INDIVIDUALISED METHODS OF PRESCRIBING EXERCISE IN CYCLING

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Dedication

To my truly remarkable sister Michelle. Your courage, determination and positive attitude to life will forever be an inspiration to me.

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Abstract

Training is a complex, multi-factorial process, which involves the manipulation of the duration, frequency and intensity of exercise. When quantifying the physiological and performance responses to training a large inter-individual variability in training responses is frequently observed. To date, the majority of research has examined the relationship between genetics and trainability. Another hypothesis, which has not been fully explored, is that the variability is also due to an inappropriate standardisation of exercise intensity or duration. This thesis, therefore, presents a series of studies that investigate the effects of individualised methods of prescribing exercise intensity and duration on performance and physiological responses in cycling.

Study 1 compared time-to-exhaustion (TTE) to time-trial (TT) performances when the duration of the trials were matched and participants were blinded to feedback. A higher mean power output was found for TTE compared to TT at 80% (294 ± 44 W vs. 282 ± 43 W respectively, $P<0.05$), but not at 100% (353 ± 62 W vs. 359 ± 74 W) and 105% (373 ± 63 W vs. 374 ± 61 W) of maximum aerobic power (MAP). Critical power (CP) calculated from the TTE trials was also higher, whereas, anaerobic work capacity (W′) was lower ($P<0.05$). The findings favour TTE over TT performances for a higher mean power output and calculated CP.

Study 2 compared the effects of three training intensities: moderate intensity (MOD), high intensity (HIT) and a combination of the two (MIX) when the duration of exercise was individualised. Participants were randomly assigned to one training group and trained 4 times per week for 4-weeks. Training duration was individualised to each participant's maximum performance. All training groups increased maximal oxygen uptake ($\dot{V}O_{2max}$), MAP, TTE and gross efficiency (GE) after training ($P<0.05$), but no differences were observed between groups ($P>0.05$). Therefore, when the duration of training is individualised, similar improvements in performance and physiological responses are found, despite differences in exercise intensity.

The CP and power law models propose power-duration relationships that describe maximum endurance capacity. Study 3 compared the predictive ability of these two models for TTE performances. It was hypothesised that the CP and power law models would reliably predict actual TTE for intensities between 80-110% MAP, but a power

law model would better predict TTE for intensities outside of this range. No significant differences for parameter estimates were found between models (CP and power law) and actual TTE for intensities ranging from 80-110% MAP. Outside of this range however, the CP model over predicted actual performance at 60% and 150% MAP ($P<0.05$), while there was no significant difference between the power law model and actual performance at these intensities ($P>0.05$). Both models were different from actual performance at 200% MAP ($P<0.05$). Therefore, a power law model can accurately predict cycling TTE for intensities ranging from 60-150% MAP.

Study 4 tested the hypothesis that the inter-individual variability for TTE performances is due to the methods used to standardise exercise intensity. A %$\dot{V}O_{2max}$ prescription was compared with an alternative based on an individual power-duration relationship (using a power law model). A power law model predicted the intensity for TTE lasting exactly 20-min and 3-min. A corresponding intensity for TTE as a %$\dot{V}O_{2max}$ was 88% and 109%. On two separate occasions participants completed two TTE trials using the power law and %$\dot{V}O_{2max}$ prescriptions, with 30-min rest between trials. There was a significant reduction in the inter-individual variability for TTE when exercise was prescribed using a 20-min power law versus 88% $\dot{V}O_{2max}$ prescription method (coefficient of variation = 29.7 vs. 59.9% respectively; $P<0.05$). However, there was no significant difference in the inter-individual variability for TTE using a 3-min power law versus 109% $\dot{V}O_{2max}$ prescription method ($P>0.05$).

Two main conclusions can be drawn from this thesis. Firstly, a power law model can accurately predict and describe cycling endurance performance across a wide range of intensities. Secondly, prescribing exercise intensity using a power law model reduces the variability in TTE by 50% when compared to a %$\dot{V}O_{2max}$ prescription method. Therefore, the methods used to standardise exercise intensity appear to be related to the variability in TTE performances. Future research should examine whether training prescribed using a power law model reduces the variability in subsequent training responses.

Key Words: Power law, %$\dot{V}O_{2max}$, Variability, Time-to-exhaustion, Training

Table of contents

Publications

<u>In review</u>

- **Coakley, SL** and Passfield, L. Cycling performance is different for time-to-exhaustion versus time-trial in endurance laboratory tests.
- Passfield, L., **Coakley, SL,** Jobson, SA, Scarf, PA. A power law describes cycling endurance performance better than critical power.
- **Coakley SL** and Passfield, L. Individualised training at different intensities results in similar physiological and performance benefits.

<u>In preparation</u>

- **Coakley SL**., Jobson, SA., Nicolò, A., Hopker, J., Giorgi, A., and Passfield, L. A power law model reduces variability in time-to-exhaustion.

<u>Conference proceedings</u>

- **Coakley, SL** and Passfield, L. A power law model reduces variability in time-to-exhaustion.
  European Congress of Sports Science, 2015, Malmö: Oral presentation

- **Coakley, SL** and Passfield, L. Individualised training duration induces similar physiological and performance benefits at different intensities.
  2nd World Congress of Cycling Science, 2014, UK
  Oral presentation: Journal of Cycling Science, 2014. 3(2): 10.

List of Figures

List of Tables

Abbreviations

ACE	Angiotensin I-converting enzyme
AMPK	Adenosine monophosphate kinase pathway
CaMK	Calcium-calmodulin kinase
CI	Confidence intervals
CP	Critical Power
CO_2	Carbon dioxide
CV	Coefficient of variation
EXP	Exponential model
ETL	Estimated time limit
GE	Gross efficiency
GET	Gas exchange threshold
h	Hour
Hb	Haemoglobin
Mb	Myoglobin
HbO_2	Oxygenated hemoglobin
HHb	Deoxygenated hemoglobin
HIT	High intensity training
HR	Heart rate
HR_{max}	Maximal heart rate
HRR	Heart rate reserve
1/time	Inverse of time (1 divided by time)
J	Joules
Kilojoules	kJ
Kg	Kilogram
Linear-P model	Second linear model
Linear TW model	Total work versus time model
Non-linear 2	2 parameter non-linear model
Non-linear 3	3 parameter non-linear model
EXP	Exponential
ETL	Estimated time limit scale
LT	Lactate threshold

OBLA	Onset of blood lactate accumulation
Min	Minute
MAP	Maximal aerobic power
$mL{\cdot}kg^{-1}{\cdot}min^{-1}$	Millilitres of O_2, per kilogram of body mass, per minute
$mmol{\cdot}L^{-1}$	Millimoles per litre
MOD	Moderate intensity
MIX	Combination of moderate and high intensity
n	Sample size
NIRS	Near-infrared spectroscopy
P	Significance level
P	Power output
r	Correlation coefficient
R^2	Coefficients of determination
$Ratio_{1:2}$	Ratio of single to double leg $\dot{V}O_{2max}$
RER	Respiratory exchange ratio
RPE	Rating of perceived exertion
Rpm	Pedal revolutions per minute
s	Seconds
t	Time in seconds
TW	Total work
SD	Standard deviation
TTE	Time-to-exhaustion
TT	Time-trial
$\dot{V}O_{2max}$	Maximal oxygen uptake
$\dot{V}O_2$	Volume of oxygen
$\dot{V}CO_2$	Volume of carbon dioxide
$\%\dot{V}O_{2max}$	Percentage of $\dot{V}O_{2max}$
$\dot{V}_E$	Minute ventilation
W	Watts
W′	Anaerobic work capacity

Chapter 1: Introduction

1.1 Background.

Over the last two decades our understanding of the physiological demands of endurance performance, and the adaptations that occur with training has greatly improved (Coyle et al., 1988; Coyle et al., 1991; Bassett and Howley, 2000; Bassett, 2002; Joyner and Coyle, 2008; Jacobs et al., 2011; Lundby and Robach, 2015). Joyner and Coyle (2008) presented a comprehensive model to suggest the determinants of endurance performance success (Figure 1.1). According to this model performance is dependent upon three key variables: maximal oxygen uptake ($\dot{V}O_{2max}$), gross efficiency (GE), and lactate threshold (LT) (Joyner and Coyle, 2008). These variables have been extensively studied in exercise physiology to determine an individual's fitness level, as well as the magnitude of training adaptations (e.g. Bouchard et al., 1999; Midgley et al., 2007; Vollaard et al., 2009).

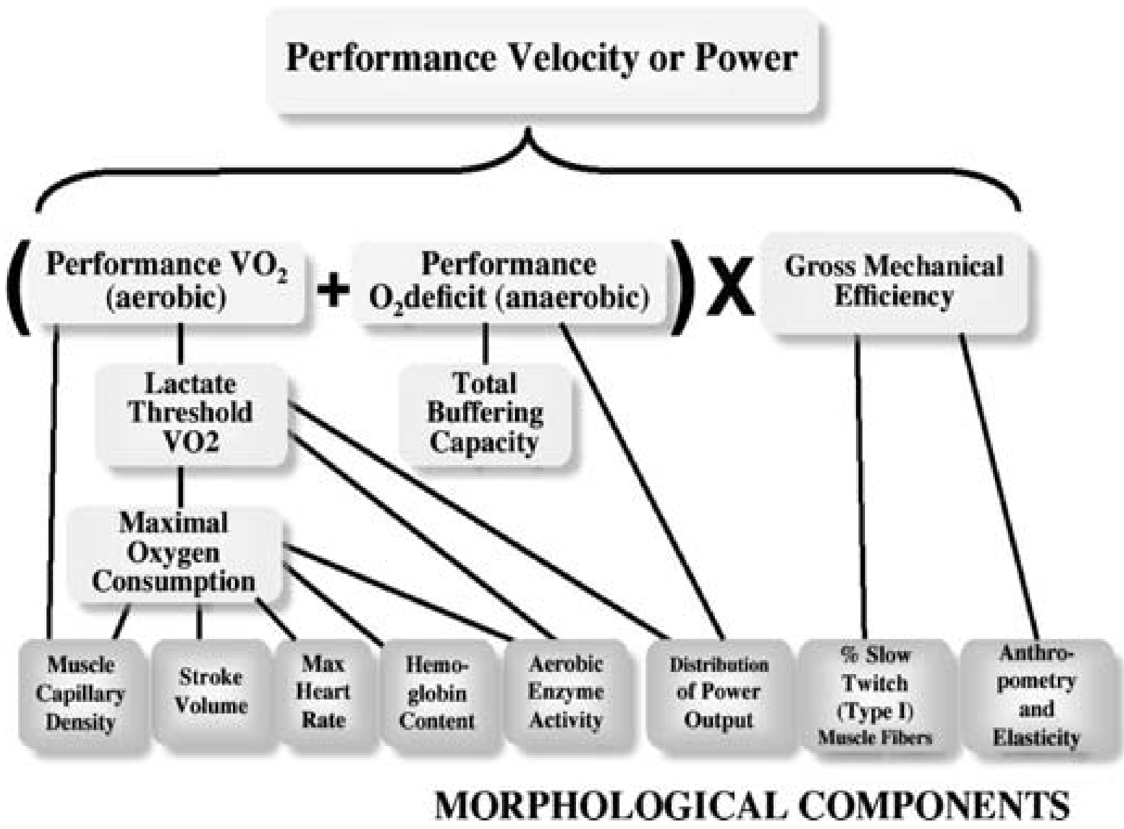

Figure 1.1: Joyner and Coyle's (2008) model explaining the physiological determinants of endurance performance. Taken from Joyner and Coyle (2008) p.37[1].

[1] Reprinted from Journal of Physiology. Vol. 586. Joyner and Coyle (2008). Endurance exercise performance: the physiology of champions, page 37, with permission from John Wiley and Sons.

An alternative way of examining endurance performance is to study the relationship between exercise intensity and time-to-exhaustion (TTE) using mathematical models. This relationship is often referred to as a 'power-duration' relationship for cycling, 'speed-duration' for running, or 'velocity-duration' for swimming. Therefore, for clarity and consistency in the terminology used in this thesis, power-duration will be referred to throughout, even when discussing other sports. A critical power (CP) model is the most common mathematical model used by researchers and applied practitioners, to explain a wide range of sports (Moritoni et al., 1981; Hill, 1993; Jones et al., 2010). The CP model proposes two parameters: critical power (CP) and anaerobic work capacity (W′) (Hill, 1993). CP represents the maximum power output that an individual can sustain for a prolonged period of time (Hill, 1993; Pringle and Jones, 2002). Whereas, W′ represents the total work that can be performed, utilising only stored energy within the muscle (Monod and Scherrer, 1965; Moritoni et al., 1981; Hill, 1993). The CP model proposes that a hyperbolic relationship exists between power output and TTE, and that below CP one can theoretically sustain exercise for an infinite amount of time (Hill, 1993; Vanhatalo et al., 2011). Lundby and Robach (2015) recently added CP to Joyner and Coyle's (2008) model of endurance performance. CP correlates well with other physiological measurements such as $\dot{V}O_{2max}$ and LT and is also sensitive to training adaptations (Moritoni et al., 1981; Jones, 2006; Jones et al., 2010). However, the CP model does not describe or predict endurance performance as closely outside the 2 to 20-min range (Hill, 1993; Jones et al., 2010). This may, therefore, limit the practical application of this model.

A power law is another way of modeling the power-duration relationship (Kennelly, 1906; Francis, 1943; Lietzke, 1954; Grubb, 1997; García et al., 2012). This model assumes a progressive decline in performances, with an increase in intensity or distance (Kennelly, 1906; Grubb, 1997). The power-duration relationship can be fitted to either a power curve or plotted on a logarithmic scale as a linear relationship (Kennelly, 1906; Francis, 1943; Katz and Katz, 1999). A power law model has previously demonstrated a strong fit for data taken from athletic events that ranged from 100 m to a marathon distance (Kennelly, 1906; Francis, 1943; Lietzke, 1954; Grubb, 1997; García-Manso et al., 2012). Therefore, this model has the potential to describe and predict endurance performance over a much wider range of performances than the CP model (i.e. > 20-min < 2-min). Previous research has found the power law model to accurately predict performances in swimming and running for a narrow range of distances/durations e.g.

200-400 m and 1-10 min respectively (Osiecki et al., 2014; Hinckson and Hopkins, 2005). However, whether a power law model can accurately predict a wide range of cycling endurance performances has not yet been investigated.

Significant performance gains, as well as physiological adaptations can occur as a result of the manipulation of the three major training components: duration, intensity and frequency (Hickson et al., 1977; Rodas et al., 2000; Hawley, 2008; Bacon et al., 2013). In particular, research has focused on the effects of the manipulation of exercise intensity on training adaptations in untrained or recreationally active individuals (Hickson et al., 1977; Bouchard et al, 1999; Rodas et al, 2000; Gibala et al., 2006; Helgerud et al., 2007; Burgomaster et al, 2008; Vollaard et al., 2009; Bacon et al., 2013). Standardised training interventions for such individuals, often favour high intensity (HIT) over moderate intensity (MOD) training for greater improvements in $\dot{V}O_{2max}$ and performance (Tabata et al, 1996; Rodas et al., 2000; Helgerud et al., 2007; Gormley et al., 2008). However, these findings are not always consistent (Gibala et al., 2006; Burgomaster et al., 2008). Additionally, the majority of these observations are based on the 'mean' response such that individual responses to training are not well understood (Mann, 2011; Timmons, 2011; Bacon et al., 2013).

Large inter-individual differences have been reported in response to training (Bouchard et al., 1999; Vollaard et al., 2009), with some studies demonstrating changes in $\dot{V}O_{2max}$ to range from no change up to ~ 50% in untrained individuals (Lortie et al., 1984; Kohrt et al., 1991; Bouchard et al., 1999). Approximately half of this variability can be explained by an individual's genetic background (Bouchard et al., 1999; Bouchard and Rankinen, 2001). Another hypothesis that has not been fully explored, is that the methods used to prescribe exercise also contribute to this variability (Mann et al., 2013). Evidence for this stems from studies that have demonstrated a large inter-individual variability in TTE and training responses, when exercise is standardised at the same percentage (%) of $\dot{V}O_{2max}$ (Coyle et al., 1988; Bouchard et al., 1999; Vollaard et al., 2009; Scharhag-Rosenberger et al., 2010). The large variability in blood lactate responses observed in these studies, suggest that the metabolic stress responses are not the same for all individuals, despite attempts to standardise the exercise intensity (Coyle et al., 1988; Scharhag-Rosenberger et al., 2010). Therefore, at the same %$\dot{V}O_{2max}$, individuals can endure exercise for different amounts of time and at different levels of metabolic stress (Coyle et al., 1988; Scharhag-Rosenberger et al., 2010). This has led researchers to question the appropriateness of the methods used to prescribe exercise, in particular when the aim is to reduce the inter-individual variability in TTE and training responses (Mann et al., 2013; Hopker and Passfield, 2014).

Chapter 2: Literature review

2.1 Physiological determinants of endurance performance.

Endurance performance can be defined as the 'capacity to sustain a given velocity or power output for the longest time possible' (Jones and Carter, 2000, p.373). Coyle's performance model provides us with a useful framework to understand the range of physiological variables that determine endurance performance success (Coyle, 1995; Coyle, 1999; Joyner and Coyle, 2008; Figure 1.1). According to this model, $\dot{V}O_{2max}$, GE and LT are key determinants of endurance performance (Coyle, 1999; Joyner and Coyle, 2008). Lundby and Robach (2015) recently discussed the potential of enhancing any of these variables ($\dot{V}O_{2max}$, GE or LT) with training in healthy individuals as well as Olympic athletes. Additionally, critical power (CP) was added as an important determinant of endurance performance, representing the upper and lower boundary of the heavy exercise intensity domain (Jones et al., 2010). Lundby and Robach (2015) concluded in their review that while $\dot{V}O_{2max}$ remains stable in world-class athletes, GE, LT and CP can be improved with specific training interventions.

2.1.1 $\dot{V}O_{2max}$.

$\dot{V}O_{2max}$ is the maximum rate of oxygen that can be taken in and utilised during high intensity exercise (Bassett and Howley, 2000). An individual's $\dot{V}O_{2max}$ level provides us with information regarding the integrated capacity of the cardiovascular, pulmonary and neuromuscular system to performance exercise (Jones and Poole, 2005). $\dot{V}O_{2max}$ is one of the most widely measured variables in exercise physiology, and is often used to prescribe training intensity (Howley et al., 1995; Bouchard et al., 1999; Midgley et al., 2006; Vollaard et al., 2009; Bacon et al., 2013). In 1923, Hill and Lupton observed a linear relationship between running speed and oxygen uptake ($\dot{V}O_2$) and proposed that beyond a certain work rate $\dot{V}O_2$ reaches a plateau and cannot be increased any further. This led researchers to investigate different mechanisms that may limit $\dot{V}O_{2max}$ (Hill and Lupton, 1923; Di Prampero, 1985; Di Prampero and Ferretti, 1990; Wagner, 1992; Wagner, 1993; Noakes, 1997, Bassett and Howley, 2000). While there is no single limiting factor for $\dot{V}O_{2max}$, a predominant contributing factor is the cardiorespiratory system, with maximal stroke volume and maximal cardiac output explaining a large proportion of the variability in $\dot{V}O_{2max}$ (Ekblom and Hermansen, 1968). Other peripheral and central $\dot{V}O_{2max}$ limitations include the diffusion capacity of the pulmonary system, the oxygen carrying capacity of the blood, and the skeletal muscle characteristics (Bassett and Howley, 2000)

$\dot{V}O_{2max}$ is traditionally measured from an incremental exercise test to exhaustion, in which the intensity increases over time until volitional exhaustion is reached. Additionally, $\dot{V}O_{2max}$ can be reliably measured from a closed-loop self-paced test, in which the intensity is fixed at an RPE between 6-20 and lasts 10-min in total (Mauger and Schulthorpe, 2012; Hogg et al., 2015). Elite endurance athletes have high $\dot{V}O_{2max}$ levels, ranging from 70-85 $ml \cdot kg \cdot min^{-1}$ for males, and 60-75 $ml \cdot kg \cdot min^{-1}$ for females (Coyle et al., 1991; Lucia et al., 1998; Lucia et al., 2001; Jones, 2006; Lundby and Robach, 2015). The ability to sustain a high level of O_2 uptake during exercise is essential for endurance performance success (Joyner and Coyle, 2008). In addition, a strong correlation exists between $\dot{V}O_{2max}$ and aerobic performance in athletes of varying fitness levels (Coyle et al., 1988; Vollaard et al., 2009). But when the range of $\dot{V}O_{2max}$ is narrowed between athletes (i.e. highly trained athletes), the correlation between $\dot{V}O_{2max}$ and performance can be poor (Lucia et al., 1998; Jones, 1998; Lucia et al. 2001; Jones, 2006). For instance, two athletes with the same $\dot{V}O_{2max}$ can have very different performance capabilities (Coyle et al., 1988; Lucia et al., 1998; Vollaard et al., 2009). In addition, more recent research findings have found that the changes that occur in performance following training are not necessarily correlated with the training-induced change in $\dot{V}O_{2max}$ (R^2=0.05) (Vollaard et al., 2009). Nevertheless, as $\dot{V}O_{2max}$ is a notable physiological capacity and benchmark test used by most, a %$\dot{V}O_{2max}$ is commonly used to prescribe and quantify exercise intensity (Bouchard et al., 1999; Gormley et al., 2008; Ingham et al., 2012; Burgomaster et al., 2008).

2.1.2 Lactate threshold.

LT can be defined as the exercise intensity that corresponds to the first increase in blood lactate, or a 1 $mmol \cdot L^{-1}$ rise in blood lactate above resting level (Coyle et al., 1983; Yoshida et al., 1987; Coyle et al., 1988; Jones and Carter, 2000). An individual's ability to sustain a high %$\dot{V}O_{2max}$ at LT is considered a stronger predictor of endurance performance than $\dot{V}O_{2max}$ alone, in particular for trained athletes (Coyle et al., 1988). For instance, when cyclists completed TTE performances at 88% $\dot{V}O_{2max}$, the results showed that those with a high LT (~ 82% $\dot{V}O_{2max}$) were able to sustain the exercise intensity for more than twice as long as those with a low LT (~ 66% $\dot{V}O_{2max}$) (~ 60-min vs. 29-min).

The mitochondrial aerobic enzyme activity is considered a major determinant of LT intensity (Ivy et al., 1980; Holloszy and Coyle, 1984; Coyle et al., 1985; Coyle, 1999). Physiological explanations for improvements in LT following training include an increase in the size, number, and enzyme levels of the mitochondria (Holloszy and Coyle, 1984).

LT is determined by examining the relationship between blood lactate concentration and exercise intensity using an incremental exercise test. A rightward shift in the blood lactate curve is often associated with an improvement in endurance capacity, whereas a leftward shift is more often associated with a reduction in endurance capacity (Bosquet et al., 2002). Other threshold concepts include: maximal lactate steady state, onset of blood lactate (OBLA), gas exchange threshold (GET) and ventilatory threshold (Faude et al., 2009). However, the wide range of terminologies, as well as calculations used to date to identify an individual's threshold, can at times be confusing and often result in misinterpretation (Faude et al., 2009; Mann et al., 2013).

2.1.3 CP

CP is found to correlate well with other physiological laboratory test measurements (Poole et al., 1985; Housh et al., 1989; McLellan and Cheung, 1992; Pringle and Jones, 2002; Whipp et al., 2009). It is derived from the hyperbolic relationship between exercise intensity and TTE using a CP model (Moritoni et al., 1981; Hill, 1993). Pringle and Jones (2002) reported a strong correlation between maximal lactate steady state and CP (r=0.95) despite the power output at CP being significantly higher. In addition, CP is considered a better predictor of exercise tolerance when compared to traditional $\dot{V}O_{2max}$ and gas exchange threshold (GET) laboratory test measurements (Jones et al., 2010). This has led researchers to propose that CP is an important determinant of aerobic function, representing the upper and the lower boundary of the 'heavy' and 'severe' exercise intensity domains (Jones et al., 2010; Lundby and Robach, 2015). The CP model, as well as other proposed mathematical models, are important for their ability to describe and predict endurance performance as well as their potential for setting training intensities. The CP model is discussed in more detail in section 2.3.

2.1.4 GE

GE is expressed as 'the ratio of work accomplished to energy expended' (Gaesser and Brooks, 1975, p.1132). Professional cyclists require a high GE to be able to sustain an extremely high power output for extended durations (Faria et al., 2005). Subsequently, a decrease in efficiency is often associated with a reduction in performance (Passfield and Doust, 2000). Jobson et al. (2012) re-analysed studies that measured GE during performance trials, to determine if there was a relationship between GE and endurance performance. They reported a correlation between GE and long (40 k and 1 h; r=0.58) and short (5-min; r=0.48) time-trial (TT) cycling power output (Jobson et al., 2012). GE explained 34% and 26% of the variation in power output for long and short TTs respectively (Jobson et al., 2012). Prior MOD exercise can also affect GE (Passfield and Doust, 2000). For instance, Passfield and Doust (2000) demonstrated that prior MOD exercise significantly reduced 5-min cycling performance, as well as peak and mean power output during 30 s all out sprints (Passfield and Doust, 2000). Furthermore, the change in GE was highly correlated with the change in 5-min performance, but not the change in mean or peak 30 s power output (Passfield and Doust, 2000). Hopker et al. (2010) also found GE to be sensitive to training, with a significant increase in GE observed following HIT training.

The factors associated with differences in GE for trained and untrained individuals remain unclear, but evidence suggest genetics, fibre type distribution, and training play a key role (Holloszy et al., 1977; Jones, 2006; Hopker et al., 2013). Endurance athletes have a higher % of slow twitch (type I) fibers compared to untrained individuals (Joyner and Coyle, 2008). Type I muscle fibers exhibit a relatively high blood flow capacity and consume less O_2 for a given amount of work (Joyner and Coyle, 2008). Horowitz et al. (1994) demonstrated that individuals who possessed a 'high' % type I muscle fibers were able to maintain a 9% higher power output when compared to those with an 'average' % type I muscle fibers. This finding was observed despite both groups (high vs. average % type I fiber distribution) maintaining a similar VO_2 and energy expenditure throughout the TT (Horowitz et al., 1994). Therefore, the researchers concluded that the 9% greater power output was due to a greater GE during cycling (Horowitz et al., 1994). However, more recently, Hopker et al. (2013) found that muscle fiber type does not predict GE in cycling or endurance performance, and that training status played a more important role in predicting these variables.

2.2. Assessment of endurance performance

TTE and TT protocols are commonly used to monitor and detect changes in endurance performance in the laboratory (Coyle et al., 1988; Jeukendrup et al., 1996; Currell and Jeukendrup, 2008) and field setting (Galbraith et al., 2011; Karsten et al., 2015). TTE requires individuals to maintain a constant workload until volitional exhaustion is reached (Hopkins et al., 1999; Paton and Hopkins, 2001). On the other hand, TTs involve completing a fixed amount of work or covering a set distance as fast as possible (Jeukendrup et al., 1996; Coyle et al., 1999). The advantages and disadvantages of using both protocols to assess endurance performance have been discussed previously (Currell and Jeukendrup, 2008). For instance, while TTE protocols are often criticised for their lack of ecological validity (Jeukendrup et al., 1996), they have a similar sensitivity to TTs for detecting changes in performance (Amann et al., 2008). Additionally, while a strong correlation exists between laboratory TT and actual performance (Smith et al., 2001), TT performances are highly sensitive to fluctuations in pacing strategies (De Koning et al., 1999; Hettinga et al., 2006; Aisbett et al., 2009), Consequently, researchers have suggested that the type of test protocol used, should be largely dependent on the research question (Currell and Jeukendrup, 2008).

2.2.1 Reliability, validity and sensitivity of performance tests.

Performance measurements play a key role in research and sports science support (Currell and Jeukendrup, 2008). It is therefore important that we understand the reliability, sensitivity, and validity of such test protocols in their ability to detect changes in performance (Atkinson and Nevill, 1998; Hopkins et al., 2001; Hopkins, 2000). Jeukendrup et al. (1996) demonstrated that TTE trials are more variable and less reliable when compared to TTs. This study involved cyclists repeating a TTE, TT or a preloaded TT on six separate occasions (Jeukendrup et al., 1996). A poor within participant (also referred to as intra-individual) test-retest reliability for TTE was observed when compared to a TT or pre-loaded TT, with coefficients of variation (CV) of 26.6%, 3.5% and 3.4% respectively (Jeukendrup et al., 1996). Furthermore, when Currell and Jeukendrup (2008) reviewed previous research they noted that when TTE trials were set at intensities below $\dot{V}O_{2max}$, the CV was typically greater than 10% (Gleser and Vogel, 1971; Billat et al., 1994; McLellan et al., 1995; Jeukendrup et al., 1996; Laursen et al., 2007) compared to less than 5% CV for TTs (Hickey et al., 1992; Jensen and Johansen, 1998; Palmer et al., 1999; Smith et al., 2001; Laursen et al., 2007). However, when the intensities were set above the intensity at $\dot{V}O_{2max}$, the CV for TTE trials was markedly reduced (Currell et al., 2006; Lindsay et al., 1996; Coggan and Costill, 1984).

While some researchers favour TTs for measurements of endurance performance (Jeukendrup et al., 1996; Jeukendrup and Currell, 2005), TTE performance tests should not be disregarded as a useful measurement in the laboratory (Amann et al., 2008). The sensitivity of these measurements should also be considered when deciding on an appropriate performance test (Amann et al., 2008). Amann et al. (2008) compared the sensitivity of TTE and TT performance trials when participants were exposed to three different experimental conditions: room air, humidified hypoxic gas mixture, or humidified pure oxygen and hyperoxia. A similar sensitivity in detecting changes in performance was found between TTE and TT protocols, when participants were exposed to the hypoxia and hyperoxia environments (Amann et al., 2008). In addition, much greater effects were observed in the TTE performances when exposed to the different environmental conditions, demonstrating a 23-60% versus 1.8-4.6% change in performance for TTE and TTs respectively. Therefore, the researchers concluded that the poor reliability associated with TTE tests, should not discourage researchers from using these tests to monitor changes in endurance performance, where a higher sensitivity is required (Amann et al., 2008).

Traditionally, TTE protocols are used to assess endurance performance in the laboratory (Currell and Jeukendrup, 2008), as well as model the power-duration relationship for a wide range of sports (Hill, 1993). More recently, researchers have measured performance in the field using TT type performances (Galbraith et al., 2014; Karsten et al., 2015). Some argue that TTs are more logically valid as they more closely simulate a race event, allowing the exercise intensity to vary throughout (Hopkins et al., 2001; Jeukendrup et al., 1996). Others propose that TTE trials are still of practical use, in particular when the aim is to assess exercise capacity at a steady state (Laursen et al., 2007). Additionally, a good reliability is reported when TTE trials are used to predict subsequent TT running performances using a power law model (Laursen et al., 2007). This was demonstrated by Laursen et al. (2007), who reported a standard error of measurement of 0.67% when predicting an individual's TT speed from TTE protocols. Nevertheless, direct comparisons between TTE and TT performances are limited (Ham and Knez, 2009; Thomas et al., 2012).

2.2.2 TTE vs. TT.

The majority of studies directly comparing TTE to TT performances have focused on the effects of pacing on physiological (Lander et al., 2009; Billat et al., 2006; Thomas et al., 2012), and performance responses (Billat et al., 2001; Ham and Knez, 2009). Researchers often refer to these test protocols as even pace and variable pace performances (Billat et al., 2001; Billat et al., 2006; Ham and Knez, 2009; Thomas et al., 2012). Comparisons between such test protocols have been made for a range of sports including, rowing, running, and cycling (Billat et al., 2001; Billat et al., 2006; Ham and Knez, 2009; Thomas et al., 2012). The findings are inconsistent between studies. However, as suggested by Thomas et al. (2012), this is probably due to the differences in sports examined as well as the methods used to set the intensity. For example, Lander et al. (2009) reported a higher core body temperature and blood lactate response for even paced performances, compared to self-paced performances. In addition, this pacing strategy was associated with an increased perception of effort in seven out of nine novice rowers (Lander et al., 2009). These findings led the researchers to conclude that even paced performances are more physiologically and psychological demanding, compared to variable pace performances (Lander et al., 2009). In contrast, Thomas et al. (2012) reported a reduction in physiological strain and perception of effort during even-paced cycling performances, compared to time and work matched self-paced and variable paced cycling. The researchers therefore proposed that an even paced strategy reduces the magnitude, as well as rate of homeostatic disturbance, and thus subsequently leads to a reduction in perception of effort (Thomas et al., 2012).

Researchers have also examined the effects of even and variable pace strategies on the overall performance outcomes when the protocols were matched (Thomas et al., 2013; Billat et al., 2001; Ham and Knez, 2009). Performance in these instances was measured either by the successful completion of the task or the average intensity sustained (Billat et al., 2001; Ham and Knez, 2009; Thomas et al., 2013). Thomas et al. (2013) compared self-paced 20 km TT performance to even paced TTE performances when the power output was matched to that sustained during the self-paced trial. The results demonstrated that nine out of fifteen cyclists were unable to complete the same distance as their self-paced trial, when the mean intensity was fixed (Thomas et al., 2013). Thomas et al. (2013) therefore concluded that a higher mean power output could be achieved during self-paced, compared to matched even paced protocols. Ham and Knez (2009) reported similar findings to Thomas et al. (2013), with four out of seven cyclists terminating the even paced exercise before completing the same amount of work as that of the self-paced trial. In contrast, Billat et al. (2001) reported no differences between even and variable pace performances for running at 90, 95, 100 and 105% velocity at $\dot{V}O_{2max}$. The even and variable pace protocols were also matched, but this time the distance covered in the even paced trial was used to set the distance needed to be covered for the variable pace trial. Performance which was defined as the time taken to cover a set distance was not significantly different between participants, nor were there any differences in oxygen kinetics, or blood lactate responses (Billat et al., 2001). Despite these findings, it is evident that in actual sporting events, athletes competing against each other rarely sustain a constant exercise intensity (Ansley et al., 2004; Tucker et al., 2006) and often racing is characterised by changes in pace (Wilberg and Pratt, 1988; Tucker et al., 2006; Mauger et al., 2012). This type of pacing strategy is referred to as parabolic (Tucker et al., 2006; Mauger et al., 2012). Additionally, the effects of TTE and TT performances on calculated CP and W′ parameters are not well understood.

