1	Assessing the Use of Heart Rate Monitoring for
2	Competitive Swimmers
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4 5	Submission Type: Original Investigation
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44 ABSTRACT

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Purpose: Quantifying training intensity provides a comprehensive understanding of the 46 training stimulus. Recent technological advances may have improved the feasibility of using 47 48 heart rate (HR) monitoring in swimming. However, the implementation of HR monitoring is yet to be assessed longitudinally in the daily training environment of swimmers. This study 49 aimed to assess the implementation of HR by comparing the training intensity distribution from 50 an external measure, planned volume at set intensities (PVSI), to the internal training intensity 51 distribution measured using time in HR zones. Methods: Using a longitudinal observational 52 53 design, ten competitive swimmers (8 males and 2 females, age: 22.0 ± 2.3 yr, FINA point score: 842.9 \pm 58.5, mean \pm SD) were monitored daily for 6-months. Each session, heart rate data, 54 55 coached planned and athlete reported session rating of perceived exertion (sRPE; Modified 56 CR10 scale) were recorded. Based on previously determined training zones from an incremental step test, PVSI was calculated using the planned distance and planned intensity of 57 each swim bout. Training intensity distributions were analysed using a linear mixed model 58 (lme4, R Core Team). **Results:** The model revealed a small-to-moderate relationship between 59 60 PVSI and time in HR zone, based on the Nakagawa R squared value (range 0.14-0.42). 61 **Conclusions:** Training intensity distribution differed between the internal measure (i.e., HR) and the external measure of intensity (i.e., PVSI). This demonstrates that internal and planned 62 63 external measures of intensity cannot be used interchangeably to monitor training. Further 64 research should explore how to best integrate these measures to better understand training in swimming. 65

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67 Keywords: internal training intensity, planned external training intensity, wearable

68 technology, training intensity distribution, swimming.

69 INTRODUCTION

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The ability to effectively quantify training intensity is paramount in determining the effect of 71 72 a given exercise bout¹. Intensity can be described using an external measure (i.e., pace, 73 velocity), or an internal measure (i.e., heart rate, blood lactate)¹. Internal training intensity measures are preferred and thought to better reflect the pathophysiological response that drives 74 75 adaptation². In swimming, training intensity can be prescribed as a percentage of critical 76 velocity³, based on rating of perceived exertion (RPE)⁴, or using a session goal time in zone approach⁵. Training intensity is also commonly prescribed as a distance swum at a 77 78 predetermined velocity which is linked to a physiological anchor (i.e., a blood lactate value, heart rate range)^{6,7}. This method of planned volume at set intensities (PVSI) provides a 79 80 surrogate for internal intensity and assumes the corresponding internal physiological response to a prescribed velocity is consistently elicited. However, these methods are limited as without 81 82 a continuous measure of actual exercise intensity, it is unclear whether the training session is eliciting the desired adaptations². Therefore, other measures of intensity may provide a more 83 comprehensive understanding of both the prescribed and actual training stimulus for 84 85 swimmers.

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Heart rate (HR) offers a practical, non-invasive, and inexpensive method of quantifying 87 internal training intensity, and is used across a variety of endurance sports⁸⁻¹⁰. A major benefit 88 of HR monitoring is its portability, allowing the internal training intensity to be continuously 89 90 monitored in a range of training contexts, and the intensity distribution of the entire session to be captured. Despite their frequent use in land-based sports⁸⁻¹⁰, the use of HR monitors to 91 quantify time in HR zones in swim training has been limited^{4,5}. This lack of implementation is 92 93 most likely due to the challenges of measuring HR in an aquatic environment combined with 94 the known limitations of HR monitoring (i.e., impact of hydration, temperature, limited ability to monitor high intensity interval training, assumed linear relationship between heart rate and 95 oxygen consumption during maximal exercise)¹¹. To circumnavigate this difficulty, previous 96 97 studies have used non-waterproof HR monitors or manual palpation during swim training to capture HR measurements out of the water¹²⁻¹⁴. However, these approaches do not continuously 98 99 measure intensity during an entire training session and may not completely reflect the training 100 demands.

