research, 7*(4), 201-205.

Seiler, S. (2010). What is best practice for training intensity and duration distribution in endurance athletes? *International Journal of Sports Physiology and Performance, 5*(3), 276-291. doi: 10.1123/ijspp.5.3.276

Smith, J. C., & Hill, D. W. (1991). Contribution of energy systems during a Wingate power test. *British Journal of Sports Medicine, 25*(4), 196-199. doi: 10.1136/bjsm.25.4.196

Stoggl, T. L., & Sperlich, B. (2015). The training intensity distribution among well-trained and elite endurance athletes. *Frontiers in Physiology, 6*, 295. doi: 10.3389/fphys.2015.00295

Withers, R. T., Craig, N. P., Bourdon, P. C., & Norton, K. I. (1987). Relative body fat and anthropometric prediction of body density of male athletes. *European Journal of Applied Physiology and Occupational Physiology, 56*(2), 191-200. doi: 10.1007/BF00640643

Zinner, C., Morales-Alamo, D., Ortenblad, N., Larsen, F. J., Schiffer, T. A., Willis, S. J., . . . Holmberg, H. C. (2016). The physiological mechanisms of performance enhancement with sprint interval training differ between the upper and lower extremities in humans. *Frontiers in Physiology, 7,* 426. doi: 10.3389/fphys.2016.00426