**THE UNIVERSITY OF WINCHESTER**

Faculty of Health & Wellbeing

# Intra-individual movement variability in cycling

Chris Whittle

ORCID number: 0000-0002-0373-4910

Doctor of Philosophy

June 2023

This thesis has been completed as a requirement for a

postgraduate research degree of the University of Winchester

**Declaration:**

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

I confirm that this thesis is entirely my own work.

I confirm that no work previously submitted for credit has been reused verbatim. Any previously submitted work has been revised, developed and recontextualised relevant to the thesis.

I confirm that Studies 2 and 3 in the thesis (pages 85-104) have been published in advance of its submission and appropriately referenced in the text.

I confirm that no third-party proof-reading or editing has been used in this thesis.

## ACKNOWLEDGEMENTS

First and foremost, my thanks go to Simon and Neal. I hate to think how many hours you have both put in to support me through the entire PhD process. Without your guidance and input I doubt I would have even got past the initial idea of "doing something in cycling". Your shared knowledge has made for a fantastic supervisor team and I feel very lucky to have had such a balance of expertise at my disposal. I am only sorry that it has taken so long to get to stage and hope that any projects we share in the future won't take the best part of a decade to complete!

Secondly, the support from my academic colleagues throughout has been invaluable. Whether that was blind leading the blind conversations with Amy, time saving MatLab knowledge from David, the very supportive upgrade Viva provided by Hazel or just general encouragement from the wider department (and beyond), I appreciate all of it.

Finally, and probably most importantly, I want to acknowledge the endless patience shown by my family and friends. You have probably had it the worst. You have listened to me constantly moan about tiny little details of a seemingly endless project which you have managed to somehow maintain at least a superficial level of interest in for eight long years! Don't worry, I won't force you to read it. I will force you to come to the pub with me though.

For anyone reading this as part of their own PhD journey, I was once told that a PhD is not a mark of intelligence, it is a sign of perseverance. I can highly recommend the benefits of getting a bike and losing yourself in a ride for a couple of hours. It often gave me the head space I needed to persevere and without my bikes I don't think I would have got this far. Cheers Steve.

# Abstract

UNIVERSITY OF WINCHESTER

ABSTRACT

Intra-individual movement variability in cycling

Chris Whittle

ORCID number: 0000-0002-0373-4910

Doctor of Philosophy

February 2023

Movement variability within repeated performances of the same sporting skill has long been considered evidence of poor motor control and seen as detrimental to overall performance. Changing attitudes and improved measurement technology have led to the suggestion that this may not be true. Instead, it has been suggested that movement variability may play a functional role by allowing athletes to adapt their technique to better match the changing combinations of task constraints which can be encountered in a dynamic performance environment. To investigate whether this is the case during cycling, Study 1 of this thesis assessed the amount of variability in sagittal plane joint kinematics displayed by cyclists of differing skill levels during a simulated time trial event indoors. The lack of relationship between skill level and amount of movement variability shown here was attributed to too few task perturbations in a laboratory environment and therefore investigations were moved to a field setting.

Before field testing could be undertaken, the validity of power measuring pedals (Study 2), electro-goniometers (Study 3), a wearable inertial measurement suit (Study 4) and individual inertial measurement units (Study 5) was investigated in order to provide suitable methods of data collection for an outdoor kinematic investigation.

Study 6 investigated the variability of sagittal plane joint kinematics during outdoor time trial performance and revealed that there is a statistically significant strong negative linear relationship between a cyclist's skill level and the amount of movement variability they display. More experienced cyclists displayed significantly greater levels of movement variability than their less experienced counterparts at both the Hip-Knee and Knee-Ankle joint couplings and this was related to faster overall finishing times for the time trial event.

Following these findings, Study 7 began investigations into the underlying muscular recruitment patterns which may be driving the variable movement patterns displayed during cycling. Little evidence was seen for an established relationship between the level of variability of muscular recruitment employed by participants and the performance outcome during indoor simulated time trials on a cycle ergometer. This, again, was attributed to a lack of task perturbations in a laboratory environment and therefore future investigations in a more ecologically valid setting are recommended.

**List of Contents**

## LIST OF FIGURES

**LIST OF TABLES**

## i. COVID-19 STATEMENT

Before introducing the focus of this thesis, it is important to acknowledge the impact that the global COVID-19 pandemic had upon its completion.

At the start of 2020, reports of a novel virus emerged from Wuhan, China. This was swiftly followed by the UK government publishing the first coronavirus guidance page on GOV.UK on the 24th of January and the first two confirmed cases in the UK on the 30th of January (Wright, 2021).