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Recently, HR monitors using photoplethysmographic technology have been implemented in 102 competitive swimming 6,15 . Whilst these monitors have been shown to be both valid and reliable 103 in controlled settings^{6,15}, the feasibility of these units to quantify training intensity in the daily 104 training environment is yet to be assessed. The purpose of this study was to assess the 105 106 implementation of HR monitoring by comparing internal and planned external training intensity distributions in swimming. To do this, the association between PVSI and time in HR 107 zone was assessed over the course of a season in highly trained competitive swimmers training 108 109 in a high-performance environment.

110 METHODS

111 Subjects

- 113 Ten national-to-international level competitive swimmers [8 males and 2 females, age: 22.0
- 114 ± 2.3 yr, FINA point score: 842.9 ± 58.5 , (mean $\pm SD$)] were observed daily for 6-months.
- 115 Written informed consent was obtained from the swimmers prior to the data analysis. Approval

116 was obtained from the University of Technology Sydney Ethics Committee (ETH21-6130),

- and permission to use training data was granted by the provincial sporting institute. The
- 118 investigation conformed to the Code of Ethics of the World Medical Association.

119 Design

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A longitudinal observational design was implemented to examine the relationship between 121 122 PVSI and time in HR zone. Athletes were monitored from January to June 2021 in the period leading up to a major national competition. Training sessions (~9 sessions/week) were 123 completed in an indoor pool. The athletes attended three training camps, in outdoor training 124 125 facilities, each lasting one-to-two weeks throughout the study period. These sessions were included in the analysis. During the study period, participants completed land-based strength 126 training two times per week. Swimmers also competed in four competitions which were 127 128 included in the total sessions but were excluded for analysis as athletes chose not to wear HR monitors while competing. Prior to each training session, the coach provided the planned 129 distance and intensity of each swim bout using a modified PVSI method (see table 1) and a 130 planned session rating of perceived exertion (sRPE; Modified CR10 scale)¹⁶. Each session, 131 HR was recorded, and athletes reported their total distance swum and sRPE within 30 minutes 132 133 of training completion. All participants were accustomed to these procedures as part of their

- 134 ongoing training monitoring.
- 135 *Methodology*
- 136 Planned Volume at Set Intensities
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138 Planned volume at set intensities were calculated by allocating the coach-prescribed swimming 139 bouts into metres planned across 8 intensity zones. These zones were based on the descriptors used in Table 1^{17,18} for zones 1-5. Three custom race pace zones (800-400 m pace, 200 m pace, 140 100 m pace and faster) were also calculated, these were individualised for each swimmer and 141 142 based on a target time. Prior to analysis, all race pace work (800-100 m pace or faster) was combined into Zone 5 to align with HR-based training zones, where PVSI would represent 143 metres swum in Zone 1 (Z1m) through to Zone 5 (Z5m) as shown in Table 1. Individual 144 145 training zones were determined following an early season incremental 5 x 200 m step test¹⁹. The training intensity descriptors (see Table 1) were given to the athletes prior to the 146 observation period to allow the athletes to individually relate to the training intensity zones. 147 Training was then prescribed to the athletes as a volume, in metres, and a zone for example 148 "400m at Zone 1 intensity". This method of training prescription was familiar to the coach and 149 athletes as it formed part of their ongoing training monitoring. 150