2.3 Models to describe and predict endurance performance.

Our understanding of the relationship between exercise intensity and TTE dates back as early as 1906 (Kennelly, 1906; Hill, 1925). Since 1906, numerous mathematical models have been proposed to describe the power-duration relationship, predict world record performances, and identify optimal pacing strategies (for full review of the different mathematical models see Hill, 1993; Grubb, 1997; Bull et al., 2000). These models form hyperbolic, linear, non-linear, power law, and exponential curves and have been used for a wide range of sports including cycling (Moritoni et al., 1981; Pringle and Jones, 2002; Hill, 2004), running (Kennelly, 1906; Hughson et al., 1984; Fukuba and Whipp, 1999; Hinckson and Hopkins, 2005; Hill et al., 2011), swimming (Wakayoshi et al., 1992; Oscieki et al., 2014) and rowing (Hill et al., 2002).

In 1925, Hill's work focused on identifying the determinants of fatigue that might explain the relationship between performance velocity and time, by plotting a velocity-distance curve from world record data (Figure 2.1). From his analysis, he proposed that there is a maximal velocity that each individual can sustain, and that the decline in speed as race distance increases is related to muscle fatigue (Hill, 1925). Hill's earlier work contributed greatly to our understanding of endurance performance, and formed the basis for the development of future mathematical models describing the power-time relationship e.g. a CP model (Monod and Scherrer, 1965).

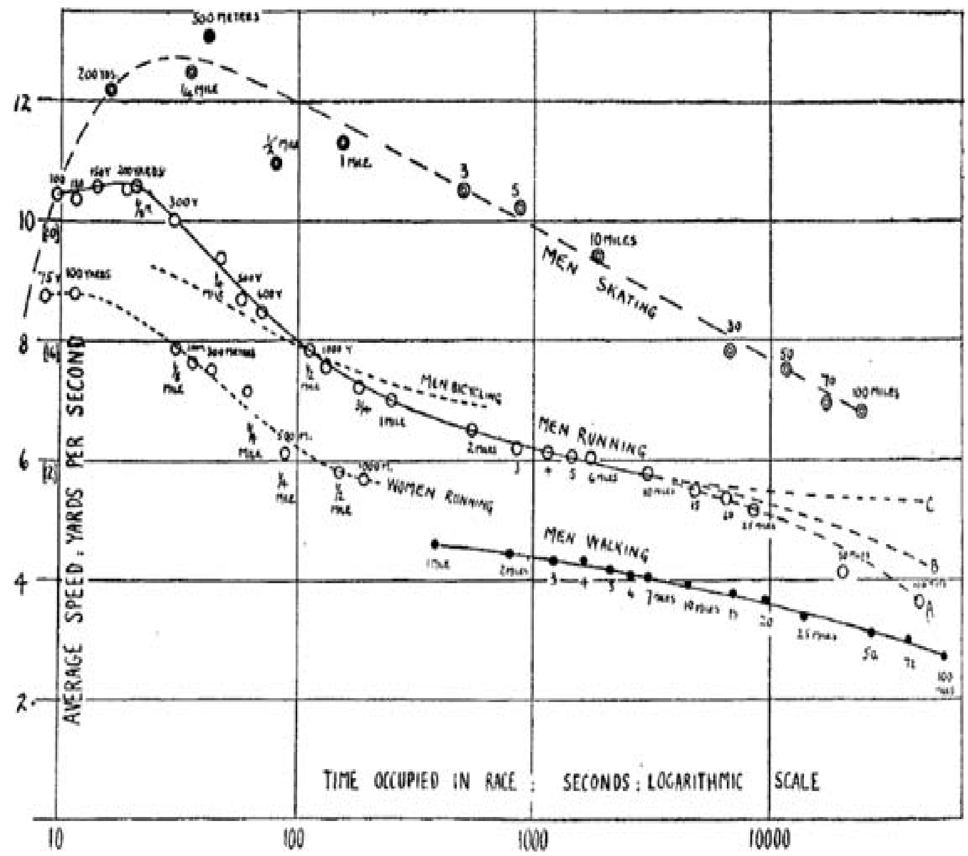

Figure 2.1: The relationship between performance times and speeds for world record speed skating, walking and running performances. Presented by Hill (1925) and taken from Joyner and Coyle (2008) p.26[2].

2.3.1 A CP model

Researchers regularly use a CP model to describe and predict endurance performance (Monod and Scherrer, 1965; Moritoni et al., 1981; Pringle and Jones, 2002; Morton, 2006; Jones et al., 2010). This model is often described as a physiological model to explain endurance performance, as it calculates the aerobic and anaerobic parameters of performance, which are referred to as CP and W′ (Monod and Scherrer, 1965; Moritoni et al., 1981; Pringle and Jones, 2002; Morton, 2006; Jones et al., 2010). The CP model

[2] Reprinted from Journal of Physiology. Vol. 586. Joyner and Coyle (2008). Endurance exercise performance: the physiology of champions, page 26, with permission from John Wiley and Sons.

assumes a hyperbolic relationship exists between exercise intensity and TTE, and from this the upper limit of sustained tolerable work can be determined (Poole et al, 1985). A series of TTE performances (typically 3-6) are required at different intensities to examine this relationship (Moritoni et al., 1981; Hill, 1993). These TTE performances can be completed in one visit, with 30-min rest between trials (Housh et al., 1989; Galbraith et al., 2014; Karsten et al., 2015) or on separate occasions (Gaesser and Wilson, 1988; Poole et al., 1990) At least five different CP models have been derived to calculate CP and W′ in cycling (see Bull et al, 2000 for review of all five models). These include; a linear-work versus time model [Linear-TW], a second-linear model [Linear-P], a 2-parameter non-linear model [non-linear 2], a 3-parameter non-linear model [non-linear-3], and an exponential model [EXP] (Bull et al., 2000). When analysed for their goodness of fit, all models have been shown to fit the data closely (Bull et al., 2000; Gaesser et al., 1995).

The Linear-TW and Linear-P models can easily be derived from a linear relationship between total work (or power output) and TTE (Pettitt, 2012). Therefore, these two models are great practical tools for coaches and applied practitioners to describe and predict endurance performance. As a result, the Linear-TW and Linear-P models will be discussed in more detail throughout this thesis, and used for analysis in subsequent experimental chapters. A detailed discussion of all the CP models is beyond the scope of this thesis and can be found elsewhere (Gaesser et al., 1995; Bull et al., 2000).

2.3.2. Comparisons between Linear-TW and Linear-P CP models

A Linear-TW and Linear-P model are considered mathematically equivalent models, but CP and W′ are derived in different ways (Bull et al., 2000; Bergstrom et al., 2014). For instance, the Linear-P model calculates CP from the y-intercept and W′ from the slope of the linear relationship between power output and TTE (Hill, 1993). In contrast, the Linear-TW model calculates CP from the slope and W′ from the y-intercept of the linear relationship between total work and TTE (Hill, 1993).

For both CP linear models, there is evidence to suggest that two TTE trials are sufficient to accurately estimate CP and W´ (Hill, 1993). Nevertheless, researchers typically use between two to seven TTE trials to reduce the errors associated with the parameter estimates (Hill, 1993). The Linear-TW model is based on the linear regression of total work, measured in kilojoules (kJ) and TTE is seconds (s). The following equation is used to examine this relationship and calculate CP and W′:

$$y = a + b * x \qquad \{\text{equation 1}\}$$

From this equation CP and W′ are calculated as follows, where t = TTE and TW = total work:

$$TW = W' + CP * t \qquad \{\text{equation 2}\}$$

CP is calculated from the slope and W′ is calculated from the y-intercept of the relationship between total work (kJ) and TTE (s) (Monod and Scherrer, 1995; Moritoni et al., 1981).

The Linear-P model on the other hand is based on the linear regression of power output, measured in watts, and the inverse of TTE in seconds. There are two equations used to examine this relationship and calculate CP and W′ (Gaesser et al., 1995). Firstly, total work must be calculated, where P = power output:

$$TW = P \times t \qquad \{\text{equation 3}\}$$

Then

$$TW = W' + CP * t \qquad \{\text{equation 4}\}$$

From these equations CP and W′ are calculated as follows:

$$P \times t = W' + CP*t \qquad \{\text{equation 5}\}$$

To calculate for P we divide by t, which yields:

$$P = W' * 1/t + CP \qquad \{\text{equation 6}\}$$

Where 1/t = inverse of time.

CP is therefore calculated from the y-intercept of this relationship, and W′ is calculated from the slope of the relationship between power output and the inverse of TTE.

When examining the goodness of fit of the Linear-TW and Linear-P models, both models fit the data closely (R^2 = 0.99 and 0.96 respectively) (Gaesser et al., 1995). Additionally, the Linear-P model calculates a higher CP parameter estimate (237 ± 24 vs. 224 ± 24 W), but a lower W′ estimate (18 ± 5 vs. 22 ± 6 kJ), when compared to the Linear-TW model respectively (Gaesser et al., 1995).

2.3.3 Practical applications and limitations of the CP models

The CP model has two main practical applications, which have been extensively reviewed by Vanhatalo et al. (2011). Firstly, the CP model represents the boundary between the heavy and severe exercise intensity domains, CP and W′ (Vanhatalo et al., 2011). Consequently, this offers athletes useful information to help set appropriate pacing strategies for races, in particular longer duration events (Jones et al., 2010). For instance, an athlete is aware that as long as they maintain an intensity below their CP, they will be able to sustain exercise for a long time, at a 'steady state' (Vanhatalo et al., 2011). However, once they go above their CP intensity this is considered a 'non-steady' state, which will result in fatigue occurring soon after (Vanhatalo et al., 2011). Additionally, CP parameters correlate well with other physiological laboratory test measurements, allowing researchers and applied practitioners to monitor and detect changes in exercise tolerance (Poole et al., 1988; Housh et al., 1989; McLellan and Cheung, 1992; Pringle and Jones, 2002; Whipp et al., 2009).

The second main practical application of the CP model is that it can reliably describe the relationship between power output and TTE within the severe-intensity domain (Vanhatalo et al., 2011; Jones et al., 2010). Furthermore, CP is reliably determined from TTE or TT performances in the laboratory and field setting (Galbraith et al., 2014; Karsten et al., 2015). Therefore, the CP model is a useful tool in applied sport that offers applied practitioners and researchers a testing method that not only measures endurance performance, but also calculates the aerobic and anaerobic parameters that can be used to explain performance. As a result, a CP model has a number of added advantages over other 'traditional' laboratory test procedures such as a $\dot{V}O_{2max}$ test.

The CP model does not describe and predict the power-duration relationship over a wide range of durations (Hill, 1993) and is restricted to performances between 2 to 20-min (Hill, 1993; Derkele et al., 2008). Outside of these durations the power-duration relationship is not truly hyperbolic (Hill, 1993; Jones et al., 2010). Additionally, the CP model assumes that there is an infinite amount of power that can be produced as time approaches zero (Hill, 1993). This therefore, limits the practical application of the model as CP can only be predicted when TTE is performed within specific time points (Hill, 1993).

2.3.4. Power law model

An alternative way of modeling endurance performance is to use an approximate law of fatigue, commonly referred to as a power law model or a log-log model (Kennelly, 1906; Grubb, 1997). Kennelly (1906) used this model when examining the relationship between velocity and distance for various athletic (walking, running, rowing, skating, swimming) and horse racing (trotting, pacing, running) events. A power law model assumes a progressive decline in performance with an increase in intensity or distance (Kennelly, 1906; Grubb, 1997). The relationship between intensity (or distance) and TTE is fitted to either a power law curve, or plotted on a logarithmic scale as a linear relationship (Kennelly, 1906; Francis, 1943; Lietzke, 1954; Grubb, 1997; Katz and Katz, 1999; García-Manso et al., 2012) (Figure 2.2). When modeled in this way, researchers have demonstrated a strong fit for data describing an extremely wide range of athletic events and horse races (Kennelly, 1906; Francis, 1943; Grubb, 1997; Katz and Katz, 1999). The slope of the log-log curve is the exponent of the power law model (Kennelly, 1906) (Figure 2.2).

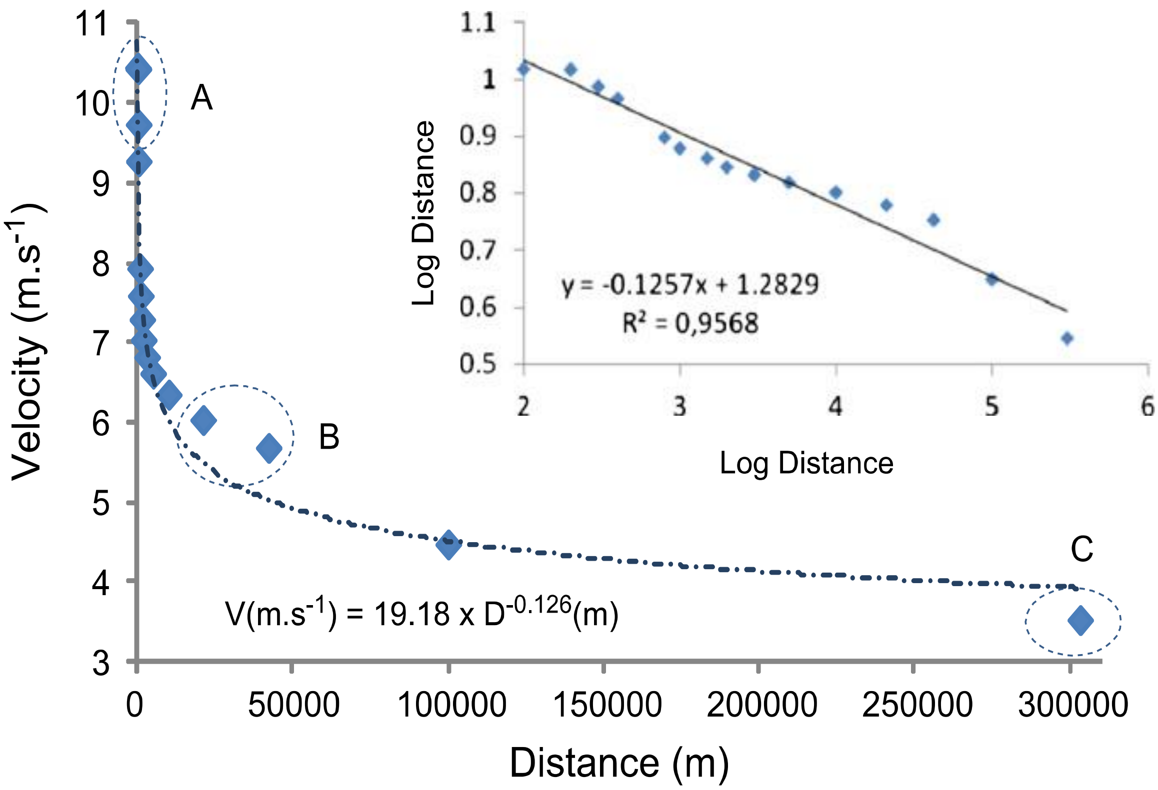

Figure 2.2: The power law relationship derived from the mean speed for world records events: 60, 100, 150, 300, 400, 800, 1000, 1500, 3000, 5000 and 10,000, half-marathon and 24 h race. The relationship is plotted both as a power law curve and a linear relationship on a logarithmic scale. Taken from García-Manso et al. (2012) p. 326[3].

The relationship between intensity (or velocity) and TTE (or distance) can be modeled using a power law curve, such that the equation is:

$$Y = cX^b \qquad \{\text{equation 7}\}$$

Where X = distance (or TTE), Y = velocity (or power output), c = normalization constant and b = scaling exponent (García-Manso et al., 2012).

Or it can be plotted on a logarithmic scale as a linear relationship (Kennelly, 1906; García-Manso et al., 2012). The equation for this is the equation of a line but both sides of the relationship are logged.

[3] Reprinted from Journal of Theoretical Biology. Vol. 300. García-Manso et al. (2012). The limitations of scaling laws in the prediction of performance in endurance events, page 326, with permission from Elsevier.

$$\text{Log}(Y) = \log(c) + b\log(X) \qquad \{\text{equation } 8\}$$

2.3.5 Practical applications and limitations of a power law model

A power law model has been most commonly used to estimate and predict world record performances, in particular for athletics (Kennelly, 1906; Katz and Katz, 1999; Savaglio and Carbone, 2000). Additionally, previous studies have found a power law model to accurately predict running and swimming performances, over a narrow range of durations or distances (Hinckson and Hopkins, 2005; Oscieki et al., 2014). However, its ability to accurately predict cycling performances has not yet been explored.

The physiological basis of a power law model is unclear. Carbone and Savaglio (2001) identified a break in a power law curve when examining running world records. They found this to occur at approximately 1000 m and proposed that this reflects the athletes' transition from aerobic to anaerobic energy expenditure. However, this finding warrants further investigation. One of the main limitations of a power law model is that it does not fit the data as closely for sprint and ultra-marathon endurance performances (García-Manso et al., 2012). This is evident from Figure 2.2, presented by García-Manso et al. (2012) who demonstrated that the mean running speed does not change for the shorter distances (e.g. 100 and 200 m) and tends to deviate from the curve for the ultra-endurance, 24 h distance events.

2.3.6 Which model better describes and predicts endurance performance?

Previous studies have compared the CP model to a power law model for goodness of fit (R^2) and predictive ability of actual performances (Hinckson and Hopkins, 2005; Osiecki et al., 2014). Hinckson and Hopkins (2005) and Osiecki et al. (2014) limited their examinations to a narrow range of durations or distances e.g. 1-10 min for running and 200-400 m for swimming respectively. Hinckson and Hopkins (2005) reported no differences between the CP and power law models when predicting actual TT performances between 1-10 min. Therefore, across a narrow range of exercise durations both the CP and power law models describe endurance performance well (Hinckson and Hopkins, 2005). Nevertheless, the results did demonstrate a lower variation of ~ 1% when a power law model was used in comparison to CP for predicting performances (Hinckson and Hopkins, 2005). Furthermore, when Osiecki et al. (2014) examined the reliability of these two models in predicting swimming performances over 200 m and 400 m events, they found the power law to more accurately predict actual performance times. The CP model overestimated the swimmers times for 200 m and 400 m events. On the other hand, while the power law underestimated the times for 200 m and 400 m, this was not significantly different from actual performance times (Osiecki et al., 2014). Nevertheless, more research is warranted to investigate the predictive ability of the power law model over longer and shorter durations (Hinckson and Hopkins, 2005).

2.4. Variability in TTE.

When assessing endurance performance, a notable observation is the large 'inter-individual' and 'intra-individual' variability in TTE performances when exercise is fixed to a % of maximum (e.g. %$\dot{V}O_{2max}$, %HR_{max}, %MAP) (Coyle et al., 1988; Currell and Jeukendrup, 2008). Inter-individual variability refers to the variability across different individuals responses for one measurement. On the other hand, intra-individual variability refers to the day-to-day variability of same individual when measurements are repeated.

2.4.1 Intra-individual variability

Currell and Jeukendrup (2008) reviewed the intra-individual variability for measurements of cycling TTE performances (Table 2.1). According to their review the CV for TTE performances can vary between 1.7-55.9% depending on the intensity of the trial (Table 2.1.) TTE trials performed at intensities above an individual's $\dot{V}O_{2max}$ tend to have a lower intra-individual variability (Coggan and Costill, 1984; Graham and McLellan, 1989; Lindsay et al., 1996) compared with trials set below $\dot{V}O_{2max}$ (Gleser and Vogal, 1971; Maughan et al., 1989; McLellan et al., 1995; Jeukendrup et al., 1996; Laursen et al., 2007). In addition, Hopkins et al. (2001) found that TTE trials lasting approximately 60 s demonstrated the lowest CV. These research findings contribute greatly to our understanding of the reproducibility of TTE, and are particularly useful when determining if a meaningful change has occurred following an intervention e.g. identifying responders and non-responders to training (Scharhag-Rosenberger et al., 2010).

Table 2.1: Previous studies reporting the intra-individual variability for TTE performances when prescribed at different intensities. Taken from Currell and Jeukendrup. (2008). p.304[4].

Table II. Reliability of time-to-exhaustion (TTE) protocols

Study	Subjects (n, sex, age)	Training status	$\dot{V}O_{2max}$ (mL/kg/min)	Mode	Performance measure	Trials	Fam	Inter-trial time	Mean time to completion (sec)	CV (%)	Feedback	Enc	PM	Ergometer
Lindsay et al.[42]	12 M, 25 y	NR	65.7	Cycling	TTE 150% W_{max}	3	NR		59	1.7	NR	NR	NR	NR
Coggan and Costill[43]	9, sex NR, 26 y	Endurance trained	57.8	Cycling	TTE 125% $\dot{V}O_{2max}$	4	NR	72 h	98	5.3	NR	Verbal	NR	Electrically braked
Graham and McLellan[44]	4 M, 21 y	Trained	62.5	Cycling	TTE 120% $\dot{V}O_{2max}$	4	NR	3–4 d	145	10	NR	NR	Expired gas	NR
Billat et al.[45]	8 M, 29 y	Subelite	69.0	Running	TTE at $\dot{V}O_{2max}$	3	NR	1 wk	403	17	NR	Verbal	Expired gas	Treadmill
Laursen et al.[46]	8M, 31 y	Endurance trained	70.4	Running	TTE at mean 1500 m TT time	2	Yes	2–5 d	371	13.2	No	No	No	Treadmill
McLellan et al.[47]	15 M, 27 y	NR	47.0	Cycling	TTE 80% $\dot{V}O_{2max}$	5	NR	72 h	~1050	17.3	No	Verbal and music present	Blood, rectal probe, expired gas, HR	Electrically braked
Laursen et al.[46]	8 M, 31 y	Endurance trained	70.4	Running	TTE at mean 5 km TT time	2	Yes	2–5 d	1086	15.1	No	No	No	Treadmill
Jeukendrup et al.[1]	10 M, 25 y	Well trained competitive	72	Cycling	TTE 75% W_{max}	5	Yes		3705	26.6	% completed	Yes	No	EMB
Krebs and Powers[48]	10 M, age NR	NR		Cycling	TTE 80% $\dot{V}O_{2max}$	2	NR	1 wk		5.2–55.9		NR	NR	NR
Maughan et al.[49]	6 M, 29 y	Healthy	53	Cycling	TTE 70% $\dot{V}O_{2max}$	2	Yes	7 d	4200	5.6	NR	NR	Expired gas	NR
Gleser and Vogel[50]	8 M, 26 y	Untrained	40.5	Cycling	TTE 75% $\dot{V}O_{2max}$	3	NR	1 wk	7080	13	NR	Rode side by side, competed in teams	Expired gas, temp, ECG	Electrically braked

CV = coefficient of variation; **EMB** = electromagnetically braked; **Enc** = encouragement given; **Fam** = familiarization; **HR** = heart rate; **M** = males; **n** = no. of subjects; **NR** = not reported; **PM** = physiological measurements performed during the trial; **temp** = temperature; **TT** = time trial; $\dot{V}O_{2max}$ = maximal oxygen uptake; W_{max} = peak power output.

[4] Reprinted from Sports Medicine. Vol. 38. Currell and Jeukendrup. (2008). Validity, reliability and sensitivity of measures of sporting performance, page 304, with permission from Springer.

2.4.2 Inter-individual variability

A large inter-individual variability in TTE performances has also been reported (Coyle et al., 1988; Orok et al., 1989; Brickley et al., 2002). For instance, Coyle et al. (1988) demonstrated a mean TTE of 46-min when well trained cyclists completed TTE exercise at 88% $\dot{V}O_{2max}$. However, these times ranged largely from 12 to 75-min when examining the individual performances, with a CV of 43.7% (Coyle et al., 1988). Brickley et al. (2002) also reported a large variability in TTE performances when individuals exercised to exhaustion at the intensity corresponding to CP (Brickley et al., 2002). Average TTE at CP was reported as 29-min 34 s; however, researchers noted that these times varied largely from approximately 20-min to 40-min. It has been proposed that the methods used to standardise exercise intensity might explain some of this variability (Scharhag-Rosenberger et al., 2012; Mann et al., 2013; Hopker and Passfield, 2014).

2.5 Endurance training strategies.

Training is a complex, creative, multi-factorial process, of which its major components are duration, intensity and frequency of exercise (Fry et al., 1992; Busso et al., 2003; Hawley, 2008; Esteve-Lanao et al., 2005). One aim of a training intervention might be to improve endurance performance, and this can be achieved through the manipulation of these three components. It is widely understood that exercise intensity plays an important role in training adaptations, and that an increase in $\dot{V}O_{2max}$ is one of the most common measures used to demonstrate a training effect (e.g. Wenger and Bell, 1986; Midgley et al., 2006; Bacon et al., 2013). As a result, the majority of studies to date have examined the effects of different training intensity distributions on changes in $\dot{V}O_{2max}$ (e.g. Rodas et al., 2000; Tabata et al., 1996; Helgerud et al., 2007; Gormley et al., 2008; Neal et al., 2011).

Training intensity can be characterised under four different headings: low-moderate intensity, LT intensity, polarised intensity, and HIT intervals (Stòggl and Sperlich, 2014). A systematic review of over 50 published studies concluded that the greatest training related improvements in cardiorespiratory fitness were observed when exercise was performed at higher intensities, between 90 and 100% $\dot{V}O_{2max}$ (Wenger and Bell, 1986). A more recent meta-analysis conducted by Bacon et al. (2013), reinforces this finding concluding that HIT training results in 'slightly' greater improvements in $\dot{V}O_{2max}$ when compared to continuous MOD training. Nevertheless, the findings are inconsistent between training studies (Tabata et al., 1996; Helgerud et al., 2007; Burgomaster et al., 2008; Gormley et al., 2008; Gibala et al., 2006). For example, some studies report a greater improvement with HIT training (Helgerud et al., 2007; Gormley et al., 2008), while others report a similar improvement when compared to MOD training (Burgomaster et al., 2008; Gibala et al., 2006).

2.5.1. HIT training.

HIT involves exercising at or near an individual's $\dot{V}O_{2max}$ for repeated bouts ranging from 30 s to 5-min, interspersed with periods of passive rest or active recovery (e.g. Burgomaster et al., 2005; Tabata et al., 1996). This type of training can significantly improve the aerobic capacity of both trained (Laursen and Jenkins, 2002) and untrained individuals (Hickson et al., 1977; Rodas et al., 2000; Gormley et al., 2008). Short-term HIT training programmes ranging from 2-6 weeks can significantly increase $\dot{V}O_{2max}$ (Cunningham et al., 1979; Poole and Gesser, 1985; Tabata et al., 1996; Rodas et al., 2000; Edge et al., 2005; Daussin et al., 2007; Driller et al., 2009). Tabata et al. (1996) was one of the first to compare MOD to HIT training in physically active participants on changes in aerobic and anaerobic capacity in cycling. Experiment one, investigated the effects of 6-weeks of MOD training (70% $\dot{V}O_{2max}$), whereas, experiment two investigated the effects of 6-weeks of HIT training (170% $\dot{V}O_{2max}$). The results of these experiments demonstrated increases in $\dot{V}O_{2max}$ of 10% and 14% for MOD and HIT training respectively (Tabata et al., 1996). However, a significantly greater increase in anaerobic capacity of 28% was reported following HIT, but not MOD training (Tabata et al., 1996). Since then, numerous studies have reported findings that favour HIT over MOD training (Gormley et al., 2008; Helgerud et al., 2007; Cunningham et al., 1979; Poole and Gesser, 1985; Tabata et al., 1996; Rodas et al., 2000; Burgomaster et al., 2005; Edge et al., 2005; Daussin et al., 2007; Driller et al., 2009).

2.5.2. MOD vs. HIT training.

Milanović et al. (2015) in a recent meta-analysis of 28 studies examined the effects of endurance training and HIT on changes in $\dot{V}O_{2max}$. The researchers noted that when compared to the no-exercise control group, both HIT and endurance training models demonstrated large improvements in $\dot{V}O_{2max.}$ In addition, when direct comparisons were made between HIT and endurance training, there was a slightly greater benefit with HIT training (Milanović et al., 2015). Bacon et al. (2013) reported a similar finding in their meta-analysis. However, upon examination of the individual research studies, it is evident that these findings are equivocal, with some studies favouring HIT over MOD for greater training adaptations (Gormley et al., 2008; Helgerud et al., 2007), while others reporting no differences between training intensities (Overend et al., 1992; Burgomaster et al., 2005; Berger et al., 2006; Gibala et al., 2006; Tanisho and Hirakawa, 2009). One explanation for this might be the way in which some researchers have controlled for total volume of exercise (or energy expenditure) when comparing different exercise intensities (Helgerud et al., 2007; Gormley et al., 2008). For example, Helgerud et al. (2007) and Gormley et al. (2008) reported greater increases in $\dot{V}O_{2max}$ following HIT training when total volume of exercise was matched to the MOD group. While this method standardises the comparisons between intensities, it is not reflective of how athletes train in the applied setting. For instance it is common for an athlete to exercise for much longer durations at MOD compared to HIT (Burgomaster et al., 2008; Nimmerichter et al., 2011). Some studies have addressed this issue by setting the training volume ~ 90% lower for the HIT compared to the MOD training groups (Burgomaster et al., 2005; Gibala et al., 2006). When designed in this manner, the results demonstrated similar physiological improvements in $\dot{V}O_{2max}$ and performance, irrespective of the training intensity employed (Burgomaster et al., 2005; Gibala et al., 2006). Therefore, no noticeable differences in physiological adaptations were observed between training intensities when the training volume was set significantly higher for endurance training compared to HIT (Burgomaster et al., 2005; Gibala et al., 2006). This has led researchers to propose that HIT is a time-efficient training strategy that has benefits for both trained and untrained individuals (Gibala et al., 2007).

2.5.3. Polarised training.

Subsequent research studies have investigated the physiological benefits of combining two different exercise intensities (Neal et al., 2011; Stòggl and Sperlich, 2014; Munoz et al., 2014). This type of training distribution is often referred to as a polarised training distribution (Stòggl and Sperlich, 2014). Polarised training consists of ~75-80% of training at low intensity, ~5-10% at LT intensity and ~15-20% at HIT (Neal et al., 2011). When polarised training was compared to threshold training in runners (Esteve-Laneo et al., 2007) and cyclists (Neal et al., 2011), greater improvements in performance occurred following polarised training. In addition, 6-weeks of polarised training in well-trained cyclists resulted in significantly greater improvements in LT power output and peak power output compared to threshold training (Neal et al., 2011). Research therefore favours this intensity distribution over a threshold type training as it allows athletes enough time to recover during the 'easy' training sessions, while still exposing them to a maximal training stimulus during the 'hard' training sessions (Esteve-Laneo et al., 2007; Munoz et al., 2014). This may in turn prevent overtraining or staleness occurring in the long-term (Esteve-Laneo et al., 2007).

The training benefits following polarised training are well recognised (Esteve-Laneo et al., 2007; Laursen, 2010; Stòggl and Sperlich, 2014; Neal et al., 2011). However, whether this is a result of a 'polarised' training distribution or simply the combination of two different training intensities remains unclear. For instance, Hickson et al. (1977) reported a large increase in $\dot{V}O_{2max}$ of 44% after 10-weeks of training when HIT and endurance training were combined. Participants exercised for 40-min per session, 6 days per week. The training consisted of 3 days of HIT cycling (5-min repetitions at $\dot{V}O_{2max}$) and 3 days of running as fast as possible for 30-min on alternative days. Therefore, it is evident from the training programme that this did not follow the typical polarised training distribution. Despite this, a significant increase in $\dot{V}O_{2max}$ throughout the 10-weeks was observed, with no sign of $\dot{V}O_{2max}$ leveling off at the end of the study, despite participants reaching near elite levels in their aerobic fitness (Hickson et al., 1977). One explanation for this might be as a result of differences in functional adaptations achieved from endurance and interval training via two different pathways (Laursen, 2010) (Figure 2.3). According to this model (Figure 2.3), HIT training adaptations occur as a result of signaling the adenosine monophosphate kinase (AMPK) pathway, while high volume training adaptations are more likely to occur through signaling of the calcium-calmodulin kinase (CaMK) pathway (Laursen, 2010). Therefore, by stressing the physiological system with one type of exercise intensity, it is assumed that this will optimise one pathway only, and as a result, no further adaptations can occur unless another pathway is targeted (Laursen, 2010).

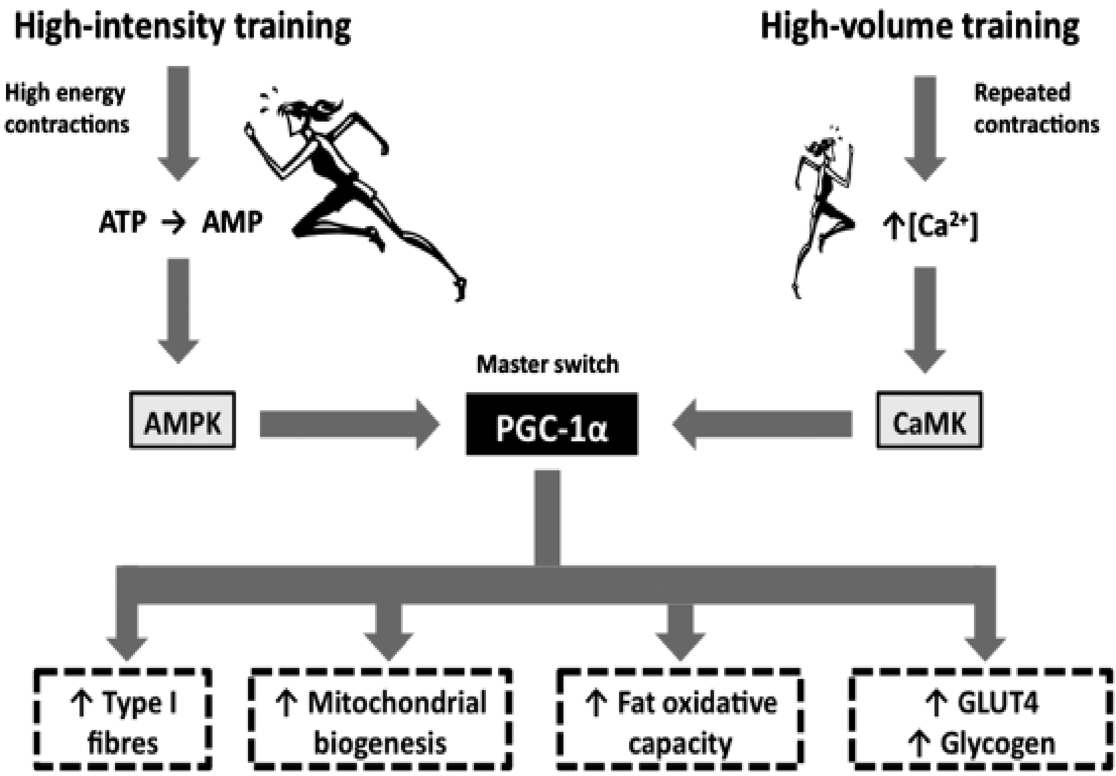

Figure 2.3: Model of AMPK and CaMK signaling pathways and how HIT and high volume training can signal two different pathways for training adaptations. Taken from Laursen (2010), p.7[5].