By the 5th of March 2020 the first UK death from COVID-19 was confirmed (BBC News, 2020) and global cases passed 100,000 on the 7th (*WHO Statement on Cases of COVID-19 Surpassing 100 000*, 2020). The exponential growth of infection numbers led to national lockdown restrictions coming into force on the on the 26th of March 2020 (Queen's Printer of Acts of Parliament, n.d.) essentially forcing all University of Winchester facilities to close.

At this time, I was conducting data collection for a goniometer-based validity paper (Study 3), which needed to be completed in order to validate the equipment before potentially using it in the following outdoor investigation. This, coupled with the fact that as a full-time member of staff I was also trying to contend with the increased workload created by the wholesale shift to online only delivery of taught content on a highly practical degree course, meant that data collection essentially ceased until all restrictions were lifted on the 18th of July 2021 (Brown and Kirk-Wade, 2021).

Despite restrictions being lifted, the effects of the pandemic continued and were still very obvious when trying to conduct the final kinematic study for this thesis (Study 6). Due to the fact that this study required almost exclusively field testing it was not appropriate to conduct data collection in the winter months for a number of reasons.

Firstly, while investigating intra-individual movement variability it was important that all participants complete their testing events in, as close as possible, matching weather conditions. This would have been far more difficult to achieve in the winter months as not only are weather conditions more variable, but it was also likely that fewer participants will be willing to undertake outdoor testing sessions in sub-par weather conditions.

Additionally, the outdoor investigation was ideally designed to recruit participants who were in "in season" form in order to get a true representation of their physical capabilities. The widespread disruption predicated by the pandemic led to the wholesale cancellation of competitive cycling events for 2020 and 2021, which would normally run from late spring through the summer months.

The result being that participants were far less likely to accurately replicate their competition level capabilities had they undergone testing immediately after the restrictions were lifted.

Due to the time constraints of the PhD registration period, and despite the concerns outlined above, the outdoor data collection was eventually conducted between October 2021 and July 2022 in a format that was somewhat scaled back from what had originally been planned. The original method featured three groups of cyclists, each featuring a minimum of 8 participants, in order to garner suitable levels of statistical power.

These three groups would have ideally been: 1) recreational cyclists who had never entered a competitive event or had limited cycling experience but were still able to complete the required 10 mile event; 2) experienced cyclists, typically cycling club members, who either spent significant time training each week or had entered a number of competitive events; and 3) elite competitive cyclists who had entered numerous competitive events, had a structured training regimen and/or made their living through cycling. It was felt that this might address some of the issues encountered during the indoor investigations where participants were, perhaps, not spread far enough along the performance spectrum to enable a true comparison of "novice" versus "experienced" cyclists (see Section 3.2.4 for more details about issues with participant groupings).

In actuality, outdoor data collection resulted in the recruitment of 11 participants (see Study 6 for details) and, although it is probably fair to say that both ends of the desired spectrum were represented in this sample, there were certainly not enough participants to group them in the way described above and provide any level of appropriate statistical power. This is something which could potentially be addressed in post-doctoral research but, as mentioned before, it was not possible to rectify given the time restrictions related to the period of registration.

## 1. INTRODUCTION

Cycling is a popular leisure activity across the globe with approximately 6.5 million people participating in cycling of some form in England alone (Statista, 2022). As with any leisure pastime, individuals are involved to varying degrees, ranging from simply commuting via bicycle to those who make a living by competing at an elite level, and a wide array of differing participation modes in between.

For those who participate at the competitive end of the cycling spectrum and want to improve performance, there is a vast array of published literature from which to draw (e.g. Gonzalez and Hull, 1989; Too, 1990; Coyle et al., 1991; Jeukendrup and Martin, 2001; Hopker and Jobson, 2012). One such publication which gained traction outside of the scientific community was the 2008 book by Malcom Gladwell entitled “Outliers”. This book introduced the “10,000-hour rule” which was quickly adopted by popular media as a way of explaining the complex interactions involved in skill development. This “rule” was based on earlier work by Ericsson, Roring and Nandagopal (2007), which reviewed published evidence suggesting that superior reproducible performance generally emerges only after extended periods of deliberate practice that result in adaptations to the participant’s physiological characteristics and cognitive mechanisms.