151 Heart Rate

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153 Swimmers recorded HR for all swim training sessions using the Polar OH1 HR monitor (Polar Electro, Kempele, Finland). The monitor was placed under the swimmers' swimming cap near 154 the temple to record the entire training session^{6,15}. At the end of each session each athlete 155 uploaded the recorded session from their personal HR monitor to a secure online athlete 156 157 monitoring system (Polar Flow; Polar Electro, Kempele, Finland; https://flow.polar.com). Each HR file was downloaded and assessed using a customised template (Microsoft Excel, 158 Microsoft, Oregon USA). All HR files were checked and coded as a full session (HR data 159 160 available for the entire session), a partial session recording (a session with any missing data),

more than 5% of data was missing. At the conclusion of the study, each athlete's peak HR 162 across the data collection period was obtained from Polar Flow and used as the maximal 163 physiological anchor point. The time in HR zones were calculated for each session. Zones were 164 based on each athlete's peak HR (Z1 50-75%, Z2 75-80%, Z3 80-85%, Z4 85-92% and Z5 165 $>92\%)^{17}$.

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- Session Rating of Perceived Exertion. 169
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171 For all training sessions both the coach planned and athlete sRPE were recorded ¹⁶. During the athletes' warm up the coach was asked to report each athlete's planned sRPE for the session. 172 This was recorded in a customised Microsoft Excel spreadsheet (Microsoft Excel, Microsoft, 173 174 Oregon USA). RPE_{diff} was calculated by subtracting the athlete reported sRPE from the coach

- planned sRPE, yielding a positive or negative RPE_{diff} value. 175
- 176 Statistical Analysis

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178 For analysis, sessions with no or partial HR recordings were excluded, sessions with missing 179 PVSI, sRPE or session that were modified data were removed and are shown in Table 2 as missing training data. The training intensity distributions from PVSI and time in HR zone were 180 181 compared using linear mixed models (LMMs). Using time in HR zone as the dependent variable LMMs were constructed for each of the 5 zones using the *lme4* package in R (R Core 182 183 Team). The time in HR zone (in seconds) was compared to the PVSI (in metres) for each 184 intensity zone, with each zone examined independently (e.g., Z1 time in HR zone compared to Z1 PVSI, Z2 time in HR zone compared to Z2 PVSI, Z3 time in HR zone compared to Z3 185 PVSI, Z4 time in HR zone compared to Z4 PVSI, Z5 time in HR zone compared to Z5 PVSI). 186 187 Given the repeated measures design, a null model was firstly specified using the individual athlete identifier as the random effect. The analysis model used PVSI and RPE_{diff} as fixed 188 effects and the individual athlete identifier as the random effect. The distribution of the 189 residuals was checked for normality using a QQ plot. Data are presented as the parameter 190 estimate, the standardised mean difference 95% confidence interval and Akaike Information 191 Criterion (AIC). The Nakagawa R squared value (R²c) was calculated using the MuMIN 192 Package in R to show goodness of fit in the LMM²⁰. The magnitude of the Nakagawa R squared 193 value was assessed using the following criteria; < 0.10; trivial; 0.10-0.29 small; 0.30-0.49, 194 195 moderate; 0.50-0.69 large; 0.70-0.89 very large; and 0.90-1.00, almost perfect²¹.

196 **RESULTS**

Missing Data 197

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Throughout the observation period, 2001 training and racing sessions (mean duration 90.4 199 minutes) were captured across the 10 athletes (Table 2). Of those, 781 sessions were excluded 200 201 from the analysis. Reasons for exclusion included missing training data, missing HR recordings, partial HR recordings, or racing sessions (Table 2). Table 3 provides further detail 202 on the training sessions (based on athlete reported sRPE) that were missing HR data. There 203 204 were 1220 individual training sessions included in the final analysis.

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207 Linear Mixed Models

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A summary of random effects, parameter estimates, model fit, and Nakagawa R squared values (R^2c) for the LMMs are shown in Table 4. The R^2c values ranged from 0.14 to 0.42 showing a small-to-moderate relationship between PVSI and time in HR zone (see Table 4). The AIC for the analysis model was higher than the null model for all zones and was accepted (see Table 4)

213 4).