Training frequency is another key feature of endurance training, with evidence that it plays an important role in improving $\dot{V}O_{2max}$ (Pollock et al., 1975; Gettman et al., 1976; Hatle et al., 2014). However, studies that have compared the effects of training frequency on changes in $\dot{V}O_{2max}$ are limited (Pollock et al., 1975; Gettman et al., 1976; Hatle et al., 2014). Therefore, to understand the relationship between the frequency of training and the magnitude of change (Δ) in $\dot{V}O_{2max}$, results were analysed from 40 previously published training studies (Table 2.2). A Pearson's correlation analysis was conducted to identify if there was a relationship between the number of training sessions completed and the %Δ change in $\dot{V}O_{2max}$. The results of this analysis are presented in Figure 2.4. Figure 2.4 (A), demonstrates a strong positive relationship between the total % $\Delta\dot{V}O_{2max}$ and the total number of training sessions completed (r=0.58; P<0.01). The results show that the greater the total number of training sessions completed for a training intervention, the greater $\%\Delta\dot{V}O_{2max}$. Figure 2.4 (B) demonstrates a strong positive relationship between

[5] Reprinted from Scandinavian Journal of Medicine and Science in Sports. Vol. 20, Laursen (2010). Training for intense exercise performance: high-intensity or high volume training? Page. 7, with permission from John Wiley and Sons.

the $\%\Delta\dot{V}O_{2max}$ per week and the number of training sessions completed per week (r=0.52; P<0.01). Again the results show that the more training sessions completed per week the greater the increases in $\dot{V}O_{2max}$ observed.

In contrast, Hatle et al. (2014) found that a high frequency (8 sessions per week) approach to the number of training sessions completed per week can have a detrimental effect on $\dot{V}O_{2max}$ and also potentially lead to over training. Whereas, a moderate frequency (3 sessions per week) approach to the number of training sessions completed per week can result in immediate improvements following just 8 training sessions in untrained individuals (Hatle et al., 2014). This was a similar finding to Pollock et al. (1975) which investigated the effects of 30-40 min of running training at frequencies of 2, 3 and 4 days per week over a total of 20-weeks on changes in $\dot{V}O_{2max}$. The results demonstrated a significant increase in $\dot{V}O_{2max}$ for all training frequencies, however, they found 4 days a week to produce the greatest increase in $\dot{V}O_{2max}$ (Pollock et al., 1975). As a result, more research is needed to determine the influence of training frequency in trained and untrained individuals.

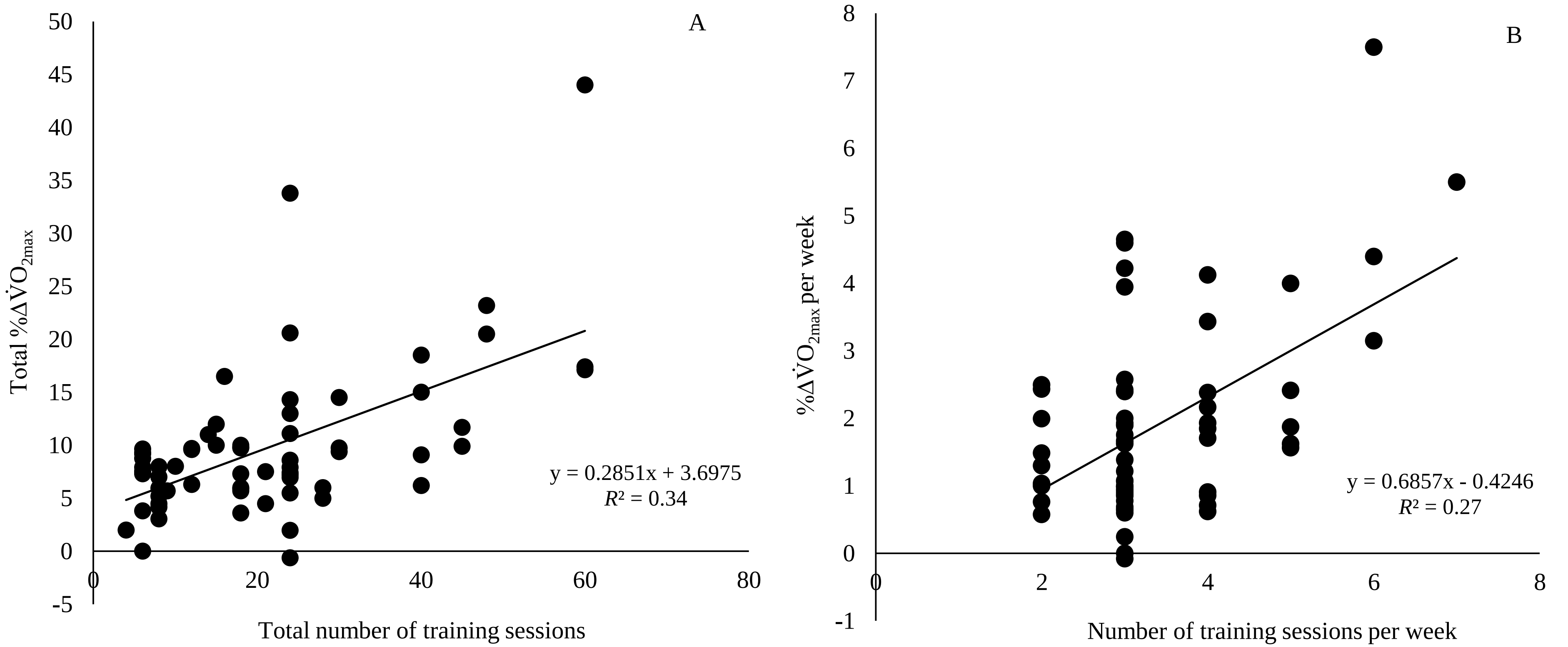

Figure 2.4: Comparisons of the relationship between $\%\Delta\dot{V}O_{2max}$ versus number of training sessions completed based on a review of 40 published training studies. A = Total $\%\Delta\dot{V}O_{2max}$ after training versus the total number of training sessions completed. B = $\%\Delta\dot{V}O_{2max}$ per week versus the number of training sessions completed per week.

Table 2.2: Analysis of 40 published training studies, demonstrating the $\%\Delta\dot{V}O_{2max}$ with different frequencies of training.

Authors	**Training status**	**Training intensity**	**No. of weeks training**	**No. training sessions per week**	**Total no. sessions**	**$\%\Delta\dot{V}O_{2max}$ per week**	**Total $\%\Delta\dot{V}O_{2max}$**
Astorino and Schubert. (2014)	Recreational	SIT	2	6	12	3.2	6.3
Bayati et al. (2011)	Recreational	HIT	4	3	12	2.4	9.6
	Recreational	HIT	4	3	12	2.4	9.7
Burgomaster et al. (2005)	Recreational	HIT	2	3	6	0	0
Burgomaster et al. (2008)	Recreational	ET	6	5	30	1.6	9.8
	Recreational	SIT	6	3	18	1.2	7.3
Burke et al. (1994)	Recreational	HIT	7	4	28	0.7	5.0
	Recreational	HIT	7	4	28	0.9	6.0
Casaburi et al. (1987)	Recreational	ET	8	5	40	1.9	15.0
Cochron et al. (2014)	Recreational	ET	6	3	18	0.9	5.7
Cunningham et al. (1979)	Sedentary	HIT	12	4	48	1.9	23.2
	Sedentary	ET	12	4	48	1.7	20.5
Daussin et al. (2007)	Sedentary	HIT	8	3	24	4.2	33.8
	Sedentary	ET	8	3	24	1.1	8.6
Edge et al. (2005)	Recreational	HIT	5	3	15	2.4	12.0
	Recreational	ET	5	3	15	2.0	10.0
Edge et al. (2013)	Recreational	HIT	5	3	6	1.9	9.7
	Recreational	HIT	5	3	6	1.8	8.8
Esfarjani and Laursen. (2007)	Trained	HIT	10	4	40	0.9	9.1
	Trained	HIT	10	4	40	0.6	6.2
Etxebarria et al. (2014)	Trained	HIT	3	2	6	2.5	7.5
	Trained	HIT	3	2	6	2.4	7.3

Franch et al. (1998)	Recreational	ET	6	3	18	1.0	5.9
	Recreational	HIT	6	3	18	1.0	6.0
	Recreational	HIT	6	3	18	0.6	3.6
Glaister et al. (2007)	Trained	ET	6	3	18	1.6	9.8
Goodman et al. (2005)	Recreational	ET	1	6	6	7.5	7.5
Gormley et al. (2008)	Recreational	ET	6	4	24	3.4	20.6
	Recreational	HIT	6	4	24	2.4	14.3
	Recreational	HIT	6	3	18	1.7	10.0
Gorostiaga et al. (1991)	Sedentary/Recreational	ET	8	3	24	0.9	7.4
	Sedentary/Recreational	IT	8	3	24	1.4	11.1
Gross et al. (2007)	Trained	HIT	3	3	9	1.9	5.7
Gunnarsson and Bangsbo. (2012)	Trained	HIT	7	3	21	0.6	4.5
Hautala et al. (2006)	Sedentary	ET	2	5	10	4.0	8.0
Hazell et al. (2010)	Recreational	HIT	2	3	6	4.7	9.3
	Recreational	HIT	2	3	6	4.6	9.2
	Recreational	HIT	2	3	6	1.9	3.8
Helgerud et al. (2007)	Trained	ET	8	3	24	-0.1	-0.6
	Trained	LT	8	3	24	0.2	2.0
	Trained	HIT	8	3	24	0.7	5.5
	Trained	HIT	8	3	24	0.9	7.2
Hickson et al. (1977)	Sedentary	POL	10	6	60	4.4	44.0
Hottenrott et al. (2012)	Recreational	ET	12	2	24	0.6	7.0
	Recreational	HIT	10	4	40	1.9	18.5
Jacobs et al. (2013)	Untrained	HIT	2	3	6	4.0	7.9
Laursen et al. (2002a)	Trained	HIT	4	2	8	1.3	5.2
	Trained	HIT	4	2	8	2.0	8.0
	Trained	HIT	4	2	8	0.8	3.1

Laursen et al. (2002b)	Trained	HIT	2	2	4	1.0	2.0
Ma et al. (2013)	Recreational	HIT	4	4	16	4.1	16.5
MacDougall et al. (1998)	Recreational	HIT	7	3	21	1.1	7.5
McKay et al. (2009)	Recreational	HIT	3	3	8	1.7	4.5
	Recreational	ET	3	3	8	2.6	7.0
Rodas et al. (2000)	Recreational	HIT	2	7	14	5.5	11.0
Skinner et al. (2000)	Sedentary	ET	20	3	60	0.9	17.1
Smith et al. (2003)	Trained	HIT	4	2	8	1.5	6.0
	Trained	HIT	4	2	8	1.0	4.2
Tabata et al. (1996)	Recreational	ET	6	5	30	1.6	9.4
	Recreational	HIT	6	5	30	2.4	14.5
Tanisho and Hirakawa. (2009)	Trained	ET	15	3	45	0.8	11.7
	Trained	HIT	15	3	45	0.7	9.9
Vollaard et al. (2009)	Sedentary	ET	6	4	24	2.2	13.0
Weber and Schneider. (2002)	Recreational	HIT	8	3	24	1.0	7.9
Wilmore et al. (2001)	Sedentary	ET	20	3	60	0.9	17.4
Ziemann et al. (2011)	Recreational	HIT	6	3	18	1.6	9.8

Where; SIT = sprint interval training, ET = endurance training, HIT = high intensity training, POL = polarised training.

2.6. Inter-individual variability in training adaptations.

When quantifying the relationship between training, physiological adaptations and improvements in performance, the vast majority of researchers do not take into account the individual responses (Borresen and Lambert, 2009; Timmons, 2011; Mann et al., 2014). Instead, researchers tend to focus solely on the 'mean' response to training when presenting their findings (e.g. Tabata et al., 1996; Burgomaster et al., 2005; Helgerud et al., 2007; Gormley et al., 2008). This often results in misleading and over simplistic conclusions (Timmons, 2011; Mann, 2011; Mann et al., 2014). The 'mean' response to training does not tell us whether some individuals respond particularly well, or particularly poorly to an intervention and therefore limits the overall outcomes of a study's findings (Mann, 2011). Table 2.3 presents an overview of previous studies that have reported a large inter-individual variability in $\dot{V}O_{2max}$ after standardised training interventions. This table further highlights the importance of taking into account the individual responses as opposed to just focusing on the mean.

The individual variability in training responses has gained increasing interest over the last decade (Hautala et al., 2006; Kivinemi et al., 2007; Manzi et al., 2009; Vollaard et al., 2009; McPhee et al., 2010; Scharhag-Rosenberger et al., 2012; Capostagno et al., 2014). The health risk factors, exercise training and genetics (HERITAGE) family studies have contributed greatly to our understanding of individual trainability (Bouchard et al., 1986; Bouchard et al., 1999; Skinner et al., 2000; Bouchard and Rankinen, 2001; Gaskill et al., 2001; Rankinen et al., 2001). Such studies have investigated the role that genetics and other factors have on cardiovascular, metabolic and hormonal responses to standardised endurance training (Bouchard et al., 1986; Bouchard et al., 1999; Skinner et al., 2000; Gaskill et al., 2001; Rankinen et al., 2001). For example, Bouchard et al (1999) investigated the effects of a standardised cycling training programme on physiological and performance responses, with a cohort of 481 sedentary participants training 3 times per week for 20-weeks. While the results demonstrated a large mean increase in $\dot{V}O_{2max}$ of 400 $ml \cdot min^{-1}$, it was found that the individual responses ranged largely from no improvement to an increase as high as 1 $L \cdot min^{-1}$ (Bouchard et al., 1999). It is evident therefore, that the trainability of some individuals can be very poor or in some cases non-existent (Bouchard et al., 1999; Vollaard et al., 2009; Borresen and Lambert, 2009). Researchers continue to investigate the factors linked to the variability in training responses. It is recognised that up to 50% of the variability can be explained by an individual’s genetic background (Bouchard et al., 1999; Bouchard and Rankinen, 2001). A number of other factors such sex, training history; initial training status, training mode, duration, intensity and frequency may also contribute to the large variability in training responses (Bouchard and Rankinen, 2001; Borresen and Lambert, 2009).

Table 2.3: Previous research demonstrating a large inter-individual variability following a standardised training interventions.

Study	Fitness level; sample size (*n*)	Duration (wks.)	Total no. sessions	Intensity	Training protocol	Mean $\Delta\dot{V}O_{2max}$ (%)	Range Lowest	Range Highest
Astorino and Schubert. (2014)	Recreational; *n*=20	2	6	HIT	4-6 x 30 s all out, 5-min recovery	6	0	20
Bouchard et al. (1999)	Sedentary; *n*=481	20	60	MOD	30-50 min at 55-75% $\dot{V}O_{2max}$	16	0	42
Hautala et al. (2006)	Recreational; *n*=73	2	10	MOD	30-min, 70-80% HR_{max}	8	-5	22
				Resistance	15 exercises x 1 set 8-12 reps	4	-8	16
McPhee et al. (2010)	Recreational; *n*=53	6	18	MIX	45-min – 4-5 reps of 6-min at 75% HR_{max} with 2-3 min reps 90% HR_{max}	10	-3	28
Skinner et al. (2000)	Sedentary; *n*=614	20	60	MOD	30-min at 50% $\dot{V}O_{2max}$	17	12	22
Vollaard et al. (2009)	Sedentary; *n*=24	6	24	MOD	45-min at 70% $\dot{V}O_{2max}$	13	-10	50
Hickson et al. (1977)	Sedentary; *n*=8	10	60	MIX	3 x running: 30-40 min – all out 3 x cycling: 6 x 5-min at $\dot{V}O_{2max}$, 2-min recovery	44	18	58
					Mean	14.8	0.5	32.3
					SD	12.7	9.7	15.7

2.6.1 Gender, age, training history, baseline $\dot{V}O_{2max}$.

Bouchard and Rankinen (2001) investigated the contribution of age, sex, race and baseline fitness level on the trainability of $\dot{V}O_{2max}$ across a large sample size of 720 participants. The results demonstrated that the largest predictor of $\dot{V}O_{2max}$ trainability was gender (5.4%), followed by age (4%), baseline $\dot{V}O_{2max}$ (1.1%) and finally race accounting for less than 1% (Bouchard and Rankinen, 2001). As a result, age, gender, race and baseline fitness contribute to approximately 11% of the overall variance reported in the HERITAGE family studies (Bouchard and Rankinen, 2001). The link between baseline fitness and $\dot{V}O_{2max}$ trainability has been previously investigated (Wilmore et al., 2001; Sisson et al., 2009; Cunningham et al., 1979). These studies have reported significantly greater increases in $\dot{V}O_{2max}$ following training in participants who have initially lower levels of $\dot{V}O_{2max}$ (Cunningham et al., 1979). Skinner et al. (2000) on the other hand found that low, medium and high responders to training could be identified across all fitness levels, proposing that initial fitness has little effect on changes in $\dot{V}O_{2max}$.

2.6.2 Genetics.

It is widely understood that two individuals with different genotypes can be exposed to the exact same training stimulus and demonstrate very different adaptive responses (Bouchard et al., 1986; Bouchard et al., 1999; Gaskill et al., 2001; Rankinen et al., 2001; Lortie et al., 1984). Evidence that genetics plays a role in trainability dates back to the initial studies on identical twins (Prud'homme et al., 1984; Hamel et al., 1986; Bouchard et al., 1986) and genetically modified rats (Troxell et al., 2003). Prud'homme et al. (1984) recruited 10 pairs of identical twins who completed 20-weeks of supervised cycling training, 4-5 times per week. While the researchers were able to identify high and low responders following the completion of the training programme, they also reported an almost eight times greater variance between pairs than within pairs for changes in $\dot{V}O_{2max}$ (Prud'homme et al., 1984). The findings provide evidence that twins tend to demonstrate similar responses to training, a pattern also found in genetically modified rats (Troxell et al., 2003). For instance, Troxell et al. (2003) identified high and low responders to treadmill training based on the rats mean running distances. They then paired the lowest to training and mated them and did the same for the highest responders. The offspring from the low responders did not differ in terms of trainability, whereas, those from the high responder category showed significant improvements in running distances by more than 60% (Troxell et al., 2003).

There is considerable interest among researchers to identify specific genes that are associated with performance (Montgomery et al., 1998; North et al., 1999). Animal and human research studies have contributed greatly to our understanding of the relationship between genetics and physical performance (Troxell et al., 2003; Bouchard et al., 1999; Gaskill et al., 2001; Rankinen et al., 2001; Lortie et al., 1984; Prud'homme et al., 1984; Hamel et al., 1986). For instance, researchers have identified two candidate genes that are linked to performance: angiotensin I-converting enzyme (ACE) (Montgomery et al., 1998) and alpha-actinin-3 (ACTN3) gene (North et al., 1999). These candidate genes have been widely researched and are linked to improvements in sprint and endurance performance (Rankinen et al., 2002), as well as the variability in training responses (Bouchard et al., 2000; Bouchard, 2012).

The link between an individual's genotype and training response has been extensively reviewed elsewhere (Bouchard, 2012) and is beyond the scope of this thesis. However, other factors such as the methods used to standardise training mode, duration and intensity have not been fully explored and might also contribute to this variability in training responses (Mann et al., 2013).

2.6.3 Training mode, duration and intensity.

Training mode, duration, and intensity, can also contribute to the individual variability in training responses (Hautala et al., 2006; Scharhag-Rosenberger et al., 2012; Wolpern et al., 2015). Hautala et al. (2006) investigated the effects of training mode on changes in $\dot{V}O_{2max}$. The study tested the hypothesis that when participants demonstrate a poor response to endurance training, they would benefit from resistance training instead in order to improve $\dot{V}O_{2max}$ (Hautala et al., 2006). The study randomly assigned sedentary males to a 2-week endurance training or resistance training programme, in a crossover design and participants completed a 2-month detraining period between interventions (Hautala et al., 2006). The results demonstrated that cardiorespiratory fitness could be improved more effectively by resistance training if the $\dot{V}O_{2max}$ response was low following endurance training and vice versa (Hautala et al., 2006). This led researchers to conclude that an individual's $\dot{V}O_{2max}$ responsiveness to exercise training could be related to the mode of exercise and that training modes need to be tailored individually in order to optimise performance improvements (Hautala et al., 2006). An alternative hypothesis might be that some individuals were provided with an inappropriate pattern of stimulus for their genotype (Timmons, 2011). However, this warrants further investigation.

As well as the link between exercise intensity and training responses, the methods used to prescribe and standardise exercise intensity might also explain some of this variability (Vollaard et al., 2009; Scharhag-Rosenberger et al., 2010; Lansley et al., 2011; Mann et al., 2014; Wolpern et al., 2015). Exercise intensity is most commonly prescribed as a % of maximum e.g. $\%HR_{max}$, $\%\dot{V}O_{2max}$, % MAP (Esfarjani and Laursen, 2007). Other methods of exercise prescription include taking into account an individual's heart rate reserve (HRR) (da Cunha et al., 2011) and aerobic and anaerobic thresholds. Prescribing exercise intensity as a fixed $\%\dot{V}O_{2max}$ can result in a large individual variation in the metabolic stress stimulus (Scharhag-Rosenberger et al, 2010) For instance, as the intensity of exercise decreases below $\dot{V}O_{2max}$ (e.g. 50-70%), the physiological responses become much more varied (Scharhag-Rosenberger et al., 2010). Scharhag-Rosenberger et al. (2010) demonstrated that at 75% $\dot{V}O_{2max}$ the metabolic strain was significantly less homogenous than at 60% $\dot{V}O_{2max}$ and this is evidenced by a higher variation in blood lactate responses when related back to each individual's LT. Furthermore, Meyer et al. (1999) demonstrated that when exercise intensity was fixed at 75% $\dot{V}O_{2max}$, differences in the intensities associated with an individual's anaerobic threshold can range from 86-118% and blood lactate responses from 1.4-4.6mmol.L^{-1}.

It is also evident that when exercise is prescribed as a $\%\dot{V}O_{2max}$ that individuals leg muscles could be working at very different relative intensities (McPhee et al., 2009; McPhee et al., 2010). This is evident when comparing an individual's single-leg $\dot{V}O_{2peak}$ expressed as a ratio of their double-leg $\dot{V}O_{2max}$ ($Ratio_{1:2}$) (McPhee et al., 2009; McPhee et al., 2010). McPhee et al. (2010) investigated the effects of an endurance-training programme on single and double leg $\dot{V}O_{2max}$. The study trained 54 untrained women, 3 times per week for 6-weeks at both MOD and HIT, prescribed based on a $\%\dot{V}O_{2max}$. The results demonstrated a large inter-individual variability in the adaptive responses of the leg muscles following the endurance-training programme. The researchers also reported a significant association between the $Ratio_{1:2}$ and an individual's muscle volume and training response (McPhee et al., 2010). For instance those with a low $Ratio_{1:2}$

demonstrated the greatest gains in training responses for single-leg $\dot{V}O_{2max}$ and quadriceps muscle volume (McPhee et al., 2010). The researchers therefore concluded that this variability was associated with the aerobic capacity of the leg muscles, which is not accounted for when exercise is prescribed as a %$\dot{V}O_{2max}$ (McPhee et al., 2010). It is important therefore, that the metabolic stimulus is accounted for when prescribing exercise intensity, particularly, if the aim is to reduce the inter-individual variability (Mann et al., 2014).

Alternative methods of prescribing exercise include: % threshold (e.g. gas exchange threshold (GET), LT, ventilatory threshold), %HRR, or based on the CP intensity derived from an individuals' power-duration relationship. Mann et al. (2013) and da Cunha et al. (2011) discussed the limitations associated with the different methods used to prescribe exercise. Mann et al. (2013) also recommended that more researchers use a % of threshold as opposed to a % maximum to prescribe exercise intensity. Some studies have investigated the benefits of prescribing exercise as a % of threshold, with evidence suggesting it provides a more consistent exercise stimulus across individuals (Lansley et al., 2011; Wolpern et al., 2015). For instance, Lansley et al. (2011) compared two methods of prescribing exercise; %$\dot{V}O_{2max}$ versus %GET on submaximal exercise responses. While this study was limited by a small sample size (*n*=9), they reported a significantly lower inter-individual variability for $\dot{V}O_2$, $\dot{V}CO_2$ and $\dot{V}_E$ responses during a performance trial set at 60% GET compared to a performance trial set at 50% $\dot{V}O_{2max}$ (Lansley et al., 2011). This was also associated with less inter-individual variability in blood lactate accumulation, exercise HR, and RPE when compared to the performance trial at 50% $\dot{V}O_{2max}$. The researchers also reported a lower inter-individual variability in TTE when exercise was fixed at % delta. For example, 80% delta was calculated as GET plus 80% of the interval between GET and $\dot{V}O_{2max}$ (Lansley et al., 2011). Furthermore, Wolpern et al. (2015) reported a more consistent training response when exercise was prescribed based on ventilatory threshold compared to %HRR. Therefore, how exercise intensity is prescribed is linked to some of the variability observed in TTE (Lansley et al., 2011; Mann et al., 2014) and training responses (Vollaard et al., 2009; Scharhag-Rosenberger et al., 2010). This has led researchers to conclude that a %$\dot{V}O_{2max}$ prescription method should not be used in research if the goal is to induce a similar metabolic strain (Vollaard et al., 2009; Scharhag-Rosenberger et al., 2010; Mann et al., 2014).

The time (and therefore energy expenditure) that an individual can sustain exercise at the same relative intensity is highly variable (Coyle et al., 1988; Vollaard et al., 2009; Scharhag-Rosenberger et al., 2010; Jacobs et al., 2011). An understanding of this variability is important in particular for researchers aiming to standardise the duration of exercise across all participants. To date, researchers have fixed the duration of exercise for all participants and prescribed exercise intensity at the same relative intensity (e.g. % $\dot{V}O_{2max}$) (Gibala et al., 2006; Helgerud et al., 2007; Burgomaster et al., 2008). However, by doing this, researchers are ignoring the individual differences in exercise tolerance (Coyle et al., 1988; Scharhag-Rosenberger et al., 2010). Coyle et al. (1988) reports a large individual difference in TTE responses when exercise is prescribed as a %$\dot{V}O_{2max}$ (Figure 2.5). Figure 2.5, shows the TTE performances for each individual, ranging from 29 to 60-min. This large variability in the times individuals can sustain the same relative intensity to exhaustion for might therefore explain differences in training responses due to a variability in the training stimulus experienced by each individual. For example, if the same cohort of participants (Figure 2.5) were recruited for a subsequent training study in which the training sessions lasted 35-min at 88% $\dot{V}O_{2max}$, one would expect that for some participants (e.g. participants 9-14) this training duration would lead to overtraining or an inability to complete the target session. Alternatively, for other participants (e.g. participants 1-7) this might result in an inappropriate pattern of stimulus, leading to undertraining and in some cases a non-response to training. As a result, it is important that researchers also take into account the variability in exercise tolerance when designing a training intervention. This might be achieved through individualised methods of prescribing exercise (Kivinemi et al., 2007; Manzi et al., 2009; Capostagno et al., 2014).

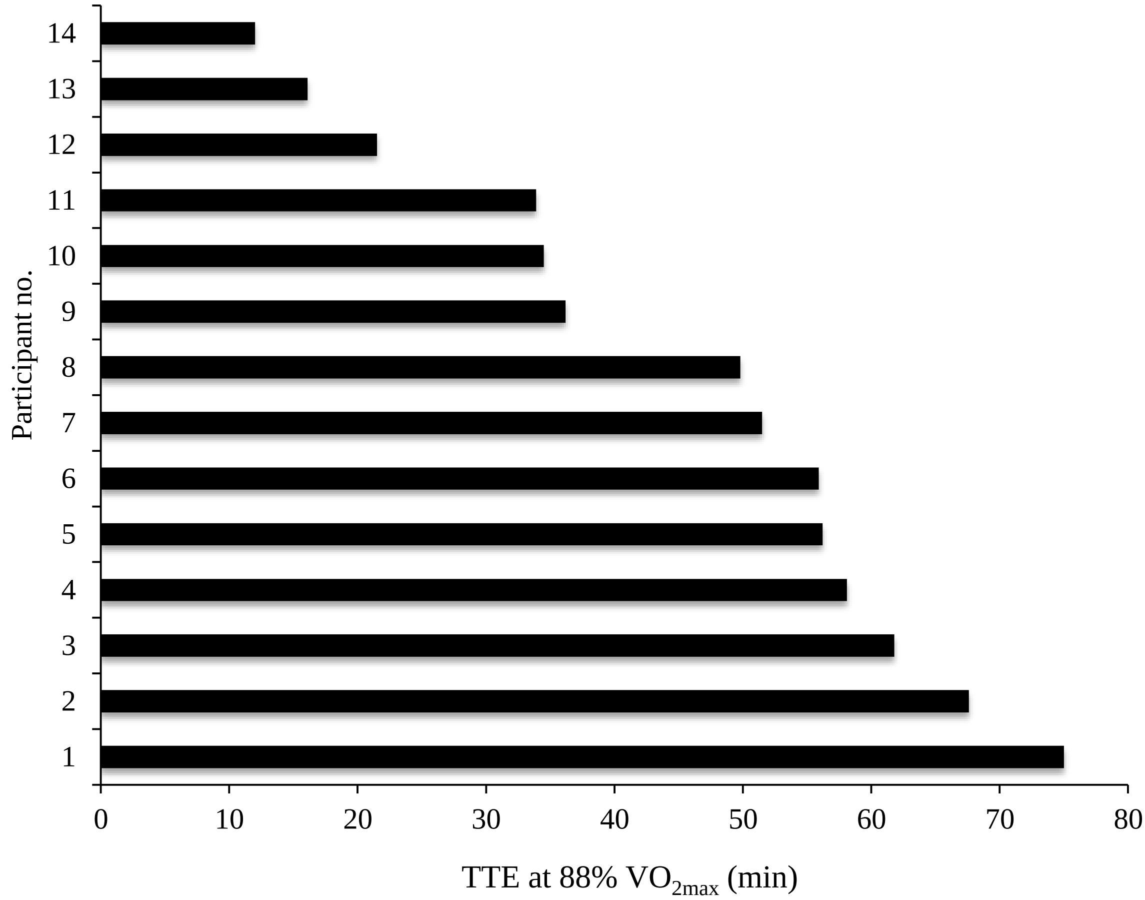

Figure 2.5: Coyle et al. (1988) TTE performance data presented to re-emphasis the variability in TTE performances when exercise is prescribed as a $\%\dot{V}O_{2max}$.

2.7 Individualised training methods.

The concept of 'individualised' tailored training has gained some interest over the last decade (Kivinemi et al., 2007; Manzi et al., 2009; Capostagno et al., 2014). Researchers have attempted to account for individual differences in exercise stress by for example using resting heart rate variability (HRV) (Kivinemi et al., 2007) or the Lamberts and Lambert sub-maximal cycling test (Capostagno et al., 2014) to individualise the training sessions. The findings of these studies suggest that an individualised placement of MOD and HIT training results in a greater improvements in maximal running velocity, but not $\dot{V}O_{peak}$, when compared to a more standardised training approach (Kivinemi et al., 2007). Nevertheless, researchers still report a large inter-individual variability in the training responses despite tailoring the intensity of the sessions for each individual (Kivinemi et al., 2007; Capostagno et al., 2014). Therefore, while an individualised training intensity prescription does demonstrate some benefits to changes in performance, no research to date has investigated the effects of individualising training durations in particular when comparing different training intensities.

2.8 Thesis aims and hypotheses.

The overall aim of this thesis was to investigate the effects of individualised methods of prescribing exercise on TTE and training responses in cycling. Research studies examining the effects of an individualised approach to exercise prescription are scarce and warrant further investigation. In addition, the hypothesis that the variability in response to physical exercise is due to an inappropriate standardisation of exercise has not been fully explored. This thesis therefore presents a series of studies that contribute to the overall research aim.

The specific aims and hypotheses of each of the experimental chapters are as follows:

1) Cycling performance is superior for time-to-exhaustion versus time-trial in endurance laboratory tests

- *Aim:* To compare TTE and TT performance when trials are performed over the same duration. Calculated CP and W′ were also compared when derived from TTE and TT performances.
- *Hypothesis:* In comparison to the TTE trials the suggested difference in ecological validity of the TT tests will alter the power output cyclists are able to sustain and in turn change calculated CP.

2) Individualised training at different intensities results in similar physiological and performance benefits.

- *Aim:* To compare the effects of three exercise intensities; MOD, HIT and a combination of the two (MIX) on physiological and performance adaptations when the training duration was individualised.
- *Hypothesis:* There will be no significant difference between exercise intensities for performance and physiological adaptations when the duration of exercise is individualised.

3) A power law describes cycling endurance performance better than a critical power model.

- *Aims:* Firstly, to determine if the CP and power law models accurately predicted and described cycling TTE for intensities within the typical CP range (80-110% MAP). Secondly, whether a power law model accurately predicted cycling TTE outside the typical CP range (60-200% MAP).
- *Hypothesis:* A power law model will predict actual TTE better than a CP model across a wide range of durations (i.e. <2-min to >20-min).

4) A power law model reduces variability in time-to-exhaustion.

- *Aim:* To compare the inter-individual variability in cycling TTE when exercise intensity was prescribed using two different methods; as %$\dot{V}O_{2max}$, or when derived from a power law model.
- *Hypothesis:* Prescribing exercise using a power law model will significantly reduce the variability in TTE when compared to a %$\dot{V}O_{2max}$ prescription.

Chapter 3: Cycling performance is different for time-to-exhaustion versus time-trial in endurance laboratory tests.