### 1.1 10,000 hours of sport

Despite Ericsson (2013) being openly critical about the overgeneralisation, misinterpretation and oversimplification of his findings, the “10,000 hours rule” gained a popular following, with some interpreting it to mean that achieving skill mastery was simply a matter of putting in significant practice hours. This easily digestible idea that 10,000 hours of practice will, almost automatically, result in elite status became a frequent topic of popular science writing to the point that Macnamara, Hambrick and Oswald (2014) were able to conduct a review of 9331 research papers about practice and skill acquisition with 88 of these papers specifically focussing on the amount of practice required. Their findings suggested that deliberate practice explained 26% of the variance in performance for games, 21% for music, 18% for sports, 4% for education, and less than 1% for professions. They therefore suggested that, although clearly important, deliberate practice is not the automatic route to success that the idea’s popular following would like to believe.

In defence of Gladwell, he did acknowledge that he hadn’t intended for the “rule” to be applied to sports or games and cited the example of chess where he “could play for 100 years and […] never be a grandmaster”. That being said, there may be mechanisms that explain the improvement in performance seen as a result of an extended period of focussed practice if Gladwell’s “rule” is considered using a relatively new perspective to investigate intra-individual movement variability.

## 1.2 Movement variability

Bartlett, Wheat and Robins (2007) identified that sports biomechanics has tended to assume that intra-individual variability in movement patterns is merely “noise” and an unimportant issue. They further suggested that this was based on researchers’ implicit assumption that movement patterns for skilled performers are invariant. This supports the suggestions of Davids, Glazier, Araújo and Bartlett (2003), Van Emmerick and Van Wegen (2000), Hamill, Van Emmerick, Heiderscheit, and Li (1999) and Newell and Corcos (1993) that movement variability has historically been considered to be either detrimental to normal function or purely evidence of random noise within the neuromuscular or measurement system. This has led to the hypothesis that this “noise” may result in an inability to convey consistent results and, therefore, that it should be discounted.

This assertion is not restricted to the field of sports science, however. For example, the majority of studies on motor learning (e.g., Konczak, Vander Velden, & Jaeger, 2009; Purtsi, Vihko, Kankaanpää & Havas, 2012) have emphasized decreased variation in performance as a hallmark of the learning process. In a similar fashion, increased variability has typically been associated with the performance decrements due to aging and disease (Kornatz, Christou and Enoka, 2005) and a decrease in efficiency (Padulo et al., 2023). Davids, Glazier, Araújo and Bartlett (2003), however, suggested that this approach to variability may not be appropriate. They instead proposed that variability in movement systems should be considered to be an essential element of normal, healthy function and that it may perform a functional role in helping individuals to adapt to the potentially changeable constraints of a given task. This agrees with work by Bradshaw et al. (2007) and Schot et al. (2002) who suggested that the true variation of the individual needs to be considered without the technological error in measurements. It is further supported by Van Emmerik, Hamill, and McDermott (2005) who emphasised that, whereas more traditional research has regarded variability as an indicator of poor motor performance, their research highlights that it may perform a more functional role.

Button, Davids and Schöellhorn (2006) and Bradshaw and Aisbett (2006) both suggested that variability in movement is important in many sport skills, particularly those that require adaptability of complex motor patterns within dynamic performance environments. They suggested that a more variable movement pattern during the execution phase of a sporting skill may enable greater adjustment for intrinsic factors, such as confidence and fatigue, and extrinsic factors, such as wind and temperature, which may influence an athlete’s performance. This changing perspective was further supported by Taylor, Landeo and Coogan (2014) who suggested that functional roles, including facilitating consistent movement outcomes and adapting to changeable task and environmental constraints, could be attributed to movement variability. In addition, Yang et al. (2018) showed elbow flexion variability and shoulder-elbow coordination variability were increased with fatigue during repeated task performance, but movement timing errors and endpoint spatial variability were mostly preserved. This led to a conclusion that increased variability with fatigue may play a role in preserving global task performance.

### 1.3 Dynamical systems theory

The idea of movement variability as a functional element of skill performance has its groundings in dynamical systems theory. Although originally developed as a way of mathematically modelling relatively simple systems, such as the two coupled variables in a double pendulum (De Bot, Lowie and Verspoor, 2007), when applied to a human being it becomes a model for interpreting complex systems based on a set of general principles (Thelen and Smith, 1994; Van Gelder, 1998; Shanker and King, 2002).

Dynamical systems theory aims to describe systems that are able to constantly adapt to the varying demands of a task (Williams, Davids, and Williams, 1999). This has clear links to areas of skill acquisition and motor control literature but has also developed to encompass elements of mathematics, physics, biology, psychology and chemistry, as well as the pioneering work of Russian