214 DISCUSSION

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The present study aimed to assess the implementation of HR monitoring in competitive 216 swimmers by comparing planned external and internal training intensity distributions. Our 217 assessment of HR monitoring in a high-performance training environment highlighted a large 218 219 amount of missing HR data (39%) when compliance checks and strategies to ensure monitor 220 use were not utilised. When comparing planned external to internal load, the results of a LMM showed a small-to-moderate relationship between PVSI and time in HR zone across the five 221 222 intensity zones. A main finding was the amount of missing data associated with longitudinal HR monitoring. Missing data can negatively impact the monitoring of training intensity and 223 may introduce statistical biases when analysing training data²². Whilst the HR monitors used 224 in the present study have been validated to measure maximal HR in swimming¹⁵, the number 225 of sessions with no HR recording (7.2%) or a partial HR recording (24.3%), reduced the 226 227 feasibility of HR monitoring in the present study. Although, it should be noted that large inter-228 individual differences in the percentage of missing data (see Table 2) were observed. It is 229 unclear whether the missing HR data in the present study was from technical or human sources. 230

231 Missing data from HR monitors due to technical problems in an aquatic environment have been reported^{4,23} and placement under the swimmers' caps may have further disrupted the consistent 232 detection of HR in the present study. Other studies have measured HR using monitors out of 233 the water with non-waterproof HR monitors or using chest straps^{6,13}. From a practical 234 235 perspective, unexplained drop out may also occur due to athletes removing their HR monitor 236 during the session, poor skin contact, loss of contact during dive starts, or low batteries. As a result, when implementing HR monitoring systems it would be beneficial to record the cause 237 238 and source of missing data. Then develop strategies to mitigate its impact on training 239 monitoring and improve the feasibility of using HR monitoring. Common strategies to overcome missing data include imputation of missing values through modelling or averages²⁴. 240 241 Practical strategies to reduce the amount of missing data could include, routine reminders to 242 wear HR monitors, ensuring monitors are worn for the entire session and having spare HR 243 monitors available. Alternatively, coaches and sports science practitioners may choose to 244 prioritise the collection of main set data from their swimmers to ensure the key training stimulus of the session is captured. There was also a small number of sessions with missing 245 246 RPE or PVSI data, or sessions that were modified due to athlete injury (9.8%) during the study 247 period. This demonstrates the difficulty collecting data daily from all participants in an applied, 248 ecological setting. Therefore, when implementing HR monitoring, coaches and sport science 249 practitioners need to be aware of the potential sources of missing HR and training data to then 250 develop practices to mitigate the occurrence.

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The small-to-moderate relationship between PVSI and time in HR zone based on the R^2c value suggests a discrepancy between the assumed internal response using PVSI and the actual internal HR response. Previous research has also found mixed results relating internal and

external measures of training intensity25. A study in open water swimming identified 255 differences between internal and external intensity distributions using session RPE, session 256 goal and time in HR zone, and distance⁵. During a season of cycling training, researchers have 257 258 also reported large discrepancies between RPE, HR and power output during high-intensity training and moderate discrepancies between these variables at low intensities¹⁰. The authors 259 suggested these discrepancies are due to the impact of HR lag (i.e., the delay or latency in HR 260 261 response to a given workload at the onset of exercise) on time in zone as an intensity measure¹⁰. 262 Moreover, HR lag may negatively impact HR monitoring in swimming more than cycling due 263 to the high prevalence of interval training in swimming and is an inherent challenge when attempting to capture training intensities in both the aerobic and anaerobic domains using heart 264 rate. In team sports, where interval training is common, differences between HR-based training 265 measures and external measures have been reported^{26,27}. In American football, where intervals 266 can contain very high running speeds, HR data alone did not have meaningful correlations with 267 external training intensity measures²⁷. When derived into a HR-based intensity measure with 268 duration (i.e., TRIMPs and HR reserve), there were only meaningful relationships with low-269 intensity external measures²⁷. In soccer, the use of time in HR zone as an intensity measure 270 was criticised as it underestimated physiological stress²⁶. Accordingly, in the present study 271 factors such as HR lag, may have impacted the relationship between PVSI and time in HR 272 zone. Consequently, coaches and sport science practitioners looking to implement HR 273 274 monitoring should be aware of these limitations and look to contextualise the HR data 275 alongside other training variables (i.e., blood lactate measures or RPE) or explore other analysis 276 options when implementing HR monitoring to assess high-intensity interval training.