3.1 Abstract.

TTE trials are used in a laboratory setting to measure endurance performance. However, the ecological validity of TTE when compared to TT performances has been questioned. **Purpose:** This study compared the mean power output for TTE trials to matched duration TTs. CP calculated from the TTE and TTs were also compared. **Methods:** Seventeen male cyclists completed three TTE trials at 80%, 100% and 105% of MAP. On a subsequent visit they performed three TTs over the same duration as the corresponding TTE trials. Mean power output, cadence, HR and RPE were recorded but cyclists were not provided with feedback on these measurements or their elapsed time. **Results:** Mean duration of exercise was 865 ± 345 s, 165 ± 98 s and 117 ± 45 s for the 80%, 100% and 105% trials respectively. Mean power output was higher for TTE vs. TT at 80% (294 ± 44 W vs. 282 ± 43 W; $P<0.01$), but not at 100% (353 ± 62 W vs. 359 ± 74 W; $P>0.05$) and 105% (373 ± 63 W vs. 374 ± 61 W; $P>0.05$) respectively. There was no difference in cadence, HR or RPE for any trial ($P>0.05$). CP was higher when derived from TTE compared to TT ($P<0.05$) while W´ was lower ($P<0.05$). **Conclusion:** TTE results in a higher mean power output at 80%, and a significant difference in calculated CP and W′ when compared to TTs. Differences in pacing strategy may be responsible for these findings. When determining CP, TTE rather than TT protocols appear superior.

Key Words*:* Pacing, Critical power, Power output, Endurance performance.

3.2 Introduction.

Constant power output TTE trials and self-paced TTs are well-established cycling performance tests (Jeukendrup et al., 1996; Schabort et al., 1998; Paton and Hopkins, 2001). TTE and TTs are commonly used to monitor progression and detect changes following experimental interventions. The ecological validity of using TTE to assess endurance performance has been questioned (Jeukendrup and Currell, 2005). For instance, it is suggested that cyclists rarely maintain a constant power output to volitional exhaustion in competition or training (Marino, 2012; Tucker et al., 2006; Jones et al., 2013). In contrast, a TT attempts to replicate a competitive situation in the laboratory, allowing athletes to self-regulate their pace in response to physiological demands (Tucker et al., 2006; Palmer et al., 1994). Furthermore, it has also been established that the variability of TTs are much lower and its repeatability superior to the TTE performances (Laursen et al., 2007; Jeukendrup et al., 1996). Consequently, it is unclear whether power output for maximal TTE and TT performances under standardised conditions are directly comparable.

One of the more common uses of a TTE trial is to determine CP from a series of exhaustive performance trials (Monod and Scherrer, 1965; Hill, 1993; Derkele et al., 2008). These trials are recommended to last between 2 to 15-min (Hill, 1993; Derkele et al., 2008). Additionally, the maximum work done in a specified time period (i.e. highest mean power output/velocity in a TT format) has been used (Galbraith et al., 2011; Galbraith et al., 2014; Karsten et al., 2015). The interchangeable use of these test protocols presumes that TTE and TT tests are equivalent for determining CP. However, the possible influence of using a specified duration TT, rather than TTE, on the subsequent CP calculation has not been assessed in trained cyclists.

The aim of this study was to compare mean power output for TTE and TT performances when the trials were performed over the same duration. CP calculated from TTE, and TT performances were also compared. It was hypothesised that in comparison to the TTE trials, the suggested difference in ecological validity of the TTs would alter the cyclists mean power output, and in turn change calculated CP.

3.3 Methods.

3.3.1 Participants.

Seventeen trained male road cyclists were recruited as participants for this study (mean ± SD; age = 31 ± 9 y, mass = 70.7 ± 9.9 kg, MAP = 366 ± 52 W and $\dot{V}O_{2max}$ = 60.4 ± 8.4 ml·kg^{-1} min^{-1}). All participants had been involved in a minimum of 250 km or 10 h of cycling per week. Participants were excluded if they were taking any medication, reported heart problems, exercise induced asthma or any injury that would interfere with testing. All participants gave their written informed consent to participate in this study that had been approved by the University of Kent's ethics committee.

3.3.2 Study design.

Each participant completed three laboratory tests on a cycle ergometer (Computrainer Pro, Racer Mate Inc, Seattle, WA, USA) on separate days with at least 48 h between each test. Prior to all tests participants were instructed to be well hydrated and to avoid food, strenuous exercise, and alcohol for 3 h, 24 h and 48 h respectively. Three laboratory tests consisted of (1) $\dot{V}O_{2max}$ test (2) 3 x TTE, (3) 3 x TT. Participants used their own bicycles for testing, equipped with a bicycle power meter to measure and record power output and a magnet to measure cadence (PowerTap Elite Wheel, CycleOps, Madison, USA). The same bicycle and power meter was used for all tests. Prior to testing the power meter's zero offset was calibrated according to the manufacturer's guidelines.

3.3.3 Procedures.

$\dot{V}O_{2max}$ test: Participants completed a maximal incremental exercise test to determine their $\dot{V}O_{2max}$ and associated MAP. The test started at 150 W and increased by 20 W every min until volitional exhaustion was reached, or the participant was no longer able to maintain the required work rate. The volume of oxygen ($\dot{V}O_2$), carbon dioxide ($\dot{V}O_2$) and minute ventilation ($\dot{V}_E$) were monitored throughout the tests using an online gas analysis system (Cortex Biophysik, Leipzig, Germany). HR was recorded continuously using the cortex system. A capillary blood sample was collected from the fingertip 1-min after testing and analysed for lactate concentration using a lactate analyser (Biosen C-line, EKF

diagnostic, Barbleben, Germany). The participant's MAP and $\dot{V}O_{2max}$ were calculated as the highest mean 30 s achieved during the test.

Performance trials: Participants returned to the laboratory on two further occasions to complete 3 x TTE and 3 x TTs. The TTs were always performed on the final laboratory visit as the duration was based upon performances in the preceding TTE. The TTE protocol was the same as that described by Karsten et al. (2015). Participants performed the TTE trials at power outputs equivalent to 80%, 100% and 105% of MAP with 30-min rest between trials. The trials were performed in this fixed order and each trial was preceded by a 5-min warm up at 150 W. Galbraith et al. (2011) has previously established that a 30-min rest allows sufficient rest between trials. The intensities for the trials were set using the cycle ergometer, but actual power values recorded from the power meter were used for analysis. Participants were instructed to adopt their preferred cadence and maintain the target power for as long as possible. Verbal encouragement was provided, however, participants were not given feedback on their elapsed time, HR, power output and cadence. The participant's TTE was reached when despite encouragement their cadence fell 10 $rev \cdot min^{-1}$ below their preferred cadence for 10 s or more. TTE was recorded to the nearest second.

For their final visit participants completed 3 x TT efforts of the same duration as previously recorded for the TTE trials at 80%, 100% and 105% MAP. Testing was performed as described for the TTE in the same fixed order with 30-min rest between trials. Each trial was preceded by a 5-min warm up at 150 W. Prior to each TT participants were informed of the duration they had achieved in the corresponding TTE and asked to complete the maximum work possible in this same time. During the TT, participants were free to change their cadence and ergometer resistance in order to complete as much work as possible. As with the TTE trials, verbal encouragement was provided but they were not given feedback on their elapsed time, HR, power output, and cadence.

Capillary blood samples were collected 1-min after each TTE and TT. RPE was recorded using Borg's (1970) 6-20 RPE scale at 1 and 5-min of exercise for the TTE and TT at 80% MAP. In addition, at 1 and 5-min of the TTE at 80%, the participants' estimated time limit (ETL) was recorded as described by Garcin et al. (2011) and previously validated by Coquart et al. (2012). Participants were asked '*how long would you be able* *to perform an exercise at this intensity to exhaustion'* and they estimated this using a 1 – 20 scale (1 = more than 16 h; 20 = to less than 2-min) (Garcin et al., 2011).

3.3.4 Statistical analysis.

A two-way repeated measures ANOVA was conducted to assess differences between TTE and TTs for mean power output, HR, cadence and RPE. This analysis was also used to compare CP and W′ parameters derived from TTE and TT performances using two linear CP models (Linear-TW and Linear-P). Where a significant main effect between trials was indicated, a paired samples t-test, with a Bonferroni correction was conducted to evaluate differences between trials. The CP and W′ parameters were estimated from the slope and the y-intercept of the relationship between power output and TTE. The Linear-TW model was generated by linear regression of total work, measured in kJ and TTE (equation 2). The Linear-P model was generated by linear regression of power output and the inverse of TTE (equation 6). Pearson's correlation was used to examine the relationship between TTE, and the measures of RPE and ETL gathered after 1 and 5-min in the 80% trial. Analysis was conducted using the SPSS statistical software package (IBM SPSS Statistics, Rel. 22.0, SPSS, Inc, Chicago, USA). R (R Core Team 2014) was used to analyse the mean power output for each decile (10%) for both TTE and TT. Statistical significance was accepted at $P<0.05$. Values are reported as the mean ± standard deviation (SD) unless stated otherwise.

3.4 Results.

Technical issues resulted in incomplete data for two participants for the 80% TT, one participant for the 100% TT, and one participant for the 105% TTE trial. These participants were excluded from subsequent analysis, and data is presented for the remaining 13 participants (Mean ± SD; age = 33 ± 9 y, mass = 72.1 ± 10.1 kg, MAP = 366 ± 57 W, $\dot{V}O_{2max}$ = 60.1 ± 9.6 ml·kg·min^{-1}).

3.4.1 Comparison between performance trials.

The mean TTE was 865 ± 345 s, 165 ± 98 s, 117 ± 45 s, for the 80%, 100% and 105% MAP trials respectively. As shown in Figure 3.1, mean power output was higher for TTE compared with TT at 80% (294 ± 44 W vs. 282 ± 43 W respectively; $P<0.01$). There were no significant differences in mean power output for TTE and TT performances at 100% (353 ± 62 W vs. 359 ± 74 W) and 105% (373 ± 63 W vs. 374 ± 61 W) respectively (P>0.05) (Figure 3.1).

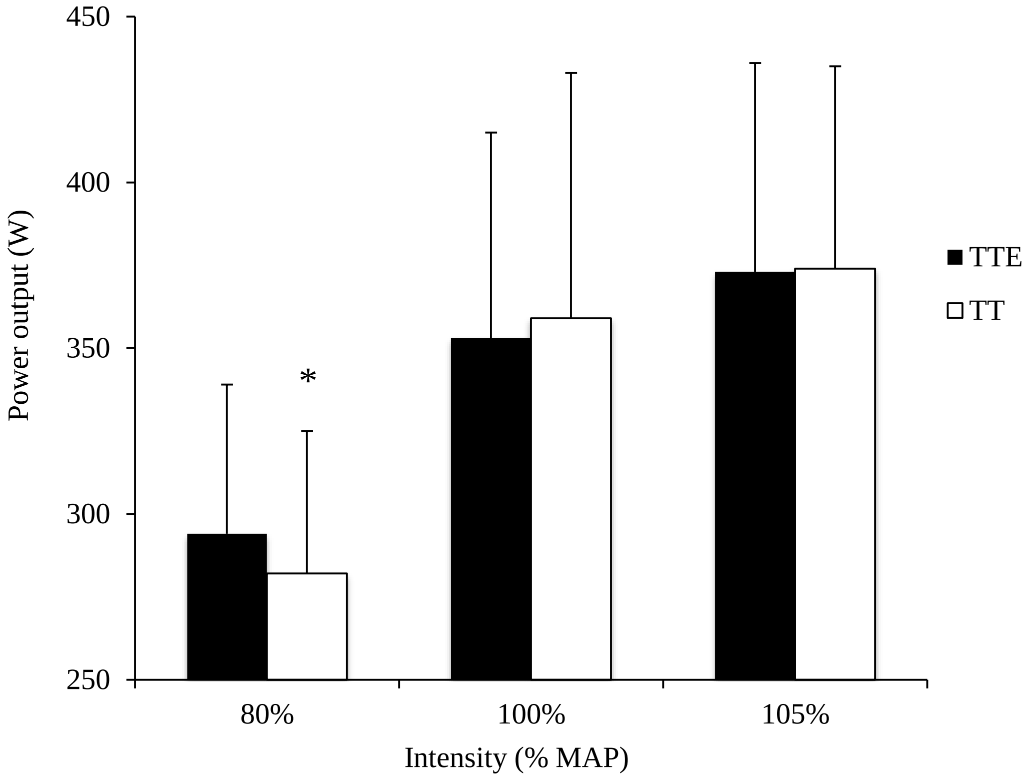

Figure 3.1: Mean (± SD) power output for TTE and TT at 80, 100 and 105% MAP.
* Significant difference between trials; P<0.05.

CP calculated from TTE was significantly higher than when calculated from TT performances using the two CP models (P<0.05) (Table 3.1). Whereas, calculated W′ was significantly lower when derived from the TTE trials compared to TT performances (P<0.05) (Table 3.1).

Table 3.1: CP and W′ parameter estimates from the Linear-TW and Linear-P models when comparing TTE to TT protocols (n=13). * Significant difference between trials; P<0.05.

		CP (W)	W′ (kJ)
TTE			
	Linear-TW	280 ± 46 *	10.73 ± 3.85 *
	Linear-P	283 ± 44 *	10.09 ± 3.96 *
TT			
	Linear-TW	265 ± 45	12.64 ± 2.91
	Linear-P	267 ± 45	12.25 ± 3.61

3.4.2 Physiological and perceptual measures.

No difference was found between trials for HR and cadence at 80%, 100%, and 105% MAP (P>0.05). There also was no significant difference between trials for RPE at 80% MAP (P>0.05). However, blood lactate was significantly higher after 80% MAP for the TTE (10.79 ± 3.10 $mmol.L^{-1}$) compared to the TT (8.10 ± 2.20 $mmol.L^{-1}$) respectively, P<0.01), but not after trials at 100% and 105% MAP (P>0.05). The relationship between TTE and measures taken of RPE and ETL after 1-min and 5-min at 80% MAP were not significant (P>0.05). There was no correlation between RPE and ETL at 1-min and 5-min of the TTE trial (P>0.05; Table 3.2).

3.4.3 Pacing strategies

Figure 3.2 compares the mean power outputs for each 10% segment of the TTE and TT performances at 80%, 100% and 105% MAP. As evident from Figure 3.2 and 3.3 participants starting pacing strategy was significantly higher for the TT compared to TTE for each of the three intensities (P<0.05).

Table 3.2: Mean (± SD): Blood lactate, HR, cadence, RPE and ETL for TTE and TT performance trials at 80%, 100% and 105% MAP. * Significant difference between trials; *P*<0.05.

	80%		100%		105%	
	TTE	TT	TTE	TT	TTE	TT
Blood lactate (mmol.L^{-1})	10.79 ± 3.10	8.10 ± 2.20 *	8.76 ± 3.18	8.42 ± 3.13	7.89 ± 2.63	7.60 ± 2.07
Mean HR (bpm)	167 ± 13	166 ± 11	163 ± 15	164 ± 11	163 ± 15	161 ± 14
Mean Cadence (rpm)	96 ± 10	96 ± 7	87 ± 12	97 ± 10	93 ± 13	96 ± 13
RPE 1-min	13 ± 2	13 ± 2	–	–	–	–
RPE 5-min	16 ± 2	16 ± 2	–	–	–	–
ETL 1-min	13 ± 3	–	–	–	-	–
ETL 5-min	13 ± 4	–	–	–	-	–

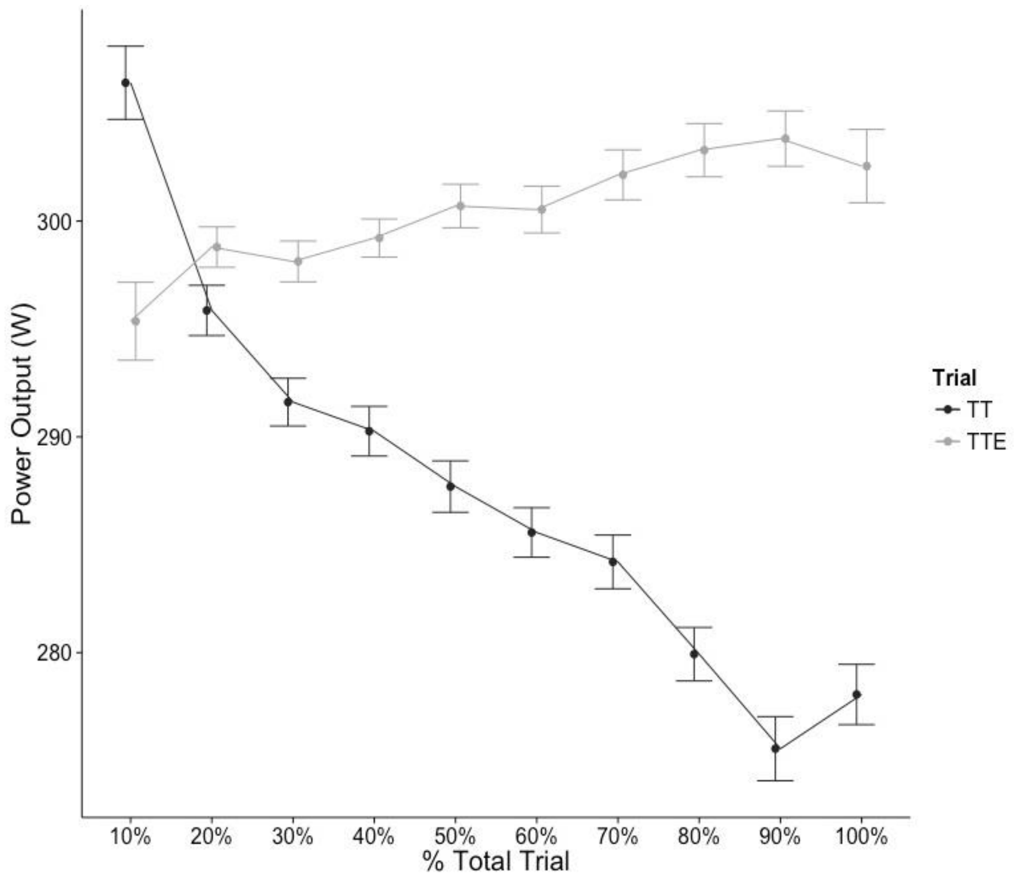

Figure 3.2: Mean power outputs for each 10% segment of TTE and TT at 80% MAP. Values are mean and 95% confidence intervals for a within participant design.

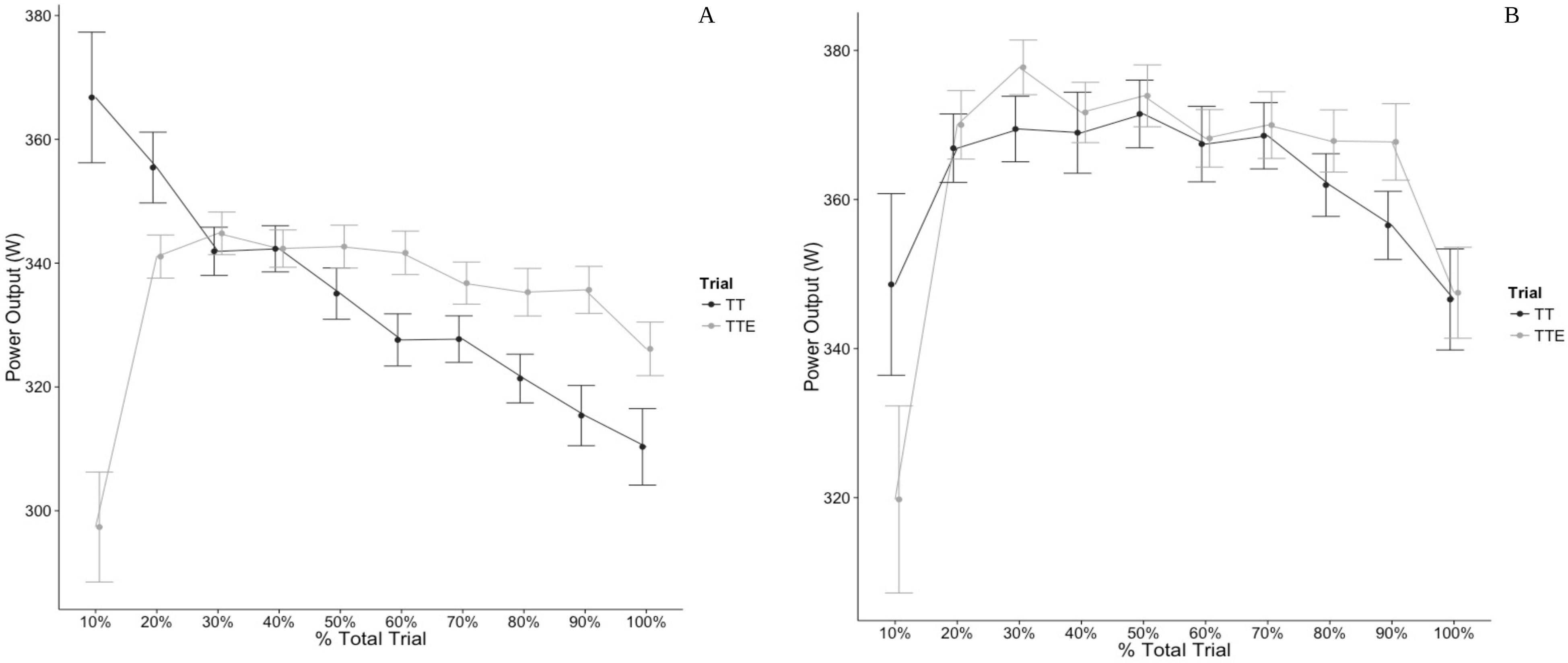

Figure 3.3: Mean power output for each 10% segment of TTE and TT at 100% (A) and 105% (B) MAP. Values are mean and 95% confidence intervals for a within participant design.

3.5 Discussion.

The main finding from this study was that mean power output for TTE was higher when compared to the TT at 80%, but not at 100% and 105% MAP. This in turn meant that calculated CP was higher when derived from TTE compared to TT. Although it was hypothesised that there would be a difference between TTE and TT, it was anticipated that TTE would result in a lower mean power output than TT due to its suggested lack of ecological validity. The higher average power output and CP found for TTE challenges the notion that this type of performance test lacks useful ecological validity (Jeukendrup and Currell, 2005; Marino, 2012). Criticism of TTE trials has also focused on their inherent variability, and has resulted in a shift towards the use of TT instead (Jeukendrup and Currell, 2005). The findings of this study indicate that TTE should not be disregarded as a measure of endurance performance in the laboratory.

Comparative data on TTE and TT performances are limited (Ham and Knez, 2009; Amann et al., 2008; Thomas et al., 2013). Moreover, previous studies were not designed to compare performances in TTE and TT directly, but rather to evaluate the effects of pacing (Ham and Knez, 2009; Thomas et al., 2012) or of changing the inspired oxygen concentration (Amann et al., 2008) on performance. Ham and Knez (2009) report performances for TTE and TT to be similar. In addition, Amann et al. (2008) found a similar sensitivity for both test protocols when detecting changes in performance, with differences in inspired oxygen concentration. In contrast to the present study, Thomas et al. (2013) reported a higher mean power output during self-paced compared to even-paced cycling trials. However, this was only found for some participants, with nine out of fifteen cyclists unable to complete the same distance as their self-paced trial when the mean intensity was fixed. It is also important to note that the higher mean power output for TTE in the present study was only found for the longest trial at 80% MAP, where the mean duration was 865 ± 345 s. No difference was found in the higher intensity trials $\geq$ 100% MAP that lasted $\leq 165 \pm 98$ s. Amann et al. (2008) compared TTE and TT performances with a trial that lasted approximately half the length of the 80% trial in the present study (458 s). Thus, their findings of comparable TTE and TT performances are consistent with the results of the present study for the shorter duration trials. However, the performance trials of Ham and Knez (2009) and Thomas et al. (2013) were notably longer than the present study (2880 s and 1920 s, respectively). As a result, other factors, such as pacing, and feedback, may have influenced the comparisons between previous studies and the present study.

The divergent performance between TTE and TT at 80% MAP in the present study may be due to differences in pacing strategy. For events lasting longer than 2-min, an even paced strategy such as that enforced in the TTE is often found to result in greater performances (Foster et al., 1993; Atkinson et al., 2003; de Koning et al., 1999; Ham and Knez, 2009). These studies suggest that a high variation in pace, only possible in a TT, is associated with a reduction in performance. For example, Ham and Knez (2009) found that participants whose relative starting strategy was > 105% of their mean speed performed worse overall. Cangley et al. (2011) noted in their field study that cyclists found it difficult to adopt a specified pacing strategy even when it is known to be superior. Therefore, to evaluate the participants' pacing strategy in the present study we calculated the mean power output sustained for each decile (10%) of both TTE and TT trials at 80%, 100%, and 105% MAP. This power output distribution is presented showing 95% confidence intervals for a within participant design (Morey, 2008) in Figure 3.2 and Figure 3.3 (A) and (B). Figure 3.2 clearly suggests participants misjudged their pacing strategy for the TT at 80%. In comparison with the TTE trial, participants can be seen to adopt a higher mean power output initially in the TT. This fast start appears to result in a progressive decline in power output throughout the TT, leading to a lower mean power output when compared to the TTE trial. This pattern of pacing has also been seen in previous research and was associated with a poorer TT performance (Foster et al., 1993; Mattern et al., 2001).

During TTE trials it is normal practice not to provide feedback on elapsed time or power output (e.g. Galloway and Maughan, 1997; Jones et al., 2013). Therefore, to standardise comparisons in the present study, no feedback was provided during either the TTE or TT performances. Previous studies that have blinded participants to any external feedback are inconsistent (Micklewright et al., 2010; Faulkner et al., 2011; Mauger et al., 2009; Wilson et al., 2012; Jones et al., 2013). For instance Wilson et al. (2012) investigated the effects of no feedback, accurate feedback, false feedback, and false negative feedback on 10-mile TT cycling performances. Their results showed no significant differences in completion times and mean power outputs when the four different feedback conditions were compared. In contrast, Faulkner et al. (2011) found that completion time as well as pacing strategies were significantly slower when participants were blinded to feedback, compared to accurate or delayed feedback conditions. Nevertheless, it is common for participants in TTs to be provided with their elapsed and remaining time, or distance, and sometimes power output too. According to Marcora et al's (2008) psychobiological model, the absence of any of these key variables can have a negative impact on performance and subsequently reduce the ecological validity of TT performances. As a result, the lack of feedback in the present study may explain the reduction in mean power output, as well as the absence of a notable end spurt that is often observed in previous TT performances (e.g. Thomas et al., 2012). However, the difference in total work completed for the TTE and TT for the 80% MAP trial was 11 kJ (by multiplying trial duration by mean power output and converting to kJ). Therefore, it is improbable that the end spurt accounted for the 11 kJ difference in work done observed between the TTE and TT in the 80% MAP trials. Future research is therefore needed to determine the effect of feedback on pacing strategy, and how this influences TTE and TT comparisons. In addition, Jones et al. (2015) proposed that other factors, such as emotion regulation or motivation, could also influence performance when no feedback is provided. However, the mechanisms responsible for these factors are unknown (Jones et al., 2015).

The exact reason for the higher mean power output in TTE at 80% remains to be explained. It seems that early in exercise even the well-trained cyclists found it difficult to gauge their perception of effort and its implications of how long it can be sustained. In the present study we measured RPE at 1-min and 5-min for both the TTE and TT at 80%, and ETL at the same points for TTE only. There were no differences in RPE between TTE, and TT, indicating that participants did not perceive that they were starting faster in the TT. This conclusion is reinforced by the observation that neither measures of RPE, or ETL, correlated with the duration of the 80% TTE trial. These findings are consistent with previous studies demonstrating a fast start to result in a decrease in speed and overall performance (Ham and Knez, 2009). The findings also highlight the related limitation of perceptual scales as previously identified in a recent review (Coquart et al., 2012). Interestingly, HR, and RPE were not different when comparing TTE and TT at any of the three intensities. But blood lactate after TTE at 80% MAP was higher than for TT. This data suggests that the participants perceived the effort to be similar in both trials, but were able to sustain a greater power output and induce a greater metabolic stress in the 80% MAP TTE trial. Previous research has found TTE type even paced strategies to be more physiologically demanding, evidenced by an increase in core body temperature and blood lactate responses (Lander et al., 2009). A TT allows athletes to self-regulate and vary their pace, whereas, TTE trials do not, and often result in a premature termination of exercise (Lander et al., 2009; Marino, 2012).

We specified TTE and TT performance trials that are typical of those used to determine CP. Dekerle et al. (2008) suggest that the determination of CP should be made from trials ranging between 2 to 15-min. In their comprehensive review, Jones et al. (2010) suggest that CP can be used to enable athletes to set appropriate pacing strategies and predict performance. Consequently, it is important that CP is determined accurately from the highest achievable performances to ensure optimal pacing strategies are set. The findings from our study demonstrate that a ~ 16 W higher value ($P<0.05$) for CP is obtained when TTE rather than TT performances are used. However, W′ was significantly lower for TTE (~ 2 kJ) compared to TT. Therefore, the results may suggest that CP and W′ are inversely related to each other, depending on the type of performance test performed. This inverse relationship has been previously found following training (Vanhatalo et al., 2008; Jenkins and Quigley, 1992), as well as differences in pacing strategy, (Bailey et al., 2011; Jones et al., 2008) and prior warm up (Jones et al., 2003). Nevertheless, Vanhatalo et al. (2011) note that an increase in CP, and reduction in W′, is related to an improvement in overall endurance performance. Whereas, an increase in W′, and reduction in CP, will only enhance high intensity, short duration performances (Vanhatalo et al., 2011). Therefore, future studies of CP should ensure that the most appropriate protocol is used for its determination.

3.6 Conclusion.

In conclusion, mean power output in TTE was greater than for TT at 80% MAP. There was no significant difference in mean power output for shorter high intensity TTE and TT performances at 100% and 105% MAP. The reason for the lower TT performance at 80% appears to be related to competitive cyclists pacing strategy by starting too fast. Early in exercise, it appears that even competitive cyclists are not sensitive to the perceptual cues that inform their effort and ability to estimate how long it can be sustained. The higher mean power output achieved during TTE performance also results in a higher calculated CP from those trials compared with TT. Therefore, researchers are advised to adopt a test protocol that maximises mean power output when determining CP.

Chapter 4: Individualised training at different intensities results in similar physiological and performance benefits.

4.1 Abstract.

Training responses can be highly variable between individuals when standardised to the same %$\dot{V}O_{2max}$. This inter-individual variability is also observed in TTE performances. The impact of individualising training duration on performance and physiological adaptations has not been previously explored, in particular when comparing different training intensities. **Purpose:** This study compared the effects of training at MOD, HIT, or a combination of the two (MIX) on performance and physiological responses when training durations were individualised. **Methods:** Thirty-four untrained participants were randomly assigned to a MOD, HIT, or MIX training group. $\dot{V}O_{2max}$, MAP, TTE and GE were recorded before and after 4-weeks of supervised cycling training (4 times per week). The MOD group cycled at 60% MAP in blocks of 5-min with 1-min recovery. Training duration for the MOD group was individualised to 100% of pre-training TTE. The HIT group cycled at 100% MAP for 2-min with 3-min recovery between repetitions. Training duration for the HIT group was set as the maximum number of repetitions completed in the first training session. The MIX group completed two MOD and two HIT sessions each week, on alternative days. **Results:** Total training time for the MOD, HIT, and MIX groups were ~16, 3 and 8 h respectively. All intensity groups increased $\dot{V}O_{2max}$, MAP, TTE and GE after training (P<0.05), but there was no difference between groups for these measurements (P>0.05). **Conclusion:** When training durations are individualised similar improvements in performance and physiological responses are found despite differences in exercise intensity.

Key Words*:* Gross efficiency; MIX training; $\dot{V}O_{2max;}$ Time-to-exhaustion.

4.2 Introduction.

A large inter-individual variability in the response to physical exercise is frequently observed, particularly when exercise is standardised to a %$\dot{V}O_{2max}$ (Bouchard et al., 1999; Vollaard et al., 2009; McPhee et al., 2010). Bouchard et al. (1999) was one of the first to highlight this variability following a standardised training intervention. The findings from this study demonstrated a large variability in $\dot{V}O_{2max}$ responses, ranging from no change to ~ 42% increase after 10-weeks of training in sedentary individuals (Bouchard et al., 1999). Typically, these individual differences have been disregarded when setting training interventions (e.g. Burgomaster et al., 2008; Gormley et al., 2008). However, more recently, researchers have attempted to account for this by using individualised methods to prescribe training (Kivinemi et al., 2007; Capostagno et al., 2014). For example, Kiviniemi et al. (2007) monitored individual changes in daily resting heart rate variability (HRV), and used this information to prescribe MOD or HIT training sessions. An increase or no change in HRV resulted in a HIT session completed on that day, whereas a decrease in HRV resulted in a MOD session (Kivinemi et al., 2007). The findings from this study demonstrated that individualised training based on HRV resulted in a greater improvement in maximal running velocity, but not VO_{2peak}, when compared to a standardised training approach (Kiviniemi et al., 2007). Nevertheless, researchers have still reported a large variability in training responses despite tailoring the intensity of the sessions for each individual (Kiviniemi et al., 2007; Capostagno et al., 2014).

To evaluate the effects of training intensity on performance and physiological responses, researchers frequently standardise the intensity of the training to a % of maximum (e.g. %HR_{max}, %$\dot{V}O_{2max}$) (Gibala et al., 2006; Helgerud et al., 2007; Gormley et al., 2008; Burgomaster et al., 2008). In addition, the duration of training is often fixed (e.g. Gormley et al., 2008). When standardised in this manner, HIT is often favoured over MOD training for greater or similar physiological and performance adaptations (Gibala et al., 2006; Helgerud et al., 2007; Gormley et al., 2008; Burgomaster et al., 2008). But these results may vary depending on whether the total volume of training between intensity groups is matched. For example, Gormley et al. (2008) and Helgerud et al. (2007) reported greater increases in $\dot{V}O_{2max}$ with HIT, compared to MOD training, when total work and training frequency were matched. But when researchers have set the volume of MOD training ~ 90% higher than HIT, no significant differences were found between groups (Gibala et al., 2006; Tanisho and Hirakawa, 2009; Burgomaster et al., 2008). It is common practice for cyclists to spend a significantly greater amount of time training at MOD compared to HIT (Nimmerichter et al., 2011). For instance, a longitudinal study of trained cyclists demonstrated a training distribution to be 73%, 22% and 5% for low, MOD, and HIT training respectively (Nimmerichter et al., 2011). Therefore, the greater increases in $\dot{V}O_{2max}$ reported in previous studies following HIT, might simply be due to an insufficient duration of training prescribed to the MOD groups (e.g. Gormley et al., 2008; Helgured et al., 2007).

A notable observation is the large inter-individual variability often observed in TTE performances (Coyle et al., 1988). Coyle et al. (1988) found that the times cyclists could sustain exercise to exhaustion at 88% $\dot{V}O_{2max}$ was highly variable, ranging from 12-75 min. Thus, at the same relative intensity, individuals can endure exercise for very different amounts of time. The impact of this variability on subsequent training adaptations is not well understood, in particular when comparing different training intensities. Therefore, this study examined the effects of training at MOD, HIT, or a combination of the two (MIX), on performance and physiological responses, when training durations were individualised to each individuals' maximum performance time. It was hypothesised that by maximising the duration of training for each individual no differences would be found between training intensities for performance and physiological adaptations.