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Heart rate measures have a limited ability to reflect the relative intensity of high-intensity 278 intermittent efforts¹⁶. In the present study, the relationship between time in HR zone and PVSI 279 at high intensity (zone 5), was moderate ($R^2c = 0.42$). Given the lack of previous research on 280 the longitudinal assessment of contemporary HR monitors in competitive swimming, it is 281 difficult to contextualise our findings within the current swimming literature. Previous 282 swimming research has documented the potential impact for HR lag¹⁵ and suggested session-283 RPE may be more sensitive as a training intensity measure than HR during high intensity swim 284 training⁴. In dry-land sports, research has demonstrated a similar discrepancy between HR-285 based measures of intensity and external measures of intensity^{8,9,16,25-28}. Since race pace 286 training is not centrally regulated, it is logical a small relationship may exist between PVSI and 287 288 time in HR zone at high intensity. However, this does not explain why the relationship in zone 289 5 was higher than the other training zones in the present investigation. It is possible that this is due to combining both maximal aerobic and race pace efforts into a single training zone, or the 290 relatively low volume of training completed in this zone²⁶. Alternatively, it may be linked to 291 the limited ability for HR to accurately monitor high-intensity training, and highlights the need 292 293 for a multivariate approach to monitor intensity. As this is the first study to assess HR in 294 swimming longitudinally, further research is required to better understand and explain the 295 relationship between PVSI and HR at high intensities.

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297 The small-to-moderate relationship between PVSI and time in HR zone may have been 298 impacted by the inherent differences between internal and planned external subdimensions of 299 training. In the present study, the PVSI measure, a distance at a predetermined velocity, was compared to the time spent in each HR zone, two different subdimensions of training load. 300 Previous studies have found similar small relationships between internal and external training 301 load and intensity measures²⁵⁻²⁷. In team sports, different monitoring methods, such as sRPE, 302 HR measures and external velocity measures were shown to provide different information 303 about a single training stimulus²⁹. A key factor driving these differences may be the varied 304

305 internal response experienced by athletes to a given external training load depending on their psychobiological state prior to the training session². Given the complexity of physiological 306 systems the likelihood of a single variable capturing the complexity of a single exercise bout 307 is low^{28,30}. Accordingly, there needs to be caution when monitoring training with a single 308 measure²⁹, and when assuming an internal response from a planned external measure. The 309 combination of several training monitoring variables in a multivariate approach has long been 310 advocated for and the benefits previously demonstrated^{4,12,28,29}. Furthermore, given that 311 different training monitoring methods can influence the calculation of training intensity 312 distribution⁸, a multivariate approach may provide a more holistic description of completed 313 314 training. For example, it may be advantageous to prescribe and monitor low-intensity (i.e., zone 1-4) bouts with HR to capture the cardiorespiratory centred training stimulus and use both RPE 315 and velocity to reflect the demands of high-intensity training (i.e., zone 5). In endurance 316 317 running, the use of running times has been suggested to more accurately reflect the sudden changes in velocity that come with high-intensity interval training⁸. Given the differences 318 between internal and external sub-dimensions of training implementing a multivariate 319 approach to training monitoring may assist in contextualising HR data. These monitoring 320 321 approaches can assist in developing a deeper understanding of training and assist in improving 322 training prescription practices for coaches and sport science practitioners.