4.3 Methods.

4.3.1 Participants.

Thirty-four healthy men and women (*n*=25 males, *n*=9 females) volunteered to participant in this study (Table 4.1). All participants were untrained, and had engaged in no more than 3 h of exercise per week for the 3 months prior to commencing the study. All participants gave their written informed consent to participate in this study that had been approved by the University of Kent's ethics committee.

4.3.2 Study design.

Participants were randomly assigned to one of three training groups; MOD, HIT, or MIX and completed 4-weeks of supervised cycling training 4 times per week. Before and after the training programme, participants completed laboratory tests that measured $\dot{V}O_{2max}$, MAP, GE, and TTE. The order of the testing procedures was as described below. All tests were performed on a stationary cycle ergometer (Lode Excalibur Sport, Lode, Grogningen, The Netherlands). Participants were given at least 48 h between tests, except for the GE and confirmation $\dot{V}O_{2max}$ test which were completed on the same day.

Table 4.1: Mean (± SD): Age, body mass, $\dot{V}O_{2max}$ and MAP for the MOD, HIT and MIX training groups before training. There were no significant differences between groups at baseline ($P>0.05$).

	MOD (*n*=11)	HIT (*n*=12)	MIX (*n*=11)
Age (yrs.)	31 ± 12	28 ± 9	26 ± 5
Body mass (kg)	76.4 ± 13.4	73.9 ± 11.2	77.2 ± 13.2
$\dot{V}O_{2max}$ (L.min^{-1})	3.4 ± 0.8	3.1 ± 0.6	3.7 ± 0.7
MAP (W)	241 ± 55	232 ± 42	259 ± 50

4.3.3 Testing procedure.

$\dot{V}O_{2max}$ test: Ergometer seat and handlebar height were recorded in order for the same position to be used for all trials. The test started at 30 W, and increased by 20 W every min until volitional exhaustion, or the participant was no longer able to maintain the required work rate. The $\dot{V}O_2$ and $\dot{V}CO_2$ were recorded using the Douglas bag method. That is expired gases were collected into airtight plastic Douglas bags (Plysu Industrial Ltd, Milton Keynes, UK). Each participant was fitted with a Hans Rudolph breathing valve (2700; Hans Rudolph, Inc., Kansas City, MO), which was connected to the Douglas bags via a plastic tube. When a participant indicated that he or she was near exhaustion

(e.g. at least 1-min of exercise remaining), gas collection was started (Hopker et al., 2012). The duration that the bags collected expired gases were recorded to the nearest second using a stopwatch. The procedure for analysing the Douglas bags was similar to that outlined by Hopker et al. (2012), and described in more detail in *section 4.3.4* below. MAP was recorded as the 1-min mean cycling power output attained during the incremental test protocol to voluntary exhaustion. HR was recorded continuously using a wireless HR monitor (Polar Electro, Kempele, Finland). A capillary blood sample was collected from the fingertip 1-min after testing and analysed for lactate concentration using a lactate analyser (Biosen C-line, EKF diagnostic, Barbleben, Germany).

GE: Following a 10-min warm up at 50 W, participants cycled at two constant pre-determined workloads: 50 W for females or 75 W for males and 50% MAP. Participants were instructed to cycle for 7-min at each of the two workloads. Expired air was collected into two Douglas bags during the last 2-min of each workload, with a total of 1-min collected into each bag. GE was calculated as the ratio of power output to power input and was expressed as a % (Passfield and Doust, 2000; Hopker et al., 2012). Power input was defined as the rate of energy expenditure ($\dot{V}O_2$ and respiratory exchange ratio (RER)) and was calculated using the same formula as Passfield and Doust (2000). Power output was determined as the average power output sustained during the test. During collection of expired air participants were asked to maintain a normal breathing pattern, completing a 'natural' inhalation prior to opening and closing the Douglas bags. Participants were given a 5 s countdown prior to performing the inhalation phase (Hopker et al., 2012). The bags were opened at the start and at the end of the inspiration phase to record a full breathing cycle. The methods used to analyse the Douglas bags were the same as Hopker et al. (2012) and are outlined below. The mean GE analysed from the two Douglas bags was recorded. RPE (Borg, 1970) and a blood lactate sample were recorded at the end of each workload.

Confirmation $\dot{V}O_{2max}$ test: Following the GE test and 20-min passive recovery participants completed a confirmation $\dot{V}O_{2max}$ test as described by Bouchard et al. (1999). The test started at 50 W for 5-min. Power output then increased to 50% MAP for 5-min, 70% MAP for 3-min and after this the resistance increased to the MAP attained in the first $\dot{V}O_{2max}$ test for 2-min. If participants were able to continue after 2-min at MAP, the power output increased by 20 W every 2-min until volitional exhaustion was reached.

Expired air was collected using Douglas bags as described previously. The mean $\dot{V}O_{2max}$ value attained from both tests was recorded as each participants $\dot{V}O_{2max}$, and if values differed by >5%, the higher $\dot{V}O_{2max}$ value was used (Bouchard et al., 1999).

TTE performance: Following a 5-min warm up at 50 W participants cycled at 60% MAP for as long as possible until volitional exhaustion was reached. Participants were instructed to maintain a target cadence based on the mean cadence of their $\dot{V}O_{2max}$ test for as long as possible, and were provided with verbal encouragement throughout. Exhaustion was determined when participants were unable to sustain the target power output or reached volitional exhaustion. Participants were not informed of the elapsed time during the trials, or their final time, which was recorded to the nearest second (s). Blood lactate samples were recorded at 5-min and at the end of the test. At 1-min, and 5-min of the trial, RPE was recorded.

4.3.4. The Douglas bag method

The Douglas bags were emptied using a vacuum pump prior to each test. Participants were fitted with a mouthpiece (2700 Hans Rudolph, Inc, Kancas City, MO), and a nose clip 30 s prior to collection. Plastic tubing connected the mouthpiece to the Douglas bags. A three way Hans Rudolph valve enabled ambient air to be inhaled during an inspiration phase, with only exhaled air diverted into the Douglas bags (Hopker et al., 2012). The O_2 and CO_2 concentration of the expired air collected in the Douglas bags were analysed using an offline gas analyser (Servomex East Sussex, UK). A calibrated dry gas meter (Harvard Apparatus Ltd, Edenbridge, UK) was used to determine the expired volume of air in the bags. A digital thermometer (810-080 Electric Temperature Instruments, West Sussex, UK) was also used to determine the temperature of the gas sample in the Douglas bags. Calibration of the gas analyser was performed prior to each test according to the manufacturer's guidelines. Each bag was analysed immediately after the test.

Training: All training sessions were supervised in the laboratory and performed on a stationary cycle ergometer. The MOD group trained at 60% MAP for the duration completed in the pre-training TTE test. The MOD training session was divided into 5-min blocks separated by 1-min rest until the target training duration was reached. The HIT group completed 2-min repetitions at 100% MAP, followed by 2-min active rest at

25% MAP, and 1-min passive rest. Participants in the HIT group were instructed to complete as many repetitions as possible in their first training session, which set the baseline for subsequent training sessions. The MIX group completed two days at HIT, and two days at MOD each week, alternating between intensities for each session. Training progression was implemented for all three training groups by encouraging the participants to complete one extra repetition or 5-min block after every two training sessions. A halfway $\dot{V}O_{2max}$ test replaced one training session in week 3 and training power outputs were adjusted as necessary.

4.3.4 Statistical analysis.

The main effects of training on the physiological and performance measurements were analysed using a two-way repeated measures ANOVA. Bonferroni *post hoc* analysis was conducted when significant interactions were found. Data were checked for normal distribution using Sharpiro-Wilk *W* test, and a one-way ANOVA showed no significant differences between groups for baseline measurements prior to training. All data was checked for normality prior to conducting parameter statistics. Effect sizes were also calculated for physiological and performance training adaptions, as partial eta-squared (η_p^2) and values of 0.10, 0.25 and above 0.40 were considered small, medium and large effect sizes respectively (Cohen, 1988). Effect sizes were included to highlight the size of the training adaptations. Pearson's correlation was conducted to examine the relationship between the pre-post % $\Delta\dot{V}O_{2max}$ or %Δ TTE and the %Δ for the other laboratory test measurements (e.g. $\dot{V}O_{2max}$/TTE, MAP, GE at 50% MAP, GE at 50/75 W). Analysis was conducted using the SPSS statistical software package (IBM SPSS Statistics, Rel. 22.0, SPSS, Inc, Chicago, USA) and the level of significance was set at P<0.05.

To analyse for individual differences in the training responses, the intra-individual coefficient of variation (CV) was identified for the physiological and performance laboratory test measurements based on previous research. These included: $\dot{V}O_{2max}$ (CV = 5.6%; Katch et al., 1982; Scharhag-Rosenberger et al., 2012; Wolpern et al., 2015), GE (CV= 1.5%; Hopker et al., 2012) and TTE (CV = 5.6%; Maughan et al., 1989). The CV's for these measurements were used to identify if participants were responders or non-responders to the training. This is the same method as used previously by other researchers (Scharhag-Rosenberger et al., 2012; Katch et al., 1982). A non-responder was defined as one who demonstrated negative changes, or improved no greater than the CV of the laboratory test measurement. A responder was one who demonstrated positive changes greater than the CV of the laboratory test measurement. The above criteria are the same as those set by Scharhag-Rosenberger et al. (2012). All values are reported as the mean (± SD).

4.5 Results.

4.5.1 Training duration.

The mean total training time for the MOD, HIT, and MIX groups was ~16 h, 3 h and 8 h respectively. There was a large inter-individual variability in the durations each individual trained for at the three different intensities (Figure 4.1). For example, total training duration ranged from ~ 8 - 24 h for the MOD group, ~ 2 – 6 h for the HIT group and ~ 6 - 13 h for the MIX group. The total training duration for each individual are presented in Figure 4.1.

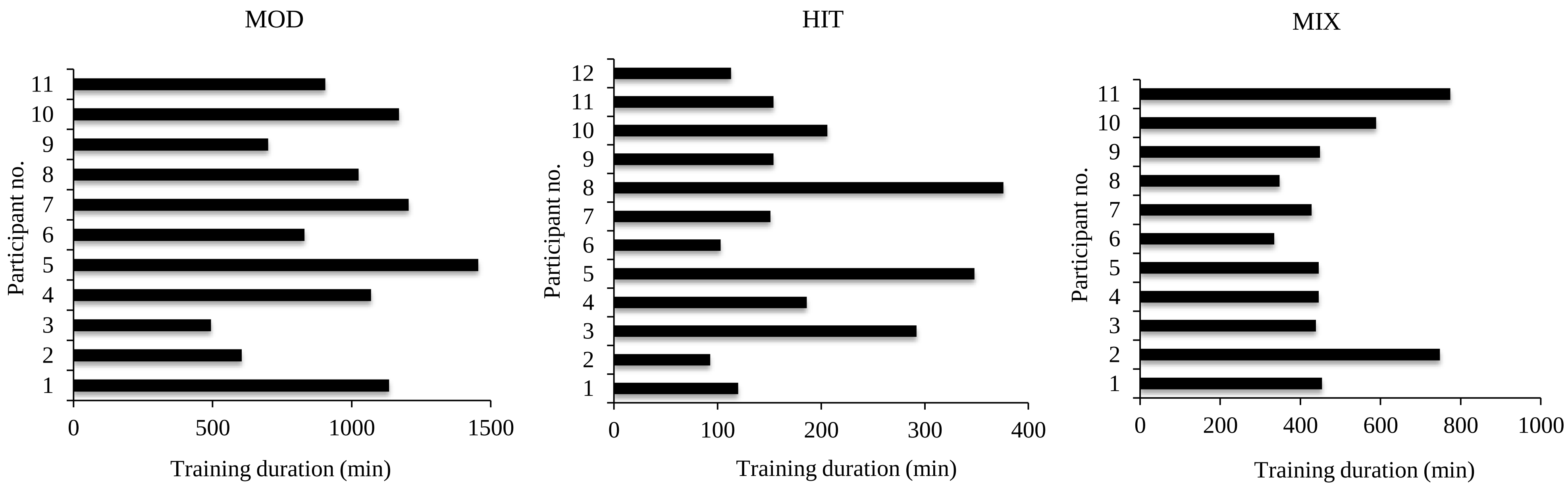

Figure 4.1. Total duration of training for each individual following 4-weeks of training at MOD, HIT or MIX.

4.5.2 Physiological and performance adaptations following training.

Significant changes in $\dot{V}O_{2max}$ (η_p^2=0.55), MAP (η_p^2=0.76), TTE (η_p^2=0.81), and GE at 50% MAP (η_p^2=0.15) were found in all three training groups following 4 weeks of training (Table 4.2; P<0.05). No significant differences between groups were found for $\dot{V}O_{2max}$ (η_p^2=0.08); MAP (η_p^2=0.03), TTE (η_p^2=0.03), GE at 50/75 W (η_p^2=0.10) or GE at 50% MAP (η_p^2=0.22) (P>0.05). There was an interaction effect for GE at 50% MAP (P = 0.02) (Figure 4.2), but differences between groups were not detected following Bonferroni *post hoc* analysis (P>0.05; n = 34).

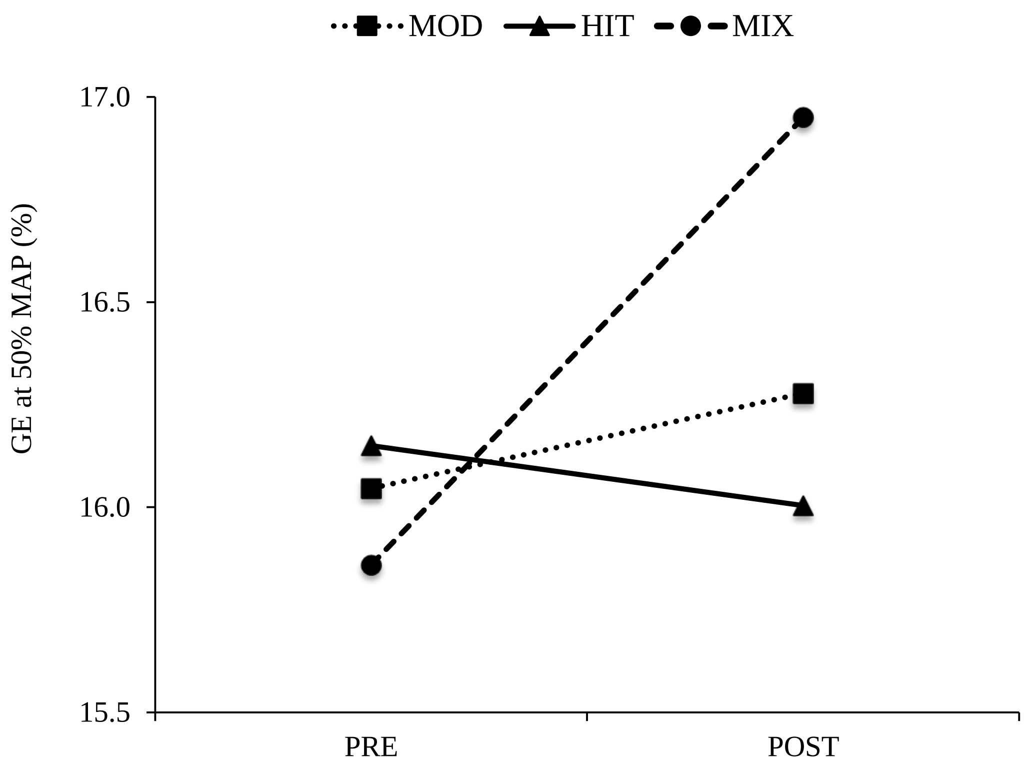

Figure 4.2: A significant interaction between training groups for GE at 50% MAP following training. *Post hoc* analysis did not detect differences between groups (P>0.05).

Sub-maximal $\dot{V}O_2$, HR and blood lactate measurements were lower following 4-weeks of training when recorded during the GE 50/75 W and GE 50% MAP tests (P<0.05). But these changes were not different between groups (P>0.05). There was an interaction effect for $\dot{V}O_2$ during the GE 50% MAP test (P=0.02; η_p^2=0.23), but differences between groups were not detected following Bonferroni *post hoc* analysis (P>0.05). RPE was lower for GE at 50% MAP (P<0.05), but not GE at 50/75 W (P>0.05) after training. But these changes were not different between groups (P>0.05) (Table 4.3).

4.5.3 Variability in training responses

Despite significant improvements in the mean physiological and performance measurements for all training groups, large inter-individual variability in training responses were observed (Tables 4.2 and 4.4). For changes in $\dot{V}O_{2max}$, 54% (6/11), 83% (10/12) and 54% (6/11) of participants in the MOD, HIT, and MIX training groups respectively, experienced a desirable change after training, and were categorised as a responders. Alternatively, 46% (5/11), 17% (2/12), and 46% (5/11) of participants in the MOD, HIT, and MIX training groups respectively, experienced an undesirable change in $\dot{V}O_{2max}$, and were categorised as a non-responders (Table 4.4).

When examining the individual participants presented in each column in Table 4.4, it is evident that 2 participants in the MOD group (18%), 5 participants in the HIT group (42%), and 5 participants in the MIX group (46%), demonstrated an improvement for all four measurements. Each participant demonstrated improvements in at least one measurement across all training groups. All participants demonstrated improvements in performance following MOD and MIX training, with only one participant (8%) demonstrating a non-response to changes in performance following HIT training.

Table 4.2: Mean (± SD): absolute $\Delta\dot{V}O_{2max}$, ΔTTE, ΔGE at 50/75 W and 50% MAP for MOD, HIT and MIX groups. Minimum and maximum absolute Δ are also presented (*n*=34).

	MOD		HIT		MIX	
	Mean ± SD	Min - Max	Mean ± SD	Min - Max	Mean ± SD	Min - Max
$\dot{V}O_{2max}$ (L.min-1)	0.23 ± 0.19	-0.04 to 0.49	0.37 ± 0.19	0.08 to 0.69	0.21 ± 0.35	-0.30 to 0.79
TTE (s)	1553 ± 721	443 to 2692	1257 ± 675	10 to 2646	1335 ± 688	258 to 2813
GE at 50/75 W (%)	0.32 ± 1.11	-1.95 to 1.95	0.28 ± 1.22	1.60 to 2.40	1.06 ± 1.17	0.75 to 2.75
GE at 50% MAP (%)	0.23 ± 1.04	-1.90 to 1.70	0.15 ± 1.06	1.75 to 1.55	1.09 ± 0.93	0.30 to 2.75

Table 4.3: Submaximal physiological and perceptual responses before and after 4-weeks of MOD, HIT and MIX training. * Significant change after training P<0.05.

		MOD	HIT	MIX
Efficiency at 50% MAP				
Lactate (mmol.L^{-1})	Pre	4.30 ± 1.57	4.15 ± 1.10	3.28 ± 0.74
	Post	2.00 ± 0.77*	2.70 ± 0.94*	2.01 ± 0.86*
HR (bpm)	Pre	138 ± 17	142 ± 18	142 ± 12
	Post	128 ± 15*	132 ± 15*	130 ± 16*
RPE (6-20)	Pre	13 ± 2	13 ± 2	13 ±1
	Post	11 ± 1*	11 ± 2*	11 ± 1*
$\dot{V}O_2$ (L.min^{-1})	Pre	2.11 ± 0.42	2.03 ± 0.32	2.27 ± 0.36
	Post	2.09 ± 0.41*	2.04 ± 0.28*	2.13 ± 0.32*
Efficiency 50/75 W				
Lactate (mmol.L^{-1})	Pre	2.41 ± 1.24	2.13 ± 0.88	1.73 ± 0.60
	Post	1.38 ± 0.38*	1.56 ± 0.53*	1.25 ± 0.38*
HR (bpm)	Pre	116 ± 19	121 ± 15	117 ± 6
	Post	111 ± 17*	113 ± 14*	107 ± 10*
RPE (6-20)	Pre	10 ± 2	10 ± 2	10 ± 1
	Post	10 ± 1	9 ± 2	10 ± 1
$\dot{V}O_2$ (L.min^{-1})	Pre	1.50 ± 0.25	1.49 ± 0.25	1.59 ± 0.25
	Post	1.47 ± 0.26*	1.45 ± 0.16*	1.46 ± 0.17*

Table 4.4: Individual responders and non-responders for changes in $\dot{V}O_{2max}$, TTE, GE at 50/75 W and 50% MAP following 4-weeks of training. Black = non-responder; white = responder, when CV's (from previously published studies) for $\dot{V}O_{2max}$, TTE, and GE are subtracted from the %Δ for each individual (*n*=34).

MOD

Participant no.	1	2	3	4	5	6	7	8	9	10	11	∑
$\dot{V}O_{2max}$ (L.min^{-1})		■			■	■	■	■				*n*=5 (46%)
TTE (s)												*n*=0 (0%)
Efficiency 50/75W (%)	■	■	■						■			*n*=4(36%)
Efficiency 50% MAP (%)		■	■	■	■							*n*=4 (36%)

HIT

Participant no.	1	2	3	4	5	6	7	8	9	10	11	12	∑
$\dot{V}O_{2max}$ (L.min^{-1})		■					■						*n*=2 (17%)
TTE (s)					■								*n*=1 (8%)
Efficiency 50/75W (%)		■			■	■		■		■			*n*=5 (42%)
Efficiency 50% MAP (%)			■		■	■	■	■		■			*n*=6 (50%)

MIX

Participant no.	1	2	3	4	5	6	7	8	9	10	11	∑
$\dot{V}O_{2max}$ (L.min^{-1})	■						■		■	■	■	*n*=5 (46%)
TTE (s)												*n*=0 (0%)
Efficiency 50/75W (%)					■				■			*n*=2 (18%)
Efficiency 50% MAP (%)									■	■		*n*=2 (18%)

4.5.4. Correlations between physiological measurements and TTE

There was also a positive correlation between the %ΔTTE and %ΔGE at 50% MAP (r=0.35; P<0.05; Figure 4.3). In addition, there was a positive correlation between the %ΔTTE and %ΔMAP (r=0.50; P<0.05). There was no relationship between %ΔTTE and %ΔGE at 50/75 W (P>0.05), or %ΔTTE and %Δ$\dot{V}O_{2max}$ (P>0.05). There was no correlation between %Δ$\dot{V}O_{2max}$ and %ΔGE at 50% MAP or 50/75 W (P>0.05). There was a positive correlation between %Δ$\dot{V}O_{2max}$ and %ΔMAP (r=0.34; P<0.05).

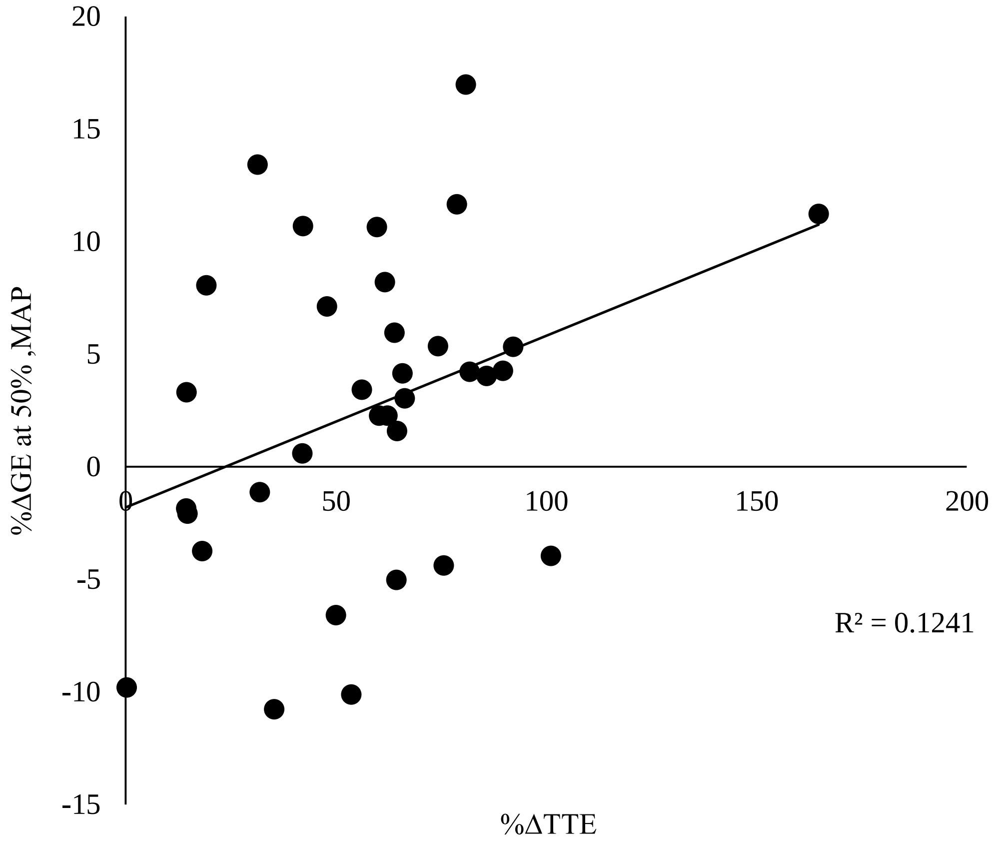

Figure 4.3. A positive relationship between %ΔGE at 50% MAP and %ΔTTE.

4.6 Discussion.

The main finding of this study was that 4-weeks of individualised training at either MOD, HIT, or MIX resulted in significant improvements in $\dot{V}O_{2max}$, MAP, TTE and GE at 50% MAP. However, no differences were observed between groups. The interaction effect for GE at 50% MAP suggests that the MIX training results in greater improvements compared to MOD and HIT training. No differences in GE at 50/75 W were observed after training or between groups. A large heterogeneity in training responses for $\dot{V}O_{2max}$, GE at 50/75 W and 50% MAP were also observed, despite individualising the training duration. Furthermore, all participants demonstrated improvements in TTE after MOD, and MIX training, with only one participant (8%) categorised as a non-responder after HIT training.

The similar physiological training adaptations observed in this study for all training intensities is consistent with the work of Burgomaster et al. (2008) and Gibala et al. (2006). These studies fixed the duration of training, and did not account for the variability seen in the times individuals could sustain exercise for at the same relative intensity (Coyle et al., 1988). The present study aimed to address this by tailoring the duration of training to each individual's maximum performance time. This resulted in a wide range of the durations that participants trained for at the same relative intensity (Figure 4.1). The mean total time spent training was ~ 80% lower for the HIT compared to the MOD group and ~ 63% lower for the HIT compared to the MIX group. Therefore, despite a substantially greater time spent training at MOD, no differences between training intensities were observed for performance, and physiological adaptations.

According to Laursen (2010), HIT and endurance training adaptations occur via two different pathways: the AMPK and the CaMK pathway. Laursen (2010) proposes that training at one exercise intensity will optimise the training adaptations that occur via one pathway only. Therefore, for other adaptations to occur, an individual needs to be exposed to another exercise intensity (Laursen, 2010). This has led researchers to investigate the physiological benefits of combining two different training intensities (e.g. Neal et al., 2011; Munoz et al., 2014). The findings from the present study demonstrate that when two different training intensities were combined (MIX group), significant increases in physiological and performance responses occurred. However, these training adaptations were not significantly different when compared to the MOD, and HIT training groups.

There was an interaction effect for GE at 50% MAP after training, but no differences were detected between groups following post hoc analysis. One explanation for this is that the ANOVA and post hoc test control for different levels of type I and type II error rates. Therefore, while the ANOVA detected a difference between the group means for GE at 50% MAP after training, the post hoc analysis did not detect this difference, and as a result it is inconclusive as to where the differences lie. Nevertheless, it is evident from Figure 4.2, that the MIX group improved their GE at 50% MAP more so than the other two training intensity groups. It should also be noted that the MOD and HIT groups, demonstrated approximately equal changes in GE at 50% MAP after training, despite a substantially longer time spent training at MOD.

The present study is one of few to take into account individual differences in performance capability when designing a training intervention (Kiviniemi et al., 2007; Capostagno et al., 2014). Despite attempts to tailor each individual's training duration, large inter-individual variability in training responses were still apparent for all physiological adaptations, but not for performance adaptations. Responders and non-responders to training were determined using the same methods as Scharhag-Rosenberger et al. (2012). A responder was categorised as an individual who demonstrated positive changes greater than the CV of the laboratory test measurement (Scharhag-Rosenberger et al., 2012). Whereas, a non-responder, was an individual who demonstrated negative changes, or improved no greater than the CV of the laboratory test measurement (Scharhag-Rosenberger et al., 2012). Upon examination of the individual responses presented in Table 4.4, it is evident that a non-responder for one measurement was not necessarily a non-responder for other variables. This is similar to the findings of Vollaard et al. (2009) following a 6-week standardised training intervention. In addition, it is evident from Table 4.4 that all participants demonstrated improvements in at least one physiological and performance measurement. The MIX group demonstrated the greatest number of responders (46%) to all laboratory test measurements, followed by HIT (42%) and MOD (18%) training groups. Additionally, the HIT group demonstrated the greatest number of responders to $\dot{V}O_{2max}$ changes (83%), followed by MIX (54%) and MOD (54%) training groups. This supports previous research that suggests the inclusion of some HIT sessions in a training intervention can reduce the number of non-responders (Bacon et al., 2013). It should also be noted that from a cohort of 34 participants, only one participant demonstrated a negative change in TTE performance following training. This participant was in the HIT training group. This is an interesting finding, which warrants further investigation. It could be speculated that by repeatedly exposing participants to their maximum duration of exercise in training, that this increased their ability to tolerate exercise to exhaustion. This could particularly be the case for the MOD and HIT groups who trained at the intensity set for the TTE performance test (60% MAP).

A significant relationship between TTE performances and GE at 50% MAP before and after training was observed. Furthermore, the training adaptations for TTE and GE were also positively correlated, with ~ 12% of the improvements in TTE following training related to changes in GE at 50% MAP. Previous research has demonstrated that a high GE is associated with a higher power output sustained during a 1 h cycling TT (Horowitz et al., 1994). In addition, others have reported differences between trained and untrained individuals for GE (Hopker et al., 2010), as well as changes in GE over the course of a competitive training season (Hopker et al., 2010). However, the correlation between the %ΔGE and the %ΔTTE performance following a training intervention has not been examined previously. From the results in Figure 4.3 it is evident that individuals who demonstrated the greatest increases in GE following training, also demonstrated the greatest improvements in TTE performance.

A positive correlation was also observed between %ΔTTE and %ΔMAP, but there was no relationship between %ΔTTE and %Δ$\dot{V}O_{2max}$. Our findings are consistent with Vollaard et al. (2009), who previously demonstrated no relationship between the training induced %Δ $\dot{V}O_{2max}$ and the %Δ TT performance following a standardised training intervention. Vollaard et al. (2009) concluded that the aerobic capacity and aerobic performance adaptations do not occur in proportion to each other, and therefore there is a poor link between these two measures. More research is therefore needed to gain a greater understanding of the relationship between physiological variables and TTE or TT performances in both trained and untrained individuals.

In conclusion, similar improvements are found in $\dot{V}O_{2max}$, MAP, GE, and TTE despite substantially greater time spent training at MOD intensity compared to HIT or MIX, in untrained participants. These findings support the contention that individualised HIT and MIX training intensities are time-efficient trainings strategies. In addition, MIX training appears to provide the greatest benefit to GE at 50% MAP and results in a greater number of responders to training when compared to MOD and HIT groups. The untrained status of the participants recruited in this study is a limiting factor. Future research should aim to also study the effect of individualised training duration at different intensities in trained and elite athletes.

Chapter 5: A power law describes cycling endurance performance better than a critical power model.

5.1 Abstract.

CP and power law models both propose exercise-intensity relationships that describe maximum endurance work capacity. **Purpose:** The aims of this study were twofold. Firstly, to determine if the CP and power law models accurately predicted cycling TTE for intensities within the typical CP range (80-110% MAP). Secondly, whether a power law model accurately predicted cycling TTE outside the typical CP range (60-200% MAP). **Methods:** Fifteen physically active males completed nine TTE trials, each separated by at least 48 h. Five trials were within the typical range of intensities for CP determination (80-110% MAP), and four trials were outside (60, 70, 150 and 200% MAP). Four models (Linear-TW, Linear-P, power law and semi-log) were generated from the five TTE trials within the typical CP range. The model fit and their prediction of actual performance were compared to the four trials performed outside the typical CP range. **Results:** There was no difference between the CP and power law models for parameter estimates when predicting actual TTE for intensities between 80-110% MAP (P>0.05). Outside of this range the power law model predicted actual TTE at 60% (95% confidence intervals (CI): 167 to 192 W; 156 to 183 W; actual vs. power law respectively, P>0.05) and 150% (95% CI: 378 to 431 W; 347 to 406 W; actual vs. power law respectively, P>0.05). Parameter estimates were similar to actual TTE for both CP models and the power law model at 70% MAP (P>0.05). The semi-log model over-predicted TTE at all intensities (P<0.05). All models were different from actual performance for the 200% MAP trial (P<0.05). **Conclusion:** The power law is better than the CP model for predicting cycling endurance performance across a wider range of exercise intensities.

Key Words: Time-to-exhaustion, Power-duration relationship, Mathematical models.

5.2 Introduction.

Maximal endurance performance is known to decrease as exercise intensity increases. The curve that describes this relationship is therefore important both in modelling expected performance, and for its potential in setting training intensities. This power-duration relationship has been a subject of extensive research, dating back as early as 1906 (Kennelly, 1906; Hill, 1925; Francis, 1943; Henry, 1955; Monod and Scherrer, 1965; Moritoni et al., 1981; Riegal, 1981; Blest, 1996; Katz and Katz, 1999; Gaesser et al., 1995; Bull et al., 2000; Vincenzo and Sandra, 2010). Physiologists have used a number of different mathematical models to describe this relationship, and predict world record performances (for review see Hill, 1993; Bull et al., 2000; Grubb, 1997). From this literature, it can be seen that two distinct curves, both exponential in nature, have been used to describe endurance performance. These two power-duration relationship curves are the power law and CP.

Kennelly (1906) was probably the first to use a power law model for relating velocity to distance for various athletic and horse racing events. He found a linear relationship between time and speed when it was plotted on a logarithmic scale (i.e. it follows a power law as the slope of the log-log curve forms the scaling exponent of the power law). The model demonstrated a strong fit for data, describing an extremely wide range of athletic events and horse races (Kennelly, 1906). Subsequently, further studies have found that a simple power law relationship exists between exercise duration and intensity (Francis, 1943; Grubb, 1997; Lietzke, 1954).

In recent years it has become popular to adopt a hyperbolic, rather than a power law curve, to model the power-duration relationship (Moritoni et al., 1981; Hill, 1993; Jones et al., 2010). From this hyperbolic curve two distinct model parameters are typically reported: CP and W´, or their speed/distance equivalents: critical speed and anaerobic distance. The term CP has been proposed to denote the maximum power output an individual can sustain for a prolonged period of time. It is typically calculated by conducting repeated TTE at different exercise intensities that result in trials lasting from between 2 and 15-min (Dekerle et al., 2008). When total work done during each trial is regressed against TTE, the slope of the resulting relationship is taken as CP (Hill, 1993). The y-intercept of this regression is interpreted as W′. It has been suggested that the amount of work that can be accomplished from fixed energy reserves within the muscle can be inferred from this parameter (Hill, 1993).

Outside of the laboratory, the CP model has been applied to a wide range of sports to evaluate pacing strategies, and predict endurance performance (Hill, 1993; Jones et al., 2010). Furthermore, CP is found to correlate with other physiological laboratory test measurements (Poole et al., 1988; Housh et al., 1989; McLellan and Cheung, 1992; Pringle and Jones 2002). For instance, Pringle and Jones (2002) report a strong correlation between maximal lactate steady state and CP. However, others have questioned the validity of using CP in this manner, and for its accuracy in predicting TTE (McLellan et al., 1992; Pepper et al., 1992). As a result, previous research has compared a CP to a power law model in predicting 1 to 10-min TT running performances (Hinckson and Hopkins, 2005). The power law model demonstrated a lower variation ~ 1% in comparison to CP for predicting performance (Hinckson and Hopkins, 2005). However, this constitutes a short and narrow range of performances, and is not representative of most common endurance activities. Furthermore, despite the narrow range, the metabolic determinants of performances outside of this range are likely to be markedly different (Whipp and Wasserman, 1972; Jones et al., 2005). Consequently, Hinckson and Hopkins (2005) concluded that further research is necessary to determine how well a power law model predicts different performance durations.

The purpose of this study was to compare the predictive ability and goodness of fit of the CP and power law models when used to model a wide range of endurance performances (i.e. from <2-min to >20-min). As the power law model is derived from a log-log transformation, the intermediate semi-log model was also evaluated. It was hypothesised that a power law model would describe actual TTE performance better than the CP model for performance intensities outside those typically used to determine CP (i.e. <2-min to >20-min).

5.3 Methods.

5.3.1 Participants.

Fifteen recreationally active males were recruited to participate in this study (mean ± SD; 28 ± 9 y; 82.9 ± 9 kg; 283 ± 28 W MAP; $\dot{V}O_{2max}$ 49.5 ± 7 $ml{\cdot}kg^{1}{\cdot}min^{-1}$). Participants were excluded if they were on any medication, reported heart problems, exercise-induced asthma, or an injury that could interfere with testing. All participants gave their written informed consent to participate in this study that had been approved by the University of Kent's ethics committee.

5.3.2 Study design.

Each participant completed 11 visits to the laboratory. The first two visits were for pre-testing and familiarisation. The remaining nine visits were for the experimental TTE trials and were separated by at least 48 h. All testing was performed on a cycle ergometer (Schoberer Rad Messtechnik, Germany). These nine visits consisted of five trials to exhaustion at intensities recommended by McLellan and Cheung (1992) for the determination of CP (80%, 85%, 90%, 100% and 110% MAP), and four trials above and below these intensities (60%, 70%, 150% and 200% MAP). The latter intensities were chosen to ensure TTE occurs outside the 2 to 20-min range. Note that for 9 participants where TTE at 60% MAP was expected to exceed 45-min, they were instead tested at 65% MAP. For clarity, all 60% and 65% trials are referred to as 60%. Prior to each laboratory visit participants were instructed to ensure they were well hydrated, not to eat within 3 h, not to exercise within 24 h, nor consume alcohol within 48 h prior to exercise. During visit 1 each participant completed an incremental exercise test to determine $\dot{V}O_{2max}$ and MAP. After a 30-min rest, participants completed two performance trials to exhaustion as part of their familiarisation. This familiarisation procedure was repeated between 2–7 days later. The familiarisation trials were conducted at 110% and 80% MAP, with a 30-min rest between each trial. Participants completed these two trials to minimise the influence of any learning effect on the experimental trial (Capriotti et al., 1999). The remaining nine visits consisted of separate trials to exhaustion organised in a random order. Only one trial to exhaustion was completed at each visit with at least 48 h between trials. Participants completed all trials within a 6-week period.

5.3.3 Procedures.

$\dot{V}O_{2max}$ test: Prior to the test, ergometer seat and handlebar height were adjusted and recorded in order that the same position was used for all subsequent trials. The test started at 100 W, and increased by 20 W every min until volitional exhaustion or the participant was no longer able to maintain the required work rate. $\dot{V}O_2$, $\dot{V}CO_2$, and $\dot{V}_E$ were measured throughout exercise using an online gas analysis system (Cortex Metalyser 3B, Leipzig, Germany). HR was recorded continuously using a wireless HR monitor (Polar Electro, Kempele, Finland).

5.3.4 TTE trials.

Prior to each trial the participants completed a 5-min warm up at 50 W. Participants were instructed to maintain a consistent cadence based on their mean cadence in the $\dot{V}O_{2max}$ test for as long as possible. Participants were given verbal encouragement to maintain their target cadence during all trials. Exhaustion was determined when participants were unable to sustain the target power output or reached volitional exhaustion. Participants were not informed of the elapsed time during the trials, or their final time, which was recorded to the nearest second. Capillary blood samples were collected 1 and 5-min after the trial ended. At 1 and 5-min of every trial RPE was also recorded (Capriotti et al., 1999).

5.3.5 CP, power law and semi-log models.

CP, power law, and semi-log models of TTE across the different intensities were derived using the data from the five trials performed within the typical CP range of 80 to 110% MAP. Two linear CP models were used to examine this relationship: Linear-TW and Linear-P. The Linear-TW model was generated by linear regression of total work, measured in kJ and TTE (equation 2). The Linear-P CP model was generated by linear regression of power output and the inverse of TTE (equation 6). A power law model was generated by linear regression of the log-log relationship between exercise intensity and TTE (equation 8). The semi-log model was constructed by regressing the log of exercise intensity on TTE. All four models were then used to predict by extrapolation of the model, the actual TTE for all trials within and outside the typical range for CP. These predictions from the four models were compared with each other and the actual performance power output. Exercise intensities ranging from 80–110% MAP, and 60–200% MAP, are referred to as 'within' and 'outside' respectively.

5.3.6 Statistical analysis.

A two-way (model; intensity) repeated measures ANOVA was used to compare the actual power output for the trials with those predicted from the CP, power law, and semi-log models. Parameter estimates between models were analysed and differences were identified using 95% confidence intervals (CI). The goodness of fit of the three models was evaluated by calculating the coefficient of determination (R^2) for all data modelled within and outside the intensity range. Bland Altman plots and the 95% confidence limits of agreement (Bland and Altman, 1986) were also calculated for the 60 and 150% MAP trials. Analysis was conducted using the SPSS statistical software package (IBM SPSS Statistics, Rel. 22.0, SPSS, Inc, Chicago, USA). The level of significance was set at $P<0.05$. All values are reported as the mean (± SD).

5.4 Results.

One participant did not complete the 60% TTE trial, but completed the other nine TTE trials and therefore was not excluded from the analysis. When TTE trials for intensities between 70-110% MAP were predicted, there was no significant difference between the CP or power law models and actual TTE performance ($P>0.05$) (Table 5.1). These trials ranged in duration between approximately 2 and 27-min. Outside of this range however, both CP models over-predicted the TTE for exercise intensities at 60%, 150% and 200% MAP ($P<0.05$). The power law model more closely predicted actual TTE performances at 60% (180 ± 21 W vs. 169 ± 23 W; actual vs. power law respectively) and 150% MAP (405 W ± 44 W vs. 375 ± 50 W; actual vs. power law respectively) ($P>0.05$) but not at 200% MAP ($P<0.05$). The semi-log model over-predicted the power outputs for all exercise intensities ($P<0.05$) (Table 5.1; Figure 5.1).

Table 5.1: 95% CI for actual TTE and predicted power output derived from the Linear-TW, Linear-P CP models, power law and semi-log model for intensities between 60-200% MAP.

% MAP	TTE (s)	Actual		Linear-TW		Linear-P		Power Law		Semi-log	
		Lower CI (W)	Upper CI (W)	Lower CI (W)	Upper CI (W)	Lower CI (W)	Upper CI (W)	Lower CI (W)	Upper CI (W)	Lower CI (W)	Upper CI (W)
60	2467 ± 1248	167	192	195	219	196	224	156	183	303	353
70	1652 ± 72	187	211	198	224	200	228	171	200	303	353
80	610 ± 208	212	239	225	253	217	248	214	244	303	354
85	484 ± 106	223	253	222	252	223	253	223	254	303	354
90	370 ± 86	237	267	235	262	235	263	239	266	303	354
100	224 ± 42	264	298	262	295	262	293	264	297	304	354
110	165 ± 27	285	322	262	295	285	324	281	321	304	354
150	62 ± 16	378	431	448	558	437	537	347	406	304	354
200	31 ± 5	490	568	695	914	677	855	398	485	304	355

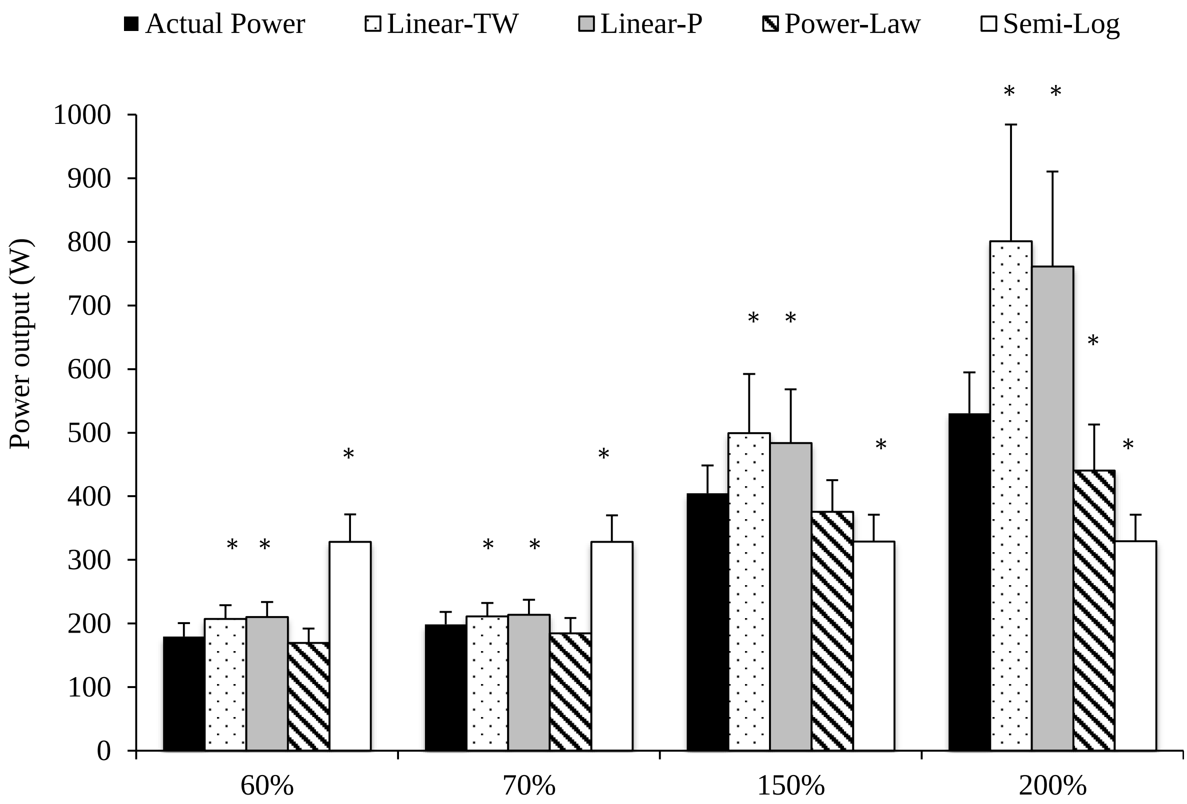

Figure 5.1: Mean ± SD; Actual and predicted power outputs (Linear-TW, Linear-P, power law and semi-log model) for trials at 60, 70, 150 and 200% of MAP. * Significant difference between actual and predicted power output; $P < 0.05$.

R^2 for the Linear-TW, Linear-P, power law and semi-log model, 'within' and 'outside' the typical CP model range are presented in Table 5.2. The power-duration relationship for one participant derived from the CP and power law models is presented in Figure 5.2. In addition, Bland-Altman plots and 95% limits of agreement are presented for the two intensities, which the power law model more closely predicts power output (60% and 150% MAP), when compared to the other models (Figure 5.3 and 5.4).

Table 5.2. R^2 values for the Linear-P, Linear-TW, power law, semi-log model, 'within' and 'outside' the typical CP model.

	Within	**Outside**
	R^2	R^2
Linear-TW	1.00	0.99
Linear-P	0.95	0.95
Power-law	0.95	0.96
Semi-log	0.91	0.58

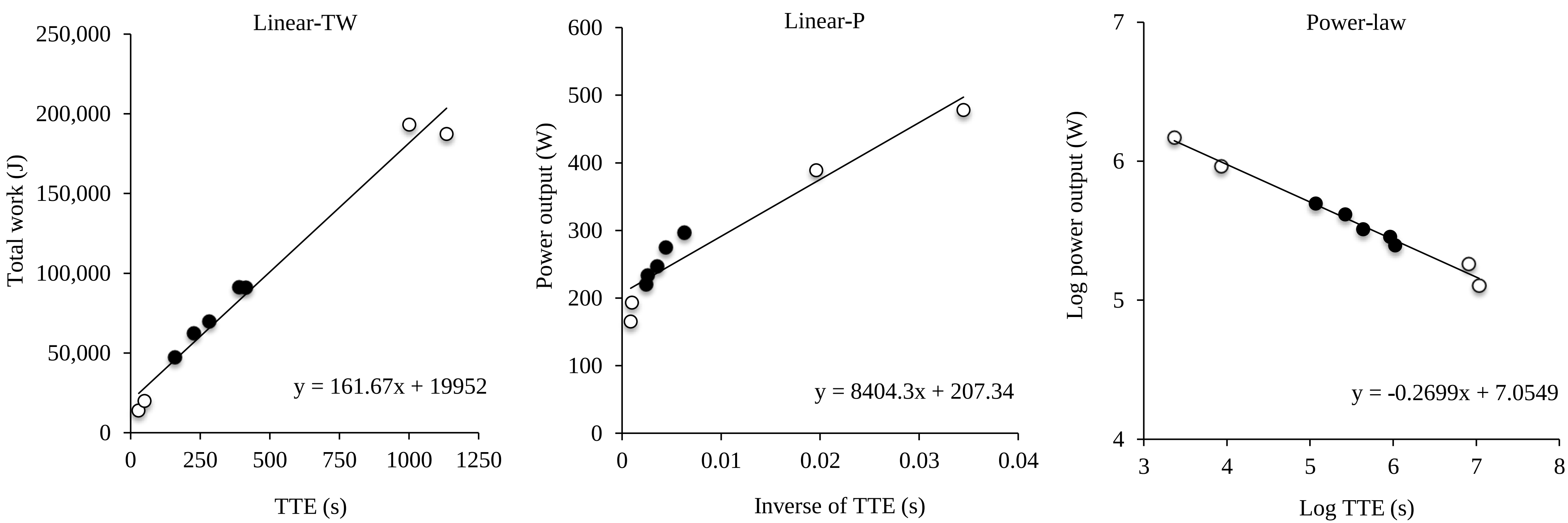

Figure 5.2: Power-duration relationship for one participant derived from a CP (Linear-TW and Linear-P) and power law model. Black circles represent 'within' the typical CP range (80-110% MAP). White circles represent 'outside' the typical CP range (60-200% MAP).

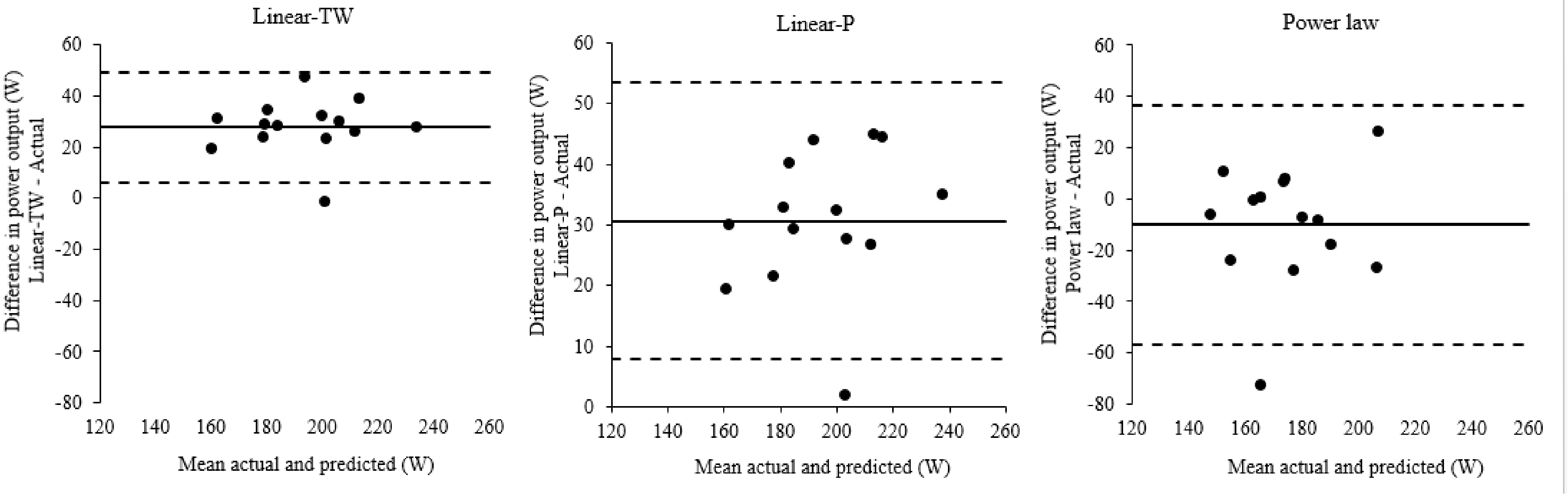

Figure 5.3 Bland-Altman plot and 95% limits of agreement between actual power output and predicted power output for the Linear-TW, Linear-P and power law models when participants completed a TTE trial at 60% MAP. Solid horizontal line represents the mean difference between predicted and actual power output. The dashed lines represent 95% limits of agreement.

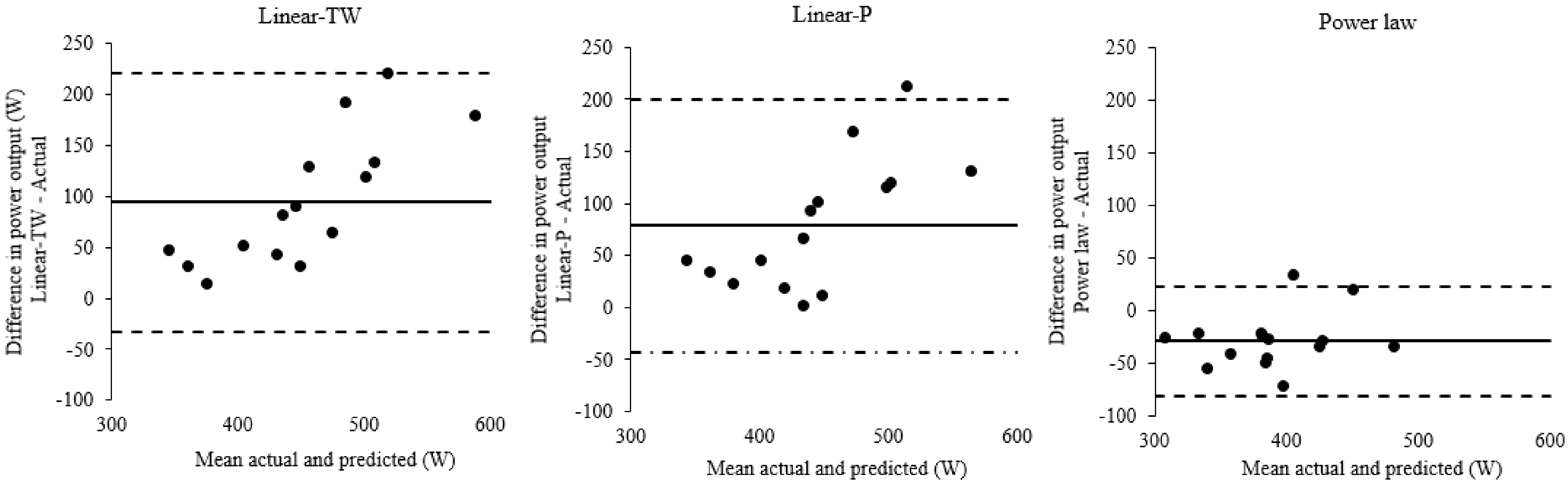

Figure 5.4: Bland-Altman plot of the relationship between actual and predicted power output for the Linear-TW, Linear P and power law models when participants completed a TTE trial at 150% MAP. Solid horizontal line represents the mean difference between predicted and actual power output. The dashed lines represent 95% limits of agreement.

5.5 Discussion.

The main finding from this study was that there was no difference between the CP (Linear-TW and Linear-P), and power law models when predicting TTE for intensities between 70-110% MAP. Outside these intensities, the power law model better predicted TTE compared with the CP or semi-log models at 60% and 150% MAP, while the CP models overestimated performances at these intensities. None of the models accurately predicted TTE performance at 200% MAP. The semi-log model overestimated TTE performance for all exercise intensities.

Our findings are consistent with those of Hinckson and Hopkins (2005), who reported no difference between models (CP versus power law) for TT between 1 and 10-min. Therefore, across a narrow range of exercise durations from ~ 2 to 20-min, it is evident that both the CP and power law model can be used to explain performance. A new finding from our study is that the power law model can reliably predict shorter and longer duration performances better than both CP models, which do not describe the power-duration relationship well for intensities < 70% and > 110% MAP.

The CP model has been extensively studied and found to reflect the power-time relationship, but its use has been criticised for only explaining performance within the narrow 2 to 20-min range of durations or equivalent distances (McLellan and Cheung, 1992; Pepper et al., 1992). In contrast, the present study finds that the power law model provides a more realistic representation of endurance performance that extends well beyond the range of the CP model. One explanation for the ability of the power law model to explain the large variation in TTE is that it assumes a progressive decline in performance with increases in intensities or distances (Grubb, 1997). In contrast, the CP model assumes that a hyperbolic relationship exists between power and time and that below CP one can sustain exercise for an infinite time (Hill, 1993; Vanhatalo et al., 2011). This notion, implicit in the CP model, does not provide as accurate a representation of endurance performance.

A CP model is often described as a physiological model to explain endurance performance (Monod and Scherrer, 1965; Hill, 1993; Pringle and Jones, 2002; Jones et al., 2010). It is proposed to represent the boundaries between the ‘heavy’ and ‘severe’ intensity domains of exercise tolerance (Jones et al., 2010) and is used by some to monitor changes following training (Gaesser and Wilson, 1988; Vanhatalo et al., 2011). However, CP can be highly sensitive to changes in cadence (~ 6% difference between 60 rpm vs. 100 rpm) as well as the type of CP model used (Gaesser et al., 1995; Bull et al., 2000). On the other hand, the physiological basis for the power law model is unclear, but this model shows potential for predicting a much wider range of performances >40-min. The semi-log model was included in this study to explain the large variations in times, but it over predicted performances at all intensities.

We note that our study is limited to demonstrations that only performances of up to ~ 40-min can be accurately predicted using a power law model. Future research should determine if a power law model can accurately predict performances of much longer durations i.e. >40-min. Previous research has demonstrated a strong fit to data of world record performance times, when a power law model is used for athletic distances between 100 m to a marathon (Grubb, 1997). Therefore, it is anticipated that the power law model would be able to predict actual TTE performances within these durations or distances.

A large variation in the TTE was observed for trials at the same relative intensity. For example, at 70% and 80% MAP, CV for TTE performances was 44% and 34% respectively. This is consistent with research by Coyle et al. (1988) who reported a large variability in TTE performances at 88% $\dot{V}O_{2max}$. Differences in metabolic stress might explain some of this variability, as exercise based on a percentage of maximum (i.e. $\%\dot{V}O_{2max}$, HR_{max}, MAP) does not take into account each individual's physiological profile (e.g. power at lactate threshold) (Lansley et al., 2011; Mann et al., 2013; Scharhag-Rosenberger et al., 2010). Future research could examine whether using a power law model reduces the variability in TTE. This method would specify exercise intensity by each individual's power-duration relationship and model a more consistent exercise stress across participants.

5.6 Conclusion.

In conclusion, a power law model more accurately predicts cycling TTE for intensities ranging from 60-150% MAP. For TTE performances predicted between 70-110% MAP there was no difference between the predictive ability of the CP and power law models. The power law model therefore offers an alternative and more reliable model to predict and describe cycling performance over a wide range of intensities.

Chapter 6: A power law model reduces variability in time-to-exhaustion

6.1 Abstract.

A large inter-individual variability in TTE occurs when exercising at a fixed $\%\dot{V}O_{2max}$. This may be because exercise intensity prescribed in this manner does not account for individual differences in metabolic stress. **Purpose:** This study aimed to compare a $\%\dot{V}O_{2max}$ prescription with an alternative based on an individual power-duration relationship (using a power law model). **Methods:** Sixteen trained male cyclists completed five visits to the laboratory separated by at least 48 h. The first three visits measured participants' double-leg $\dot{V}O_{2max}$, LT, single-leg $\dot{V}O_{2peak}$, and power-duration relationship. A power-duration relationship was derived from three TTE trials at 85%, 95% and 105% MAP, with 30-min rest between each trial, and was modeled using a power law model. A power law model predicted the intensity for TTE lasting exactly 20-min, and 3-min. A corresponding intensity for TTE at $\%\dot{V}O_{2max}$ was 88%, and 109%. The final two experimental visits involved participants completing two TTE trials upon each visit, with 30-min rest between trials. The TTE trials were set as a $\%\dot{V}O_{2max}$, or power law prescription, and were administered in a randomised order. **Results:** The inter-individual variability for TTE performance duration was significantly reduced for TTE when prescribed using a 20-min power law versus 88% $\dot{V}O_{2max}$ (CV = 29.7% vs. 59.9% respectively; $P<0.05$), but not for a 3-min power law versus 109% $\dot{V}O_{2max}$ (CV = 26.5% vs. 27.4% respectively; $P>0.05$). **Conclusion:** Prescribing exercise intensity using a power law model reduces the variability in TTE by 50% when compared to the $\%\dot{V}O_{2max}$ method. Therefore, the power law is a more consistent method for standardising exercise intensity.

Key Words*:* $\%\dot{V}O_{2max}$, Inter-individual variability, Cycling, Exercise prescription, Relative intensity.

6.2 Introduction.

$\dot{V}O_{2max}$ is one of the most widely measured parameters in exercise physiology and is often used to prescribe training (Bacon et al., 2013; Midgley et al., 2006; Howley et al., 1995; Bouchard et al., 1999; Vollaard et al., 2009). However, when training is standardised to a %$\dot{V}O_{2max}$, a large inter-individual variability in training responses is frequently observed (Bouchard et al., 1999; Vollaard et al., 2009; Scharhag-Rosenberger et al., 2012). Evidence suggests that some of this variability might be due to differences in the exercise stimulus experienced by each individual (Scharhag-Rosenberger et al., 2010; Lansley et al., 2011; McPhee et al., 2010). For instance, when an acute bout of exercise (e.g. TTE) is standardised to a %$\dot{V}O_{2max}$, there is a large variability in individual metabolic stress responses (Coyle et al., 1988; Scharhag-Rosenberger et al., 2010; Lansley et al., 2011). Additionally, it has been found that the training stimulus experienced by each individual's leg muscles can also be highly variable when exercising at a %$\dot{V}O_{2max}$ (McPhee et al., 2009; McPhee et al., 2010). This was highlighted by McPhee et al. (2010), who demonstrated an inverse relationship between training induced changes and single-leg $\dot{V}O_{peak}$, when expressed as a ratio of double-leg $\dot{V}O_{2max}$ ($Ratio_{1:2}$). It was found that individuals with a low $Ratio_{1:2}$ demonstrated greater training adaptations compared to those with a high $Ratio_{1:2}$, when exercise was prescribed as a %$\dot{V}O_{2max}$ (McPhee et al., 2009). As a result, researchers have questioned the methods used to standardise exercise intensity, and whether a %$\dot{V}O_{2max}$ prescription is the most appropriate method to use (Mann et al., 2013; Hopker and Passfield, 2014).

Alternative methods of standardising exercise intensity include using a 'threshold based model' (e.g. % of LT, GET, or ventilatory threshold) (Katch et al., 1978; Meyer et al., 1999; Lansley et al., 2011; Wolpern et al., 2015). A recent review by Mann et al. (2013) discussed the practical and physiological implications of these methods. LT or GET methods have advantages in that they take into account an individual's full physiological profile as opposed to just a % of maximum (Lansley et al., 2011). Additionally, prescribing exercise as a % GET results in a more consistent physiological response during sub-maximal exercise when compared to a %$\dot{V}O_{2max}$ (Lansley et al., 2011). Nevertheless, there are a number of limitations to these prescription methods. For instance, the methods used to identify LT and GET are inconsistent and blood lactate responses are sensitive to factors such as changes in diet and previous exercise (Mann et al., 2013).

A different approach to using a %$\dot{V}O_{2max}$ or % threshold method might be to prescribe exercise based on each individual's performance profile e.g. the power-duration relationship. Previous research has found power-duration relationship models accurately predict endurance performance for a variety of sports (Hinckson and Hopkins, 2005; Oscieki et al., 2014). Evidence suggests that a relationship exists between exercise duration and intensity, and that this relationship can be described using a power law model (Kennelly, 1906; Blest, 1996; Riegal, 1981; Katz and Katz, 1999). The power law model assumes a linear relationship between exercise intensity and time when both are plotted on a logarithmic scale (Kennelly, 1906). This model has been validated for its fit over a very wide range of athletic events (Kennelly, 1906). Therefore, the main aim of this study was to compare the inter-individual variability in TTE performances when exercise intensity was prescribed using a %$\dot{V}O_{2max}$, versus an individual power-duration relationship (using a power law model). It was hypothesised, that the use of a power law model to prescribe exercise would reduce the inter-individual variability in TTE when compared to prescribing exercise based on a %$\dot{V}O_{2max}$ method. A secondary aim was to determine whether the inter-individual variability in TTE performances was related to an individual's $Ratio_{1:2}$. It was hypothesised that there would be a relationship between TTE performances and the $Ratio_{1:2}$, with individuals who had a high $Ratio_{1:2}$ able to sustain exercise for longer than individuals with a low $Ratio_{1:2}$.

6.3 Methods.

6.3.1 Participants.

Sixteen trained male cyclists volunteered to take part in this study (mean ± SD: age = 35 ± 11 y, body mass = 76 ± 9 kg; Table 6.1) All participants were involved in a minimum of 6 h of cycle training per week, and were excluded if they reported any heart problems, exercise-induced asthma, or injuries that would interfere with testing. All participants gave their written informed consent to participate in this study that was approved by the University of Kent's ethics committee.

6.3.2 Study design.

Participants visited the laboratory on five occasions, each separated by at least 48 h. All tests were conducted on a cycle ergometer (Schoberer Rad Messtechnik, Germany). Participants were instructed to be fully hydrated and to avoid food, strenuous exercise, and alcohol for 3 h, 24 h and 48 h respectively prior to each visit. The first three visits were aimed at gathering data on each individual's physiological profile, which was then used to prescribe the exercise intensities for the final two experimental visits. During the first visit, participants completed a sub maximal LT test and a double-leg $\dot{V}O_{2max}$ test. The ergometer seat and handlebar height was adjusted for each participant and recorded to ensure the same position was used for subsequent trials. For visit two, participants completed a single-leg $\dot{V}O_{2peak}$ test, and for visit three they completed three TTE trials at different power outputs equivalent to 85%, 95% and 105% MAP, with 30-min rest between trials. The information from these TTE trials was used to determine each individual's power-duration relationship, which was needed to calculate the intensities for the power law prescription method. For the final two visits participants complete two TTE trials for each visit, separated by 30-min rest. The two methods of prescription for these trials were set using a fixed %$\dot{V}O_{2max}$ or a power law model. Participants either completed two TTE trials as a %$\dot{V}O_{2max}$ or two TTE trials at the intensity predicted from a power law model. The lower intensity trials (88% $\dot{V}O_{2max}$ or a 20-min power law) were completed first followed by the higher intensity trial (109% $\dot{V}O_{2max}$ or a 3-min power law), after 30-min rest. These prescription methods were administered in a randomised order in a crossover design.

Table 6.1: Descriptive data for each participant: MAP, double-leg $\dot{V}O_{2max}$, %$\dot{V}O_{2max}$, at LT, single-leg $\dot{V}O_{2peak}$ and $Ratio_{1:2}$.

Participant no.	MAP (W)	Double-leg $\dot{V}O_{2max}$ ($L.min^{-1}$)	% $\dot{V}O_{2max}$, at LT	Single-leg $\dot{V}O_{2max}$ ($L.min^{-1}$)	$Ratio_{1:2}$ (%)
1	353	3.74	63	3.16	85
2	363	5.15	69	3.89	76
3	319	3.93	65	3.51	89
4	329	4.04	68	3.27	81
5	341	4.15	79	3.60	87
6	277	3.49	67	2.55	73
7	390	4.98	67	4.11	83
8	350	4.54	64	3.87	85
9	395	5.09	62	4.21	83
10	345	4.73	63	4.04	85
11	307	3.66	69	2.91	80
12	308	4.07	74	3.15	77
13	357	4.47	63	3.13	70
14	407	4.68	78	3.95	84
15	395	4.83	63	3.55	74
16	384	4.54	58	3.74	82
Mean	351	4.38	67	3.54	81
±SD	37	0.52	6	0.47	6

6.3.3 Preliminary trials.

LT: Participants completed a submaximal exercise test to determine the intensity corresponding to their LT. Participants cycled at different submaximal work rates increasing by 25 W every 5-min in a continuous manner. Participants were instructed to maintain a preferred cadence, but to keep this consistent throughout the test. $\dot{V}O_2$, $\dot{V}CO_2$, $\dot{V}_E$, and HR were recorded throughout the tests using an online gas analysis system (Cortex Biophysik, Leipzig, Germany). Earlobe blood lactate samples were collected within the last 30 s of each stage and analysed for blood lactate concentration using a lactate analyser (Biosen C-line, EKF diagnostic, Barleben, Germany). Once the participant's blood lactate reached a target value of 4 $mmol.L^{-1}$ the test was terminated, and following a 20-min rest, participants commenced the $\dot{V}O_{2max}$ test. LT was determined using lactate e software (Newell et al., 2007), which calculated the intensity associated with a 1 mmol. L^{-1} increase in blood lactate concentration above baseline.