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324 A limitation of the present study was that only planned velocities, rather than actual velocities 325 were measured. Understanding if the swimmers successfully achieved the prescribed velocities would have provided additional information to contextualise the HR data. As such, it is 326 327 important for the results to be interpreted as the difference between internal training intensity 328 and planned, rather than actual external training intensity. An additional limitation was the use of peak HR from the season with PVSI zones based on velocities from pre-season. These 329 330 limitations may have reduced the amount of explained variance in the models and impacted 331 our results. A further limitation was the large amount of missing HR data, which led to differences in the number of sessions analysed for each athlete and potentially biased the types 332 of sessions analysed in the study. Finally, there are several considerations to be addressed when 333 quantifying training in this cohort. In this study, training was completed in a range of 334 environments (i.e., training camps, varying environmental conditions and 25 and 50m pools) 335 which may have increased variation in the results. Future studies may look to assess the impact 336 337 of these factors on the relationship between measures of training intensity.

338 PRACTICAL APPLICATIONS

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The use of HR provides insight into the internal intensity experienced by swimmers during 340 training. However, the current findings suggest when using HR data to quantify training 341 intensity distribution, it should not be interpreted in a similar manner to when PVSI is used. 342 This finding highlights the importance of continuing to use the pre-existing method(s) of 343 prescribing and monitoring training when introducing a new method, such as HR monitors into 344 a competitive training environment. Moreover, considering the limitations of each method of 345 346 training monitoring, a multivariate approach incorporating both internal and external training 347 intensity measures, could be adopted. Prescribing and monitoring training using HR-based measures of intensity for aerobic training and using RPE or PVSI-based methods for work 348 above maximal aerobic capacity may help improve our understanding of athlete training. To 349 ensure robust data collection when using HR monitors, an awareness of the sources of missing 350 data (i.e., technological, or human error) should be established. Then, measures to account for 351 the missing data, or to mitigate missing data in the first place should be implemented. By 352 353 implementing these approaches coaches and sport science practitioners can gain a more

354 comprehensive understanding of completed training, which can help support future training355 prescription.

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357 CONCLUSION

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Longitudinal HR monitoring can provide valuable insight into an athlete's internal response 359 during training. Based on the current findings, strategies to minimise missing HR data may be 360 needed within the training environment. Also, the small-to-moderate relationship between the 361 planned external measure (PVSI) and the internal measure (time in HR zone) highlight that the 362 363 two methods of training load monitoring cannot be used interchangeably. Coaches and sport 364 science practitioners should consider implementing a multivariate approach to training monitoring using both internal and external measures of intensity to better understand the 365 training. Future research should look to develop strategies to mitigate missing HR data, account 366 for the potential impact of HR lag on training analysis and asses how HR monitoring can be 367 implemented effectively in a multivariate approach to training monitoring. 368

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Table 1 Descriptors used to describe planned volume at set intensity. Adapted training zones from Jamnick, Pettitt, Granata,
 Pyne and Bishop ¹⁷

Physiological anchor	Z1 (m)	Z2 (m)	Z3 (m)	Z4 (m)	Z5 (m)
%HR _{peak}	50-75%	75-80%	80-85%	85–92%	> 92%
Blood lactate	< 2.0	2.0–2.5	2.5-3.5	3.5-5.0	> 5.0
RPE	<11	11–12	13–14	15–16	17-19

469 RPE - Rating of Perceived Exertion, $%HR_{peak}$ - percentage of peak heart rate, Z1 - Zone 1, Z2 - Zone 2, Z3 - Zone 3, Z4 - Zone 4, Z5 - Zone 5

473 Table 2 Training characteristics of each participant throughout the data collection period including a summary of missing

and excluded data.