Double-leg $\dot{V}O_{2max}$: Participants completed a 5-min warm up at 150 W. The $\dot{V}O_{2max}$ test started at 120 W and increased by 20 W every min until volitional exhaustion was reached, or the participant was no longer able to maintain the required work rate. $\dot{V}O_2$, $\dot{V}CO_2$, $\dot{V}_E$ were recorded throughout. A blood lactate sample was measured 1-min after the test. The participants' MAP and $\dot{V}O_{2max}$ were calculated as the highest 60 s mean achieved during the test. Approximately 10-min after completing this test, participants were familiarised to the single-leg $\dot{V}O_{2peak}$ test protocol by completing 6-min of cycling at 20, 40 and 60 W respectively. This is a similar protocol to that used by McPhee et al. (2010).

Single-leg VO_{2peak}: Participants completed a single-leg $\dot{V}O_{2peak}$ test on the right leg only. Prior to commencing the test participants completed a double-leg warm up at 150 W for 5-min. The single-leg VO_{2peak} test was performed on the same ergometer as the $\dot{V}O_{2max}$ test, but the left pedal removed and replaced with a 10 kg counter-weight. Participants rested their left foot on a step, while their right foot was securely strapped to the pedal. The test started at 40 W and increased by 10 W every min until volitional exhaustion was reached, or a cadence of 60 rev·min^{-1} could not be maintained (McPhee et al., 2010). $\dot{V}O_2$, $\dot{V}CO_2$, $\dot{V}_E$, and HR were recorded throughout as described above. The ratio of $\dot{V}O_{2peak}$ attained from the single-leg $\dot{V}O_{2peak}$ test was compared to the $\dot{V}O_{2max}$ attained from the double-leg $\dot{V}O_{2max}$ test for each participant (Ratio$_{1:2}$) (McPhee et al., 2010).

After a 30-min rest, participants completed two TTE trials as part of a familiarisation to the power-duration relationship test protocol (as described below). The familiarisation trials were set at 85% and 105% MAP, which were the upper and lower intensities used to determine the power-duration relationship. As this was for familiarisation only, subjects were allowed as much time to recover between trials as needed. The familisarisation trials were included to minimise the influence of any learning effect on the experimental trials (Capriotti et al., 1999).

Power-duration relationship: The TTE protocol was similar to Karsten et al. (2015). Participants performed the TTE trials at power outputs equivalent to 85%, 95% and 105% of MAP with 30-min rest between trials. The trials were performed in this fixed order and each trial was preceded by a 5-min warm up at 150 W. Galbraith et al. (2011) has previously established that a 30-min rest allows sufficient rest between trials. Participants were instructed to maintain their mean cadence from the $\dot{V}O_{2max}$ test and sustain the target power output for as long as possible. They were not provided with any verbal encouragement or feedback on elapsed time and power output. Feedback on cadence was only provided when it fell 10 rev·min^{-1} below their target, and participants were given a 10 s countdown before the test was terminated. TTE was recorded to the nearest second (s).

6.3.4 Experimental trials.

The final two experimental visits required participants to complete two TTE trials for each visit, separated by 30-min between trials. The test protocol criteria were the same as described above for the power-duration relationship visit, but the intensities were prescribed as a power law model versus a % $\dot{V}O_{2max}$. Figure 6.1 presents a flow chart of the steps performed to calculate the intensities for the power law and %$\dot{V}O_{2max}$ prescription methods.

Power law prescription method: The power law model was derived from the three TTE trials at 85%, 95% and 105% MAP. Exercise intensity (mean power output) and TTE for each of these trials was log transformed. A power law was generated from a linear regression of the log-log relationship between power output and TTE. The slope and the y-intercept of this relationship were calculated, and a power law model was used to predict by extrapolation the intensity for TTE trials lasting exactly 20-min and 3-min.

%$\dot{V}O_{2max}$ prescription method: The $\dot{V}O_2$ responses from the submaximal LT test were used to determine the VO_2-power regression relationship for each individual. This relationship was then used to calculate the %$\dot{V}O_{2max}$ corresponding to the power outputs prescribed for the 20-min and 3-min power law method. The mean %$\dot{V}O_{2max}$ for the group was then used as the intensity for the subsequent %$\dot{V}O_{2max}$ TTE trials. This resulted in exercise intensities equivalent to 88% $\dot{V}O_{2max}$ and 109% $\dot{V}O_{2max}$.

6.3.5 Physiological and perceptual responses to exercise.

Muscle oxygenation: Vastus lateralis muscle oxygenation was continuously measured during all trials (except for the 3-min power law and 109% $\dot{V}O_{2max}$ trial), using a near-infrared spectroscopy device (Protamon, Artinis, Zatton, The Netherlands). The NIRS probe was wrapped in cling film before positioning it to the right vastus lateralis to prevent sweat interfering with the signal. The probe was positioned longitudinally on the distal section of the right vastus lateralis, approximately 10-12 cm above the knee joint (Wang et al., 2012), and secured to the leg with kinesiology tape. Muscle oxygenation was measured by emitting continuous wavelengths of 780 and 850 nm light on the exercising leg. These wavelengths allow for the detection and differentiation in concentration changes of the two major forms of chormophores haemoglobin (Hb) and myoglobin (Mb) (i.e. HbO_2 - oxy Hb + Mb and HHb – deoxy Hb + Mb). It is generally considered that the myoglobin contribution is the more minor component, and is difficult to differentiate from Hb using a tw-wavelength NIRS device; therefore, in line with previous researchers this will be ignored for the sake of clarity.

Data were recorded at 25 Hz, and for the purposes of further analysis, a 30 s moving average was applied. NIRS data were first expressed relative to a baseline taken from the final 30 s of the standardised warm-up conducted prior to each trial. The amplitude of oxygenated hemoglobin (HbO_2) and deoxygenated hemoglobin (HHb) responses was calculated as the difference between the baseline and the average of each min of the TTE test. Using similar methods to Bonne et al. (2015), these values were then expressed as a % of the end test value to identify the % of maximal HbO_2 and HHb at which each individual was exercising.

RPE: Participants were asked to self-rate their RPE throughout the TTE trials. Participants were asked to rate their RPE after the first minute of exercise for the 20-min power law or 88% $\dot{V}O_{2max}$ trial, or after 30 s of exercise for the 3-min power-law or 109% $\dot{V}O_{2max}$ trial. Following this, they were instructed to report whenever their perception increased. The RPE value and time point at which RPE increased were recorded throughout the TTE trials. The testing procedure was similar to that used by McKumura et al. (2010). RPE values were plotted against time (s), and the slope of the linear relationship between RPE and time was calculated for each individual.

6.3.6 Statistical analysis.

The coefficients of variation (CV) were determined for the TTE trials and the associated physiological and perceptual responses. CVs were calculated as the ratio of the SD around the mean, expressed as a percentage. Inter-individual variability was defined as the differences between participants for the same trial and is referred to as variability throughout. Comparisons between the variances in TTE, physiological and perceptual responses for the $\%\dot{V}O_{2max}$, and power law methods were made using the F-distribution test (Bland, 2000), calculated using MedCalc Software (MedCalc vs. 11.3, Mairckerke, Belgium). Pearson's correlation was used to examine the relationship between TTE ($\%\dot{V}O_{2max}$ and power law prescription) and the $Ratio_{1:2}$, $\%\dot{V}O_{2max}$ at LT, RPE slope, %HHb and $\%HO_2b$. Bland Altman plots and the 95% confidence limits of agreement (Bland and Altman, 1986) were also calculated for the relationship between actual and predicted TTE when prescribed as a $\%\dot{V}O_{2max}$. Analysis was conducted using the SPSS statistical software package (IBM SPSS Statistics, Rel. 22.0, SPSS, Inc, Chicago, USA). Data are presented as the means (± SD). The level of significance was set at $P<0.05$.

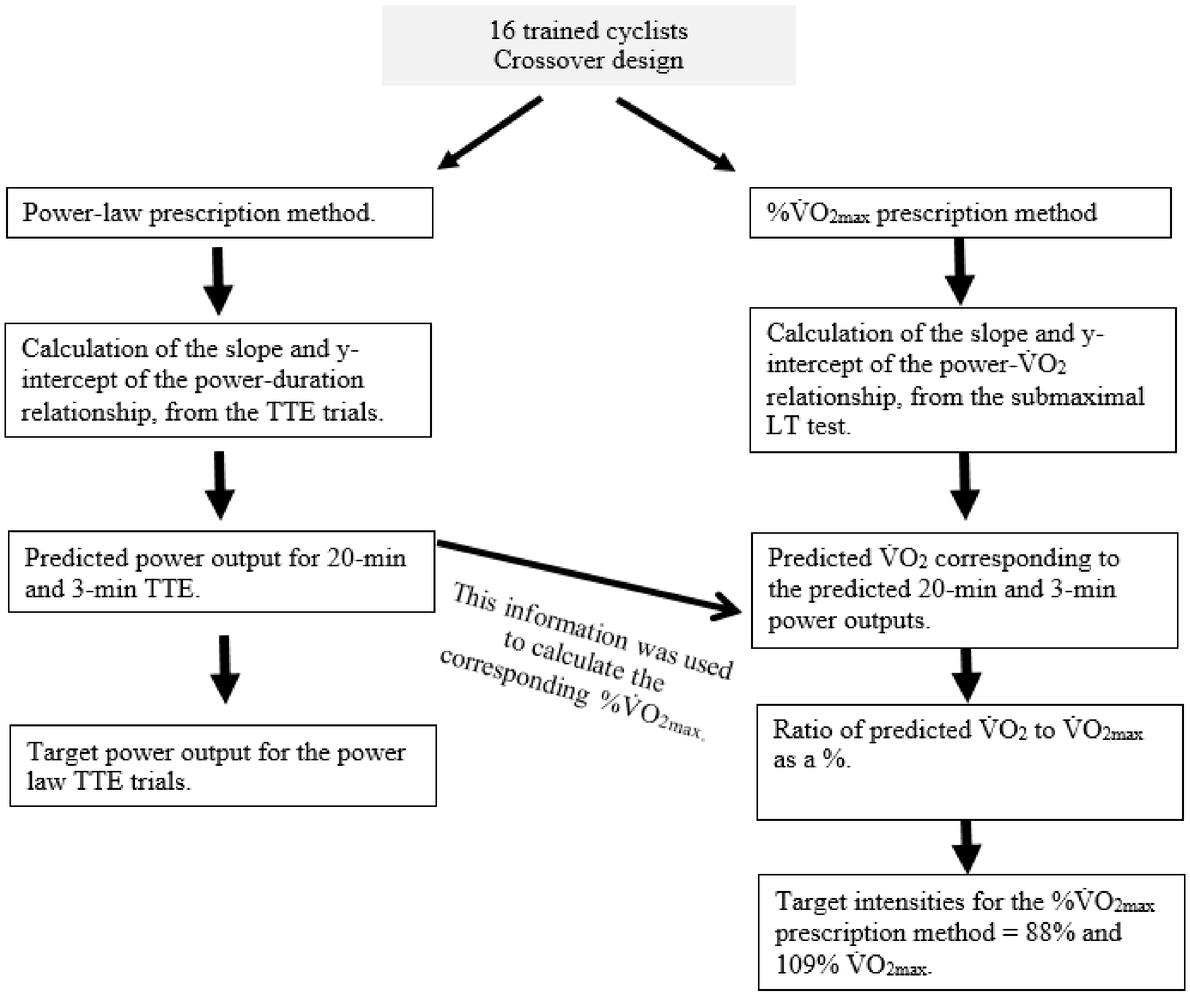

Figure 6.1. Flow chart of the procedures for setting exercise intensity as a $\%\dot{V}O_{2max}$ and power law model.

6.4 Results.

6.4.1 Variability in TTE.

The inter-individual variability for TTE performances was significantly lower when prescribed based on a 20-min power law versus 88% $\dot{V}O_{2max}$ (P<0.05; CV = 29.7% and 59.9% respectively; Figure 6.2, A). However, there were no significant differences in mean power output (275 ± 39 W vs. 278 ± 37 W) or the duration of exercise (1113 ± 330 vs. 1130 ± 677 s) for the 20-min power law and 88% $\dot{V}O_{2max}$ trials respectively (P>0.05) (Figure 6.2, B).

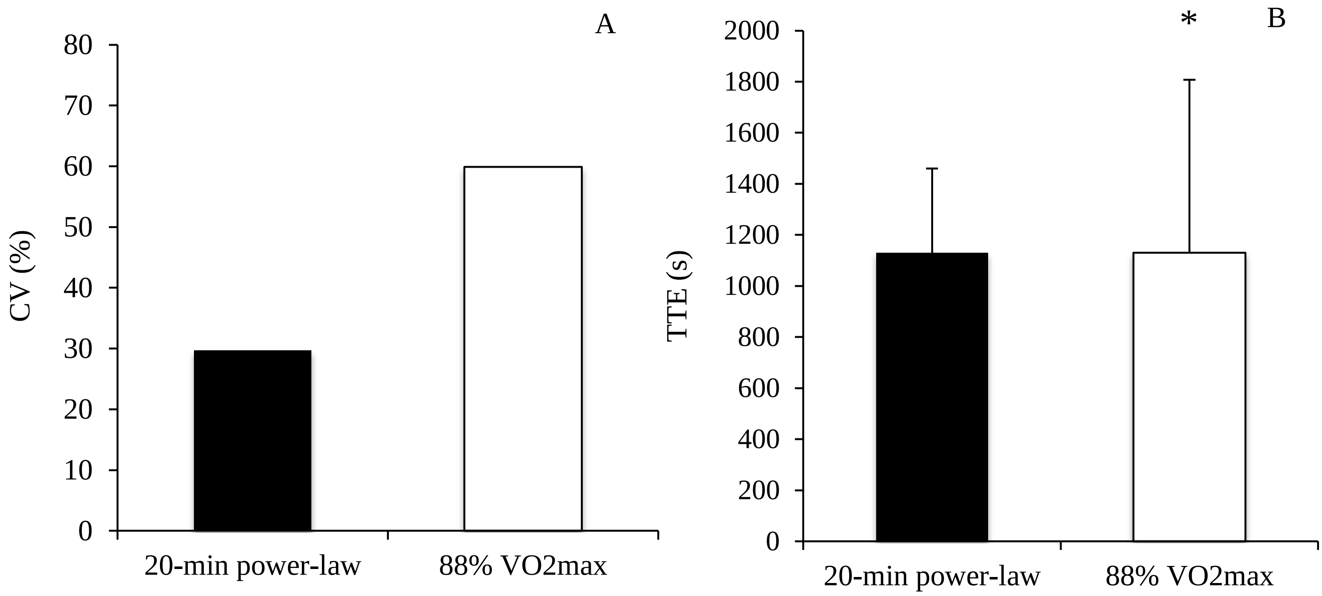

Figure 6.2: TTE performances when exercise was prescribed as a 20-min power law versus 88% $\dot{V}O_{2max}$ prescription. A = CV for TTE performances B = mean (± SD) TTE performances * Significantly greater inter-individual variability for TTE performances; P<0.05.

The inter-individual variability for TTE performances was not different when prescribed as a 3-min power law versus 109% $\dot{V}O_{2max}$ (P>0.05; CV 26.5% and 27.4% respectively). There was no significant difference for mean power output (343 ± 37 vs. 347 ± 42 W) or the duration of exercise (153 ± 41 vs. 138 ± 38 s) for the 3-min power law and 109% $\dot{V}O_{2max}$ trials respectively (P>0.05).

A power law model was used to predict TTE when exercise was prescribed at 88% and 109% $\dot{V}O_{2max}$. Comparisons were made between predicted TTE and actual TTE. There was a strong correlation between predicted and actual TTE performances at 88% $\dot{V}O_{2max}$ (r=0.95; P<0.05) (Figure 6.3). There was no correlation between predicted and actual TTE performances when a power law model predicted TTE at 109% $\dot{V}O_{2max}$ (r=0.38; P>0.05).

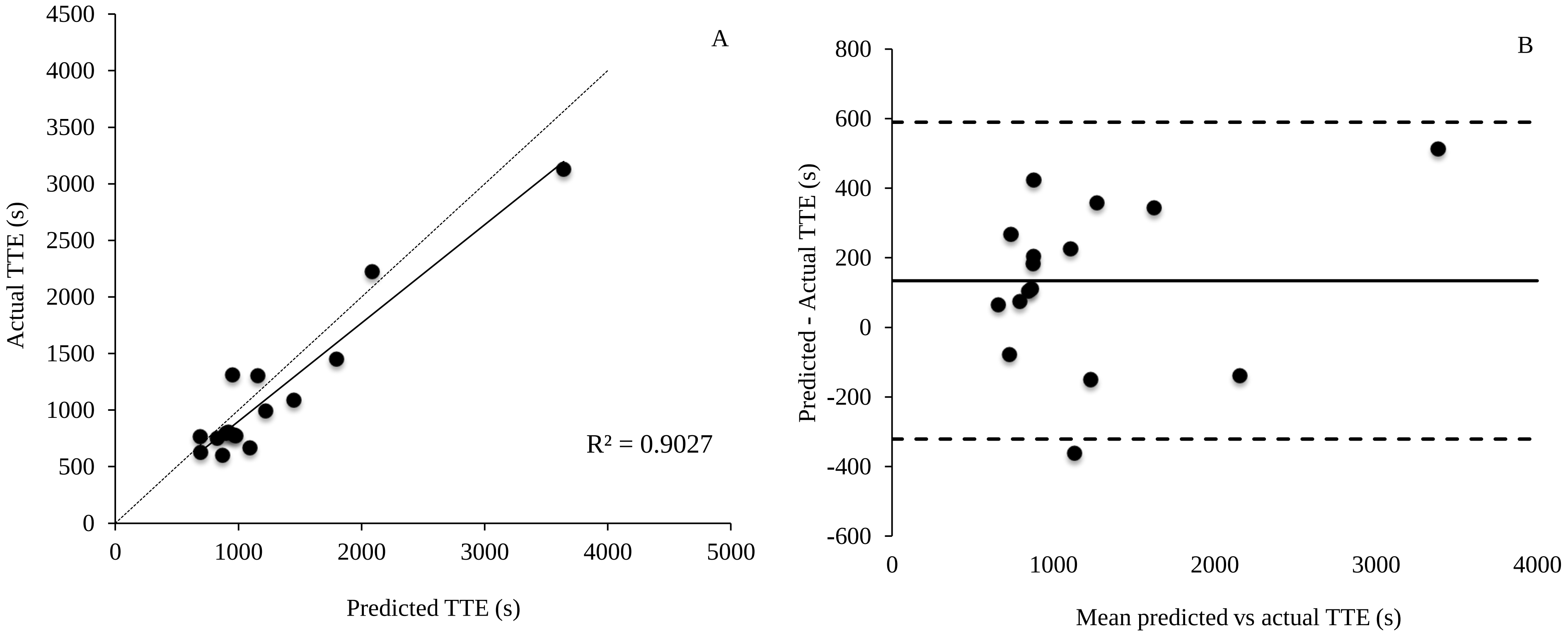

Figure 6.3: Demonstrates a relationship between predicted (using a power law model) and actual TTE when exercise is prescribed as a $\%\dot{V}O_{2max}$. A = a strong positive correlation between actual and predicted TTE. B = Bland Altman plot of the relationship and limits of agreement between predicted TTE (using the power law model) and actual TTE when exercise was prescribed as a $\%\dot{V}O_{2max}$. The solid horizontal line represents the mean difference between predicted and actual TTE. The dashed line represents the 95% limits of agreement.

6.4.2 Physiological and perceptual responses to exercise.

There were no significant differences in the inter-individual variability for physiological responses (end blood lactate, HR_{max}, muscle oxygenation) during the TTE performances when prescribed as a power law versus $\%\dot{V}O_{2max}$ (P>0.05). There was no correlation between muscle oxygenation (HbO_2 and HHb) and TTE for both the 20-min power law and 88% $\dot{V}O_{2max}$ trials (P>0.05).

There was a significant positive correlation between $\%\dot{V}O_{2max}$ at LT and TTE when exercise was set at 88% $\dot{V}O_{2max}$ (r=0.54; P<0.05; Figure 6.4, A). There was no correlation between $\%\dot{V}O_{2max}$ at LT and TTE when prescribed using a 20-min power law method (P>0.05). A significant positive correlation was found between $Ratio_{1:2}$ and TTE for the 20-min power law trial (r=0.57; P<0.05; Figure 6.4, B), but not the 88% $\dot{V}O_{2max}$, 3-min power law or 109% $\dot{V}O_{2max}$ trials (P>0.05).

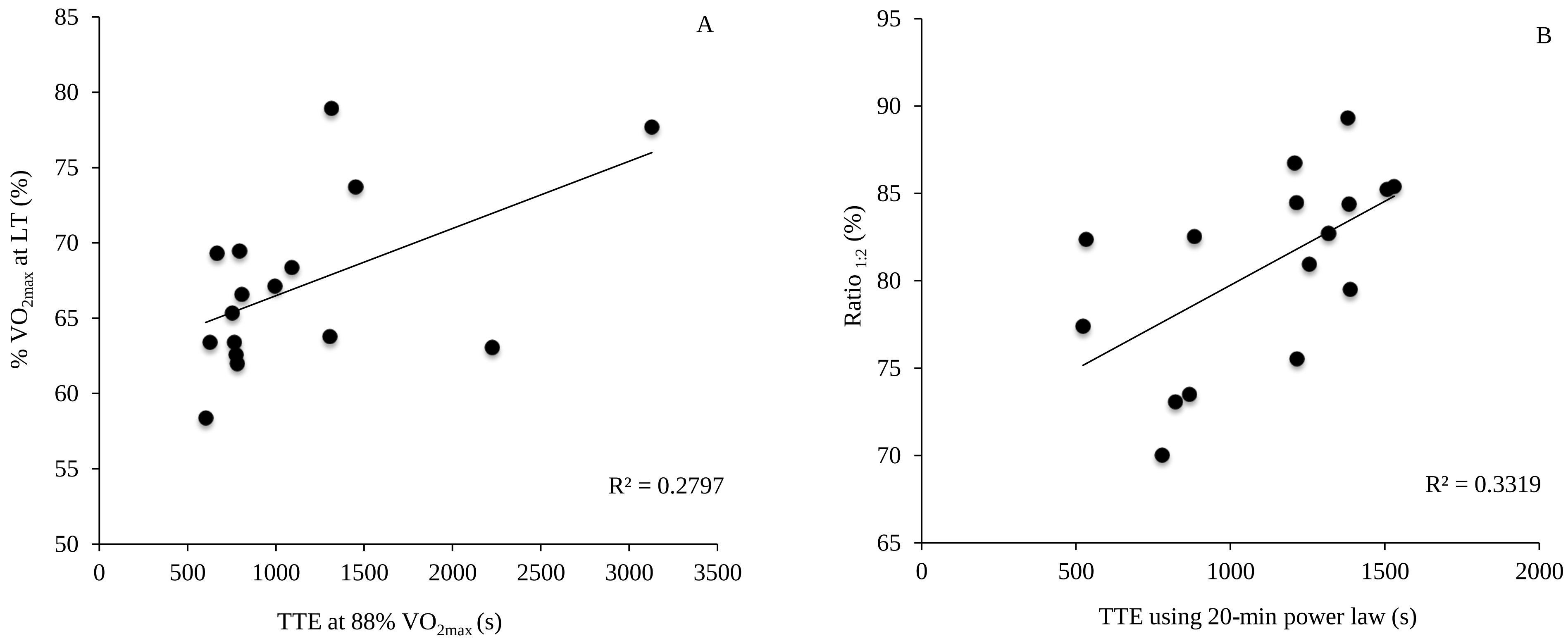

Figure 6.4. A = a positive correlation between participants $\%\dot{V}O_{2max}$ at LT and TTE when exercise was prescribed at 88% $\dot{V}O_{2max}$. B = a positive correlation between participants $Ratio_{1:2}$ and TTE when exercise was prescribed using the 20-min power law prescription method.

Figure 6.5 provides an example of how the slope of the RPE and time relationship was plotted for one participant. There was no difference in the variability for the slope of the RPE for the 20-min power law compared to the 88% $\dot{V}O_{2max}$ trial (CV = 41% vs. 45% respectively; P>0.05). There was also no difference in the variability for the slope of the RPE for the 3-min power law compared to the 109% $\dot{V}O_{2max}$ trial (CV = 46% vs. 36% respectively; P>0.05; n=10). Due to six participants forgetting to self-rate RPE for the higher intensity trials (3-min power law vs. 109% $\dot{V}O_{2max}$) these data were recorded from 10 participants. A significant negative correlation was observed between the slope of the increase in RPE and TTE for the 20-min power law (r=-0.68; P<0.05), but not for the 88% $\dot{V}O_{2max}$ method (r=-0.19; P>0.05).

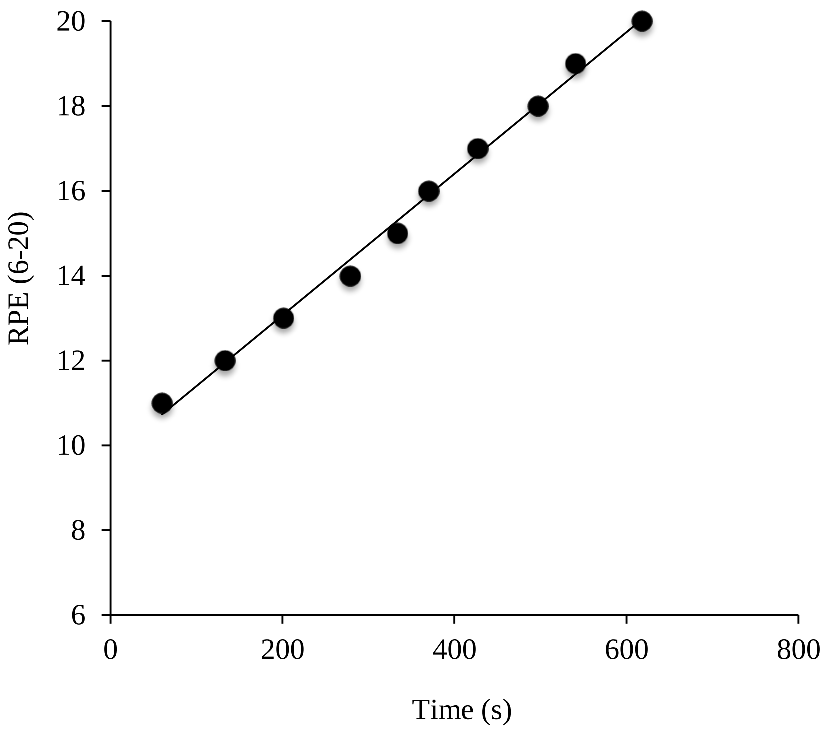

Figure 6.5: Slope of the relationship between RPE and time for one participant.

6.5. Discussion

The main finding from this study was that the variability for TTE performances was significantly reduced when exercise intensity was prescribed using a 20-min power law compared to 88% $\dot{V}O_{2max}$. The variability in TTE was not different when exercise intensity was prescribed as a 3-min power law compared to 109% $\dot{V}O_{2max}$. A power law is a mathematical model that has been used by physiologists to describe the power-duration relationship, and accurately predict world record performances for distances from 100 m up to a marathon (Kennelly, 1906; Francis, 1943; Grubb, 1997; Blest, 1996; Katz and Katz, 1999). The power law model assumes a progressive decline in performance with an increase in intensity or distance (Grubb, 1997). It takes into account an individual's power-duration relationship when prescribing exercise, which follows an exponential curve or can be described as a linear relationship when plotted on a logarithmic scale (Kennelly, 1906). In order to directly compare prescription methods (power law vs. %$\dot{V}O_{2max}$) the present study matched the intensity derived from the power law model to a %$\dot{V}O_{2max}$. This in turn meant that there were no significant differences in the mean TTE duration or power output sustained between methods. As a result, direct comparisons can be made between the two prescription methods (power law vs. %$\dot{V}O_{2max}$). Therefore, the findings of this study demonstrate that a power law model is a significantly more consistent method for prescribing exercise intensity lasting 20-min. This is evident from the 50% reduction in CV for the times individuals could sustain exercise to exhaustion for, when using a 20-min power law compared to an 88% $\dot{V}O_{2max}$ prescription method.

In agreement with the findings of the present study, Coyle et al. (1988) reported a large variability in TTE despite all subjects exercising at the same relative exercise intensity. The findings of Coyle et al. (1988) demonstrated that TTE performances ranged from 12-75 min (with a CV of 43.7%), when trained cyclists exercised to exhaustion at 88% $\dot{V}O_{2max}$. Moreover, Coyle et al. (1988) suggested that the %$\dot{V}O_{2max}$ at LT was a strong predictor of endurance performance, with individuals who had a high LT able to sustain the target intensity for more than twice as long as those with a low LT (Coyle et al., 1988). The present study supports these findings. A similar variability in TTE performances was observed in this study, ranging from 10-52 min with a CV of 59.9% when exercise was prescribed at 88% $\dot{V}O_{2max}$. Additionally, a positive correlation was found between participant's %$\dot{V}O_{2max}$ at LT and TTE when prescribed at 88% $\dot{V}O_{2max}$. In contrast, there was no correlation between participants' %$\dot{V}O_{2max}$ at LT and TTE when prescribed using a 20-min power law. This suggests that a power law model accounts for differences in metabolic stress when prescribing exercise intensity.

A positive correlation between an individuals' $Ratio_{1:2}$ and TTE for the 20-min power law prescription method was also observed. This relationship suggests that participants who had a high $Ratio_{1:2}$ were able to sustain exercise for longer than those with a low $Ratio_{1:2}$. This was an interesting finding and adds to the work of McPhee et al. (2010) who demonstrated a relationship between the variability in training induced adaptations and an individuals' $Ratio_{1:2}$. However, surprisingly, there was no correlation between an individual's $Ratio_{1:2}$ and TTE for the 88% $\dot{V}O_{2max}$ prescription method. This was an unexpected finding considering the relationship between $\%\dot{V}O_{2max}$ at LT and TTE when prescribed as 88% $\dot{V}O_{2max}$. Upon further examination of the data however, there is no correlation between an individual's $Ratio_{1:2}$ and $\%\dot{V}O_{2max}$ at LT(r=0.14; P>0.05) and therefore, they appear to be determined by two different mechanisms.

Similar to this study's findings, recently published research has demonstrated a reduction in the variability of physiological, perceptual and training responses, when a 'threshold model' was used instead of a $\%\dot{V}O_{2max}$ method (Lansley et al., 2011; Wolpern et al., 2015). While a threshold model offers a useful alternative to the $\%\dot{V}O_{2max}$ prescription, there are a number of limitations to the calculations of this measure. For instance, the methods and terminology used to determine LT and ventilatory threshold are inconsistent and can be confusing (Mann et al., 2013). Moreover, a highly controlled testing environment is required to accurately determine an individual's threshold, and therefore limits the practical application of these measurements (Mann et al., 2013). The power law model might prove a more favourable option for applied sports practitioners and athletes, as reliable performance measurements can be collected both in the laboratory and the field (Karsten et al., 2015). Additionally, a strong correlation exists between predicted TTE (using the power law model) and actual TTE when exercise is prescribed as a $\%\dot{V}O_{2max}$ (Figure 6.3). The power law model was able to explain 90% of the variability in TTE when exercise was prescribed as a $\%\dot{V}O_{2max}$. This offers further support for the practical application of a power law model. As well as a method to prescribe exercise intensity a power law can also accurately predict TTE performance. Future research is needed to compare the power law to other prescription methods (e.g. LT, GET or ventilatory threshold) and determine the variability of TTE using each of these methods. In addition, research should investigate whether a power law prescription method reduces the variability observed in training responses.

In conclusion, using a power law model to prescribe exercise reduces the variability in TTE by 50%. However, some variability in TTE performances still exist and therefore warrants further investigation. For instance, factors such as intra-individual variability were not accounted for in this study, and are reported to have a CV as high as 17.3% based on previous research of a similar intensity (McLellan et al., 1995). Nevertheless, it does appear to be the case that the methods used to standardise exercise intensity explain some of the variability in TTE. Future research should examine whether training standardised using the power law model can reduce the known variability in training responses.

Chapter 7: General discussion

7.1 Summary.

A large inter-individual variability in the observed response to physical exercise is consistently reported (Bouchard et al., 1999; Coyle et al., 1988; Vollaard et al., 2009; Scharhag-Rosenberger et al., 2010; Scharhag-Rosenberger et al., 2012). To date, the majority of research has focused on the hypothesis that genetic factors contribute to this variability (e.g. Gaskill et al., 2001; Bouchard and Rankinen, 2001; Bouchard et al., 1999; Bray et al., 2009; Ehlert et al., 2013). Another, less investigated hypothesis is that this variability is also due to an inappropriate standardisation of exercise intensity or duration (Mann et al., 2013; Hopker and Passfield, 2014). Evidence to support this hypothesis stems largely from the individual variation often seen in training responses, as well as the individual differences in metabolic stress during an acute bout of exercise (Bouchard et al., 1999; Vollaard et al., 2009; Coyle et al., 1988; Scharhag-Rosenberger et al., 2010; Scharhag-Rosenberger et al., 2012). Such studies standardise exercise intensity as a %$\dot{V}O_{2max}$ despite the fact that this method fails to take into account an individual's full physiological profile (e.g. power at threshold) (Mann et al., 2013). Subsequently, alternative methods of prescribing exercise need to be examined in an attempt to elicit a more consistent stimulus across all individuals during exercise. Therefore, the overall aim of this thesis was to explore the basis, and investigate the effects of individualised methods of standardising exercise intensity and duration on TTE and training responses in cycling.

The first experimental chapter (Chapter 3) of this thesis compared the two most common methods used to measure endurance performance: TTE and TT. The findings demonstrate that when TTE and TTs are matched for duration and no feedback is provided, mean power output is higher for the TTE trial at 80%, but not 100% and 105% MAP. This in turn meant that CP calculated from the TTE trials was higher than that from the TT. The second experimental chapter (Chapter 4) investigated the effects of three training intensities (MOD, HIT, and MIX) on performance and physiological adaptations when the duration of training was individualised. Four weeks of MOD, HIT or MIX training improved $\dot{V}O_{2max}$, MAP, GE at 50% MAP (for MOD and MIX) and TTE, but there were no differences between groups. GE at 50% MAP demonstrated the greatest increase after MIX training, though this was not statistically different from the MOD and HIT groups. Furthermore, there was a large inter-individual variability in physiological training responses ($\dot{V}O_{2max}$ and GE), but a consistent improvement in performance across all intensity groups when the duration of training was tailored to each individual (97% responders; 3% non-responders). The final two experimental chapters (Chapters 5 and 6) examined the hypothesis that a power law mathematical model would predict TTE across a wide range of exercise intensities and reduce the variability in TTE. A power law was able to accurately describe and predict TTE for intensities between 60-150% MAP. In addition, when exercise intensity was prescribed based on an individual's power-duration relationship (using a power law model) a 50% reduction in the variability of TTE performances was observed when compared to the %$\dot{V}O_{2max}$ prescription method.

7.2 TTE trials to assess endurance performance.

Researchers and sport scientists commonly use information gathered from TTE trials to monitor and detect changes in endurance performance (Currell and Jeukendrup, 2008). In addition, TTE trials are used to determine an individual's power-duration relationship, and subsequently calculate CP and W′ parameters, as well as predict future performances (Derkele et al., 2008; Hill, 1993). While the measurement error is considerably higher for TTE compared to TT, the 'signal-to-noise' ratio (change in performance divided by the error of measurement) is found to be similar (Amann et al., 2008). Chapter 4 is one of few studies to directly compare TTE and TT performances (Ham and Knez, 2009; Thomas et al., 2012). In addition, the absence of feedback in an attempt to standardise the comparisons between TTE and TT has not been examined previously. The main finding from this study was that the mean power output was higher in the TTE compared to TT at 80%, but not at 100% and 105% MAP. Consequently, calculated CP was higher when derived from the TTE trials compared to the TT, whereas, W′ was lower. Upon examination of the individual performances for both the TTE and TT, it is evident that the participants consistently sustained a higher mean power output for the TTE compared to TT at 80% MAP (Figure 7.1). Only one participant was found to sustain a 1 W lower mean power output for the TTE compared to the TT. The higher mean power output consistently observed for TTE at 80% provides further evidence that TTE should not be disregarded as a measure of endurance performance in the laboratory (Laursen et al., 2007; Amann et al., 2008).

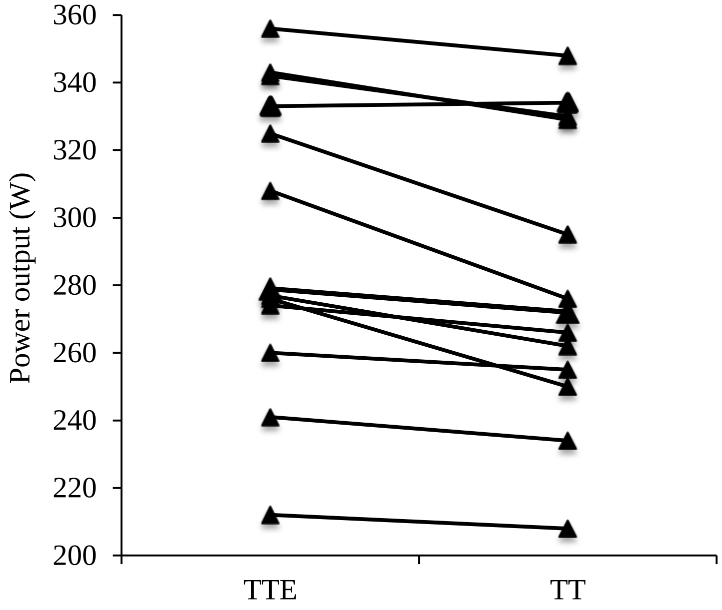

Figure 7.1. Individual mean power output sustained for TTE versus TT performances at 80% MAP. * Significant difference between trials; *P*<0.05.

It should not be overlooked that factors such as pacing (Foster et al., 1993; Atkinson et al., 2003) and the absence of feedback (Marcora et al., 2010; Jones et al., 2013) may have influenced the findings of this comparison. Figure 3.2 in Chapter 3 presents the mean power output sustained for each decile (10%) for both TTE and TT performances. From figure 3.2 it is evident that participants may have misjudged their pacing strategy for the TT at 80% MAP. In comparison, for the TTE at 80% MAP, participants are seen to adopt a higher mean power output initially in the TT. This fast start appears to result in a progressive decline in power output throughout the TT, leading to a decrease in overall average power sustained. It is unclear whether the absence of feedback led to this reduction in power output. Nevertheless, taking into account the important role feedback has on performance outcomes (Marcora et al., 2010; Faulkner et al., 2011), this suggestion seems valid. These factors therefore need to be considered when deciding on the most appropriate performance test to use. Although it should be noted that pacing and the absence of feedback does not appear to have influenced performances for intensities at or above 100% MAP (Figure 3.3, A and B in Chapter 3).

TTE trials are traditionally used to examine the power-duration relationship in cycling (Hill, 1993; Derkele et al., 2008; Jones et al., 2010). Although, more recently, TT type performance tests have also been used in the field (Karsten et al., 2015; Quod et al., 2010).

Some argue that TTs are more ecologically valid as they more closely simulating a race event or a training session allowing individuals to vary their exercise intensity throughout (Hopkins et al., 2001; Jeukendrup et al., 1996). However, others argue that TTE are still of practical use, particularly when investigating physiological responses where a fixed power output is important (Laursen et al., 2007; Amann et al., 2008). Mean calculated CP was higher when derived from TTE compared to TT performances. Whereas, mean calculated W′ was lower for TTE compared to TT performances. Figure 7.2 presents the individual calculated CP and W′ parameters derived from the TTE and TT performances using the Linear-P CP model. As evident from the figure a consistently higher CP and a lower W′ is evident for most participants (Figure 7.2). Therefore, it appears to be the case that CP and W' are inversely related and highly sensitive to the test protocol employed. These findings add to previous research that has found CP to be sensitive to changes in cadence (~ 6% difference between 60 rpm vs. 100 rpm) as well as the type of CP model used (Bull et al., 2000). CP is considered a useful parameter to help athletes to set appropriate pacing strategies and predict performances (Jones et al., 2010). Additionally, W′ is considered a mechanical measure of the finite work capacity that an individual can perform above their calculated CP (Jones et al., 2010), and has been used to prescribe HIT sessions alongside CP (Pettitt et al., 2015). Nevertheless, Vanhatalo et al. (2011) propose that an increase in CP and reduction in W′ will result in an improvement in endurance performance. Whereas, an increase in W′ is only related to an improvement in high-intensity, short duration performances (Vanhatalo et al., 2011). Consequently, it is important that researchers adopt a test protocol that maximises mean power output when determining CP.

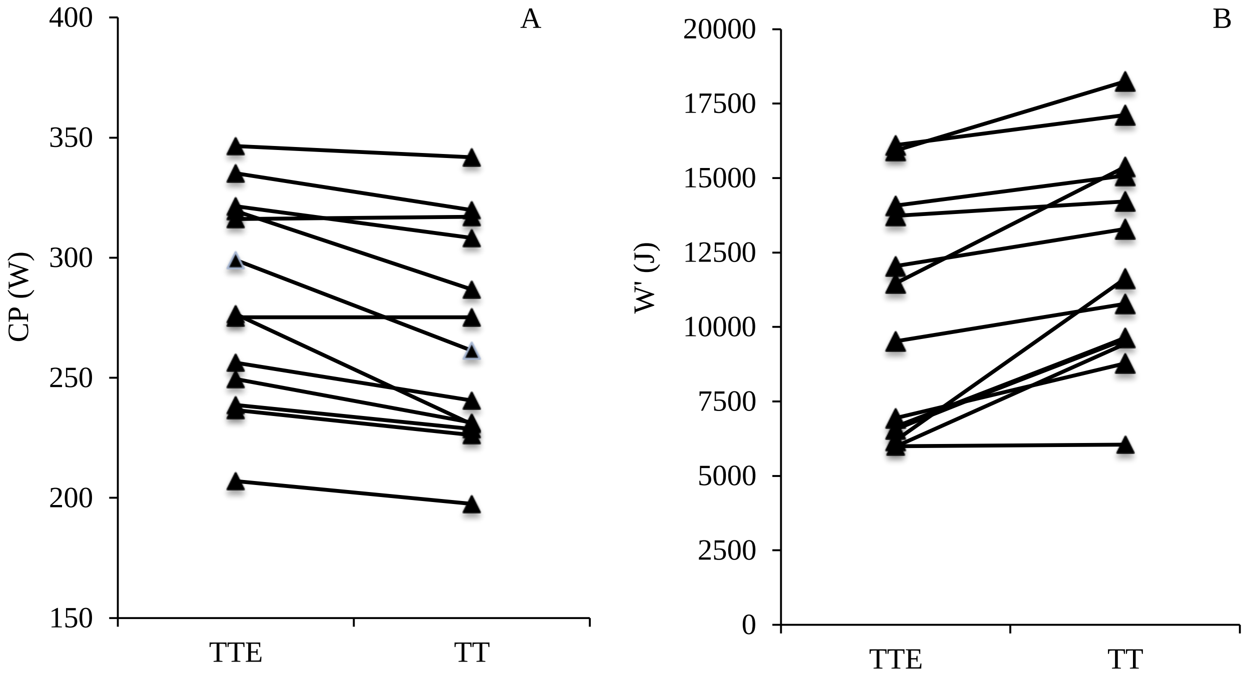

Figure 7.2. Individual calculated CP (A) and W′ (B) parameters for the Linear-P CP model derived from TTE and TT performances.

7.2.1 Inter-individual variability at different exercise intensities

A consistent observation and theme throughout this thesis, is the large inter-individual variability in TTE performances when exercise intensity is standardised as a %MAP or %$\dot{V}O_{2max}$. This was particularly noticeable in Chapter 6 where participants completed nine TTE trials on separate occasions at intensities that ranged from 60-200% MAP (Table 7.1). Table 7.1 presents the mean inter-individual variability for TTE performances. It is evident from the results that the CV for TTE is much lower at the upper intensities compared to the lower intensities. Coyle et al. (1988) previously highlighted this variability in TTE when exercise intensity was set at 88% $\dot{V}O_{2max}$ (Coyle et al., 1988). However, the magnitude of this variability when examining a range of different exercise intensities has not been previously reported. Instead the majority of research has focused on the intra-individual variability for TTE (for review see Currell and Jeukendrup, 2008). Nevertheless, it is not surprising that the findings from these studies demonstrate a similar pattern of variability to that observed in Chapter 6 and presented in Table 7.1. For example, previous research has reported that for intensities at or above $\dot{V}O_{2max}$, the intra-individual variability is much lower (typically 1.7-17% CV), than for intensities below $\dot{V}O_{2max}$ (typically 5.6-55.9% CV) (Gleser and Vogal, 1971;

Maughan et al., 1989; McLellan et al., 1995; Jeukendrup et al., 1996; Laursen et al., 2007; Coggan and Costill, 1984; Graham and McLellan, 1989; Lindsay et al., 1996). An understanding of the intra-individual variability of TTE performances has allowed researchers to determine if a meaningful change has occurred following an intervention (Currell and Jeukendrup, 2008). On the other hand, the impact of the inter-individual variability of TTE performances on training responses is less well understood, and may contribute greatly to the variability in training responses frequently observed (Bouchard et al., 1999; Vollaard et al., 2009; Scharhag-Rosenberger et al., 2012). It is important therefore, that researchers not only account for the intra-individual variability in TTE, but also recognise the magnitude of the inter-individual variability. This is particularly important when prescribing training at lower exercise intensities. Furthermore, the CVs reported in Table 7.1 provide further support that exercise should not be standardised as a % of maximum if the overall aim is to produce a consistent exercise stimulus for all participants.

Table 7.1: Mean (± SD and CV) TTE performances when set at intensities between 60-200% MAP. The minimum and maximum performances for the group are also reported (*n*=15). Data are presented from findings in Chapter 6. *n*=15 except for the 60% and 65% intensities, which have *n*=6 and *n*=9 participants respectively.

% MAP	Mean ± SD	Min (s)	Max (s)	CV (%)
60	1575 ± 626	852	2470	40
65	2963 ± 1248	1529	4821	42
70	1652 ± 721	612	2866	44
80	610 ± 208	348	1081	34
85	484 ± 106	325	765	22
90	370 ± 86	245	498	23
100	224 ± 42	147	299	19
110	165 ± 27	110	211	17
150	62 ± 16	32	83	26
200	31 ± 5	20	38	18

7.3 Methodological and practical benefits of using a power law model

7.3.1 A power law describes and predicts endurance performance.

An understanding of the power-duration relationship provides coaches and sport scientists with an informative, practical tool to predict and monitor endurance performance. Since 1906, physiologists have used a number of mathematical models to describe this relationship (Kennelly, 1906; Monod and Scherrer, 1965; Moritoni et al., 1981; Jones et al., 2010). Nevertheless, the CP model is the most common mathematical model used to date in cycling (Monod and Scherrer, 1965; Jones et al., 2010). Previous research has demonstrated the practical benefits of using this model across a wide range of sports (Hill, 1993; Jones et al., 2010). In particular a CP model is used for setting appropriate pacing strategies and calculating aerobic and anaerobic parameters of endurance performance (Hill, 1993; Pringle and Jones, 2002). Research has also reported a good reliability for the calculation of CP in both laboratory and field settings (Karsten et al., 2015) and is correlated with an individual's maximal lactate steady state (Pringle and Jones, 2002). However, there are a number of limitations to this model, such as the model's inability to extrapolate outside the 2 to 20-min range and its assumption that below CP one can sustain exercise intensity for an infinite amount of time (Vanhatalo et al., 2011). Chapter 6 investigated the hypothesis that an alternative model (a power law) would more accurately predict and describe endurance performances outside the typical durations used to determine CP (>2-min to <20-min). This hypothesis was based on evidence demonstrating that a power law model has a strong fit for performance data across a wide range of durations in athletics (Kennelly, 1906; Francis, 1943; Monod and Scherrer, 1965; Katz and Katz, 1999). Previous research has examined the predictive ability of a power law model, but only for a narrow range of durations or distances (e.g. 200-400 m distance in swimming and 1-10 min range in running) (Osiecki et al., 2014; Hinckson and Hopkins, 2005). Additionally, the ability of a power law model to predict endurance performance for cycling has not previously been examined. The findings in Chapter 6 demonstrate that the power law model could reliably predict TTE for intensities ranging between 60-150% MAP (~ 1 to 41-min). While the CP model was able to accurately predict TTE for intensities between 70-110% MAP (~ 2 to 27-min), it overestimated TTE at 60%, 150% and 200% MAP. Therefore, it was concluded that the power law and CP model accurately describes and predicts endurance performance within a narrow range of intensities (>70% to <150% MAP). Outside of this range, however, a power law model should be used for a more accurate prediction of longer and shorter endurance performances. More research is needed to determine if a power law model can predict performances >40-min and if it can be applied to other sports. We know from previous research that a power law model fits the data closely for world record athletic distances between 100 m to a marathon (Grubb, 1997). Therefore, it is expected that its ability to predict performances would be as good up to this distance. If this were the case, it would provide sport scientists and researchers a more reliable model to predict endurance performance across a much wider range of durations, compared to the CP model. A power law model may also be of use for predicting a sub 2 h marathon record (Joyner et al., 2011; Hunter et al., 2015).

7.3.2 A power law reduces the variability in TTE.

As well as accurately predicting TTE performances, Chapter 6 demonstrates that a power law model can reduce the inter-individual variability in TTE by up to 50% when compared to the traditional %$\dot{V}O_{2max}$ prescription method. This provides evidence that the methods used to standardise exercise intensity contribute to the inter-individual variability in TTE performances. This is an important finding considering the large variability in metabolic and training responses frequently reported when exercise is standardised as a %$\dot{V}O_{2max}$ (e.g. Vollaard et al., 2009; Scharhag-Rosenberger et al., 2010; McPhee et al., 2010). Thus, the power law model is a simple, non-invasive and practical alternative that researchers and applied practitioners can use to prescribe exercise intensity. More research is needed to determine if a power law prescription can reduce the variability in subsequent training responses that are frequently observed (Bouchard et al., 1999; Vollaard et al., 2009). Wolpern et al. (2015) recently demonstrated a reduction in training response variability when a threshold model (based on the first and second ventilatory threshold) was used to prescribe exercise compared to a %HRR method. They reported a more consistent increase in $\dot{V}O_{2max}$ response when training was prescribed using a threshold method (100% responders) compared to a %HRR (41.7% responders; 58.3% non-responders) (Wolpern et al., 2015). Therefore, it is anticipated that a power law prescription method would demonstrate a similar consistency in the training responses to that found when using a threshold method; this warrants further investigation.

A power law model also demonstrated a strong correlation between predicted TTE and actual TTE when prescribed as a $\%\dot{V}O_{2max}$ (r = 0.95). Therefore, from the raw data collected in Chapter 6, it is possible to predict participants TTE performances, if exercise was prescribed using other prescription methods e.g. %CP, % LT, %OBLA and %MAP (Table 7.2). To do this, the same methods as described in Chapter 6 (Figure 6.1) were used, but this time relating the power output predicted from the 20-min power law to a % of CP, LT, OBLA, MAP and single-leg $\dot{V}O_{2peak}$. A power law model was then used to predict by extrapolation, participants expected TTE for each of these methods (Table 7.2). Table 7.2 reports the mean predicted TTE for the 16 participants as well as the predicted SD and CV. An F-distribution test was used to determine if the predicted variances in TTE were significantly different from the actual variances in TTE when prescribed using a power law. The results suggest that no differences in the inter-individual variability for TTE would be observed if exercise was prescribed as a %CP, %OBLA or using a power law model. Alternatively, when prescribed as a %MAP or %LT, the inter-individual variability for TTE performances is expected to be significantly more variable when compared to a power law method. This variability is similar to that already found when exercise was prescribed as a $\%\dot{V}O_{2max}$. Surprisingly, the %LT method demonstrated a high inter-individual variability for predicted TTE performances. Although the predicted mean TTE is much higher for this prescription method (1553 s) compared to the others, which may explain some of this variability. However, this warrants further investigation. Nevertheless, these predictions provide further evidence that the traditional $\%\dot{V}O_{2max}$ and %MAP methods should be avoided when prescribing exercise, in particular if the aim is to elicit a consistent exercise stimulus for all participants. Sport scientists and researchers should instead aim to provide a training stimulus that produces a defined metabolic strain across all athletes and thus produces predictable adaptive responses (Scharhag-Rosenberger et al., 2010). Future research should compare the power law prescription method to a %CP or %OBLA to determine which method produces the most consistent exercise stress stimulus and training response.

Table 7.2: Predicted TTE, and CV if exercise was prescribed as a %CP, %OBLA or %MAP, in comparison to actual TTE performances when prescribed using a power law method. * Significantly greater CV when compared to the power law prescription method.

Predicted performance	Power output (W)	TTE (s)	TTE CV
99% CP	276 ± 36	1250 ± 319	26
128% LT	276 ± 34	1533 ± 1259	82 *
111% OBLA	276 ± 36	1302 ± 458	35
78% MAP	275 ± 29	1388 ± 673	48 *
138% Single-leg MAP	276 ± 32	1595 ± 1357	85 *
Actual performance	**Power output (W)**	**TTE (s)**	**TTE CV**
88% $\dot{V}O_{2max}$	278 ± 37	1130 ± 677	60 *
20-min Power law	275 ± 39	1113 ± 330	30

7.4 Is there an optimal training intensity when training is individualised?

Numerous studies have examined the physiological and performance benefits of MOD, HIT (Gormley et al., 2008; Helgerud et al., 2007; Burgomaster et al., 2008; Gibala et al., 2006; Rodas et al, 2000; Bacon et al., 2013), and more recently polarised training intensities (Neal et al., 2011; Manzi et al., 2009; Laursen, 2010). Findings are inconsistent between studies, in particular when direct comparisons are made between MOD and HIT (Gormley et al., 2008; Helgerud et al., 2007; Burgomaster et al., 2008; Gibala et al., 2006). It was hypothesised that this was due to the methods used to standardise training duration. For example, in some instances where MOD and HIT, training are matched for energy expenditure or training duration it might be the case that MOD group were not provided with a sufficient training stimulus (e.g. Gormley et al., 2008). Therefore, an individualised approach to training duration was expected to better identify if there were any differences in the physiological and performance adaptations that occur with different training intensities. Chapter 5 examined the effects of MOD, HIT, and MIX training on physiological and performance responses when the training duration was individualised. This was expected to induce a maximum training benefit for all participants regardless of the exercise intensity they were exposed to. The main finding from this study was that when training was distributed in this way similar physiological and performance benefits were found for all training intensity groups. These findings are consistent with that of

Burgomaster et al. (2008) and Gibala et al. (2006) who compared MOD and HIT training, but fixed the duration of training. The considerably lower time spent exercising at HIT compared to MOD (~80%) or MIX (~63%) adds further support for the contention that HIT exercise is a time efficient training strategy (Gibala et al., 2006). In addition, the differences between the exercise intensities is lost when training is organised in this manner as individualised training ensures participants gain a maximum benefit from the training and are not just training for a specified amount of time.

It is difficult to determine whether any additional benefits from training were a result of individualised training durations without the inclusion of a control group. However, based on a similar analysis previously used by other researchers (Scharhag-Rosenberger et al., 2012; Wolpern et al., 2015) responders and non-responders for physiological and performance adaptations were identified (Table 4.4, Chapter 4). From Table 4.4 in Chapter 4 of this thesis it is evident that there was a large inter-individual variability in physiological responses e.g. $\dot{V}O_{2max}$ and GE. In addition, two notable observations are apparent from the data. Firstly, there appears to be a reduction in the number of non-responders observed for improvements in $\dot{V}O_{2max}$ following individualised HIT training (17%), compared to individualised MOD (46%) and MIX (46%) training (Figure 7.3). The individual magnitudes of the $\dot{V}O_{2max}$ training adaptations are presented in Figure 7.3. As evident from Figure 7.3 (B), the participants who completed the HIT training appear to show greater increases in $\dot{V}O_{2max}$ and a greater number of responders. However, this was not statistically significant when compared to the other training groups. These findings are in agreement with Bacon et al (2013) who reported that HIT training demonstrates greater increases in $\dot{V}O_{2max}$ compared to endurance type training. A second observation was the consistent improvement in TTE performances for all training groups, despite differences in training intensity. Figure 7.4 below presents the individual TTE performances before and after training for a cohort of 34 participants, with only one participant in the HIT group demonstrating a non-response to training (Table 4.4. and Figure 7.4). This is an interesting finding given that majority of research focuses on the individual changes in $\dot{V}O_{2max}$ as a parameter to demonstrate a training effect (Bouchard et al., 1999). It also further highlights the importance of training studies measuring endurance performance as well as physiological adaptations, as an improvement in performance is the ultimate aim for athletes.

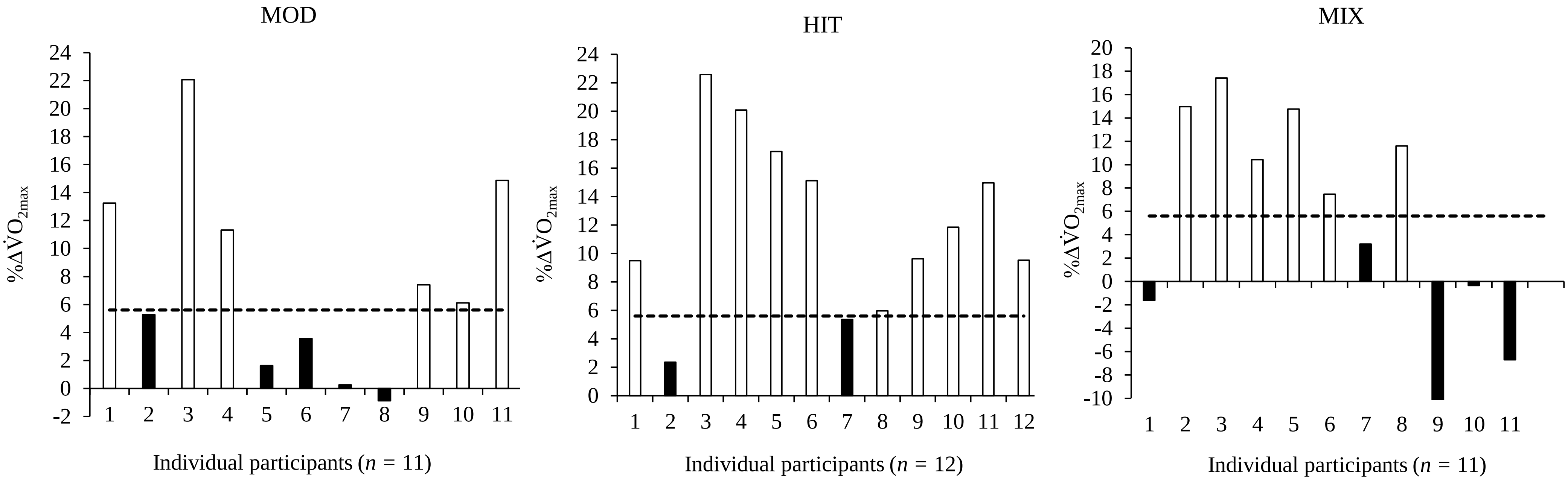

Figure 7.3. Individual $\%\Delta\dot{V}O_{2max}$ after MOD, HIT or MIX training. Responders (white bars) are categorised as an improvement greater than 5.6% and non-responders (black bars) are categorised as a decrease or improvement no greater than 5.6%. (*n*=34). The dashed line represents a 5.6% $\Delta\dot{V}O_{2max}$.

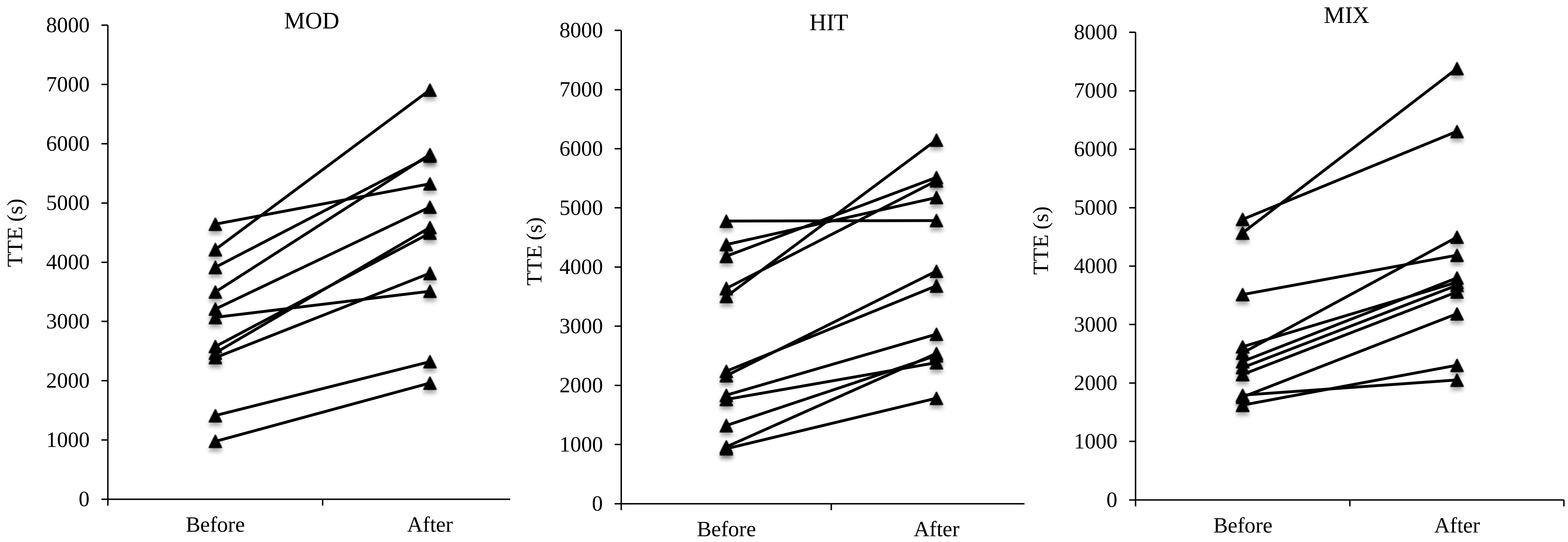

Figure 7.4: TTE performances before and after training for the MOD, HIT, and MIX group (n=34).

In scientific literature, an increase in $\dot{V}O_{2max}$ is frequently used to demonstrate a training effect (Bouchard et al., 1999; Hickson et al., 1977; Helgerud et al., 2007; Gormley et al., 2008; Midgley et al., 2006). This has led researchers to examine the effects of different training strategies on the improvement in $\dot{V}O_{2max}$, with some demonstrating large increases following standardised training interventions (Hickson et al., 1977; Rodas et al., 2000). While the study in Chapter 5 of this thesis demonstrated significant increases in $\dot{V}O_{2max}$ after 4-weeks of training, this was not different between intensity groups. In addition, the magnitude of the increase in $\dot{V}O_{2max}$ was not as large as some other studies have reported (Hickson et al., 1977; Rodas et al., 2000). For example, Hickson et al. (1977) and Rodas et al. (2000) reported $\dot{V}O_{2max}$ increases of approximately 4.4% and 5% per week following MIX and HIT training respectively. Data from the training study in Chapter 5 demonstrate an increase in $\dot{V}O_{2max}$ corresponding to approximately 2.5%, 3% and 2% per week with MOD, HIT and MIX training respectively was observed. That this study did not demonstrate as large an increase in $\dot{V}O_{2max}$ as previous studies (Hickson et al., 1977; Rodas et al., 2000) might be explained by the high number of training sessions (6-7 sessions per week) prescribed in previous studies. Comparisons of the relationship between $\%\Delta\dot{V}O_{2max}$ versus the number of training sessions were presented in Chapter 2 of this thesis (Figure 2.4). This analysis of 40 published studies demonstrated a greater increase in $\dot{V}O_{2max}$ with a greater number of training sessions. This finding warrants further investigation, in particular as it contradicts previous studies that were designed specifically to examine the influence of training frequency on training responses (Hatle et al., 2014; Pollock et al., 1975). Therefore, future research should examine the longitudinal training adaptations for $\dot{V}O_{2max}$ (>10 weeks) following different exercise intensities with a greater number of sessions per week and an individualised training duration.

7.5. Relationship between GE, single-leg VO_{2peak} and endurance performance

The findings in Chapter 4 demonstrate a strong positive correlation between the %Δ GE at 50% MAP and %Δ TTE after training in recreationally active participants. From the results presented in Figure 4.3 it is evident that those individuals who demonstrated the greatest increase in GE following training also had the greatest increase in TTE performances. This finding adds to previous research that has reported a high GE to be associated with a higher power output sustained during a 1 h cycling TT in trained cyclists (Horowitz et al., 1994; Jobson et al., 2012). It was also interesting to note that while there was a correlation between %ΔGE and %ΔTTE performance, there was no correlation between %Δ$\dot{V}O_{2max}$ and TTE performances. This finding is consistent with that of Vollaard et al. (2009). More research is needed to gain a greater understanding of the relationship between physiological parameters and endurance performances tests (TTE and TT) in both trained and untrained individuals.

A relationship between the $Ratio_{1:2}$ and TTE performances when prescribed using a power-law was also observed in Chapter 6. It appears to be the case that prescribing exercise intensity using a power law accounts for individual differences in metabolic stress, but not differences in the ratio of single to double leg $\dot{V}O_{2max}$. Furthermore, there was no relationship between %$\dot{V}O_{2max}$ at LT and $Ratio_{1:2}$, suggesting that different mechanisms are responsible for these two measurements. Additionally, $Ratio_{1:2}$ explained 33% of the variability in TTE performances when prescribed using a power law model.

7.6. Practical messages and applications in the field

- The type of performance test (TTE vs. TT) used to derive CP and W′ can significantly alter these parameter estimates.

- When training is individualised to an individual's maximum performance capability, it does not appear to matter what training intensity they are exposed to when the aim is to improve endurance performance.

- An increase in GE appears to be more closely related to improvements in endurance performance than $\dot{V}O_{2max}$. Therefore, researchers and coaches should focus on training strategies that optimise GE as opposed to $\dot{V}O_{2max}$. The findings of this thesis suggest that GE results in greater improvements following MIX training as opposed to MOD or HIT.

- Coaches and applied practitioners can use either a CP or power law model to accurately predict cycling TTE performances between 2 and 27-min. For durations outside of this range a power law model should be used. This model reliably predicts TTE performances for durations between 1 and 41-min, with the potential of predicting a much wider range of performances.

- A power law model can be used to prescribe exercise intensity. This model elicits a more consistent exercise stimulus across individuals, compared to a traditional $\%\dot{V}O_{2max}$ prescription method, when used to prescribe an acute bout of exercise. This model will help coaches optimise their training prescription methods.

7.7. Future directions

The findings of this study highlight a number of key areas that warrant further investigation. Firstly, it is evident from Chapter 5 that a power law model accurately predicts TTE performances for intensities between 60-150% MAP (~ 1-41-min). However, further investigation is needed to determine if it is possible to predict cycling TTE performances >40-min, and whether this model can be used in a field setting. Additionally, it is unclear whether any physiological parameters can be derived from this model, similar to that of a CP model.

Secondly, a power law prescription method reduces the inter-individual variability in TTE performances. Whether this finding translates to more consistent training responses is yet to be investigated. Future research should therefore use a power law model to prescribe exercise, comparing it to other methods such as the %CP, %OBLA. A more consistent exercise stimulus would enable athletes to enhance their performance with more focused training and perhaps produce a more predictable training response.

8.4. Conclusions

The results of this thesis provide evidence that the inter-individual variability in TTE performances are partly related to the methods used to standardise exercise intensity. By using a power law model the variability in TTE performances can be reduced when compared to a $\%\dot{V}O_{2max}$ method that is more commonly used by researchers to date. More research is needed to investigate whether a similar reduction in training response variability can be achieved when using a power law model to standardise exercise intensity. A more standardised exercise prescription method may help to further our understanding of the concept of responders and non-responders to training.

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