Participants	Weekly Volume (km)	Total Swim Sessions	Full Recording	Partial Recording	No Recording	Racing Sessions	Missing Training Data	Partial Sessions Excluded	Total Included Sessions	% HR Data Included
Participant 1	38.63	209	60	104	20	25	20	60	98	47%
Participant 2	38.63	213	163	12	10	28	19	8	146	69%
Participant 3	36.79	208	128	47	7	26	25	18	135	65%
Participant 4	47.56	138	94	12	8	24	5	1	99	72%
Participant 5	37.98	203	108	50	23	22	18	28	116	57%
Participant 6	37.06	209	127	43	16	23	25	31	114	55%
Participant 7	50.89	220	160	31	3	26	17	6	171	78%
Participant 8	36.15	193	111	28	37	17	18	12	109	56%
Participant 9	41.83	209	120	50	13	26	28	32	115	55%
Participant 10	43.07	199	118	50	8	23	21	31	117	59%
Total		2001	1189	427	145	240	196	227	1220	61%

* Exclusion criteria for heart rate analysis are discussed in the methods. Sessions were excluded if >5% of heart 476 rate data was missing, HR- heart rate, km - Kilometres,

Table 3 Number of sessions excluded based on athlete reported sRPE

Training Zone	Number of sessions excluded based on athlete reported sRPE
Z1	37
Z2	44
Z3	20
Z4	25
Z5	64

sRPE - Session Rating of Perceived Exertion, Z1 - Zone 1, Z2 - Zone 2, Z3 - Zone 3, Z4 - Zone 4, Z5 - Zone 5

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Table 4 The parameter estimated and 95% confidence intervals for the null model and the analysis model for each of the 5 zones for the relationship between planned volume at set intensities 1 2 and time in heart rate zone.

	Random ef	fects			Fixed effe	cts								Model Fit	
	Between Pa Differences							Planned Volume at Each Set Intensity (m)			RPE _{diff}				·
Models	Intercept	SD	Residuals	SD	Intercept	95% CI		Estimate	95% CI	SMD	Estimate	95% CI	SMD	AIC	R ² c
				I	T		Zone 1	T		•	•		T	T	
Z1 null model	238240.00	488.10	928778.00	963.70	3957.60	(3617.61, 4296.96)	•						•	20267.60	0.20
Z1 model	237387.00	487.20	850615.00	922.30	3510.00	(3159.23, 3860.60)		0.21	(0.16, 0.25)	<0.001	143.00	(95.09, 190.89)	0.29	20165.20	0.27
		-	-				Zone 2								
Z2 null model	27289.00	165.20	217397.00	466.30	617.52	(500.81, 734.64)								18489.20	0.11
Z2 model	28208.00	168.00	194764.00	441.30	404.10	(281.29, 527.00)		0.11	(0.09, 0.13)	< 0.001	31.24	(8.32, 54.15)	0.18	18360.40	0.21
					•	•	Zone 3							•	
Z3 null model	19447.00	139.50	192378.00	438.60	394.10	(295.70, 493.72)				•			•	18338.00	0.09
Z3 model	18272.00	135.2	182571.00	427.30	312.89	(214.79, 411.40)		0.16	(0.12, 0.20)	0.001	26.73	(4.54, 48.92)	0.20	18278.10	0.14
					r	-	Zone 4			•	•		•		
Z4 null model	29800.00	172.60	155019.00	393.70	253.87	(378.54, 409.95)							•	18080.60	0.16
Z4 model	25218.00	158.80	137764.00	371.20	194.49	(83.05, 306.22)		0.43	(0.36, 0.50)	0.002	6.71	(-12.66, 26.08)	0.04	17940.20	0.24
	•			•			Zone 5			•			•	·	
Z5 null model	2942.00	54.24	29055.00	170.46	60.36	(21.70, 98.98)							•	16031.90	0.09
Z5 model	1591.00	39.89	18137.00	134.68	-5.60	(-34.45, 23.43)		0.22	(0.21,0.24)	0.006	-16.48	(-23.62, -9.35)	-0.41	15495.70	0.42

Significance determined as $p \le 0.05$, AIC - Akaike's information criterion, **Bold** = best model fit, CI - confidence interval, m - Metre, R^2c - Nakagawa R squared value, RPE_{diff} - Difference between athlete reported and coach planned rating of perceived exertion, SD - Standard deviation, SMD - Standardised mean difference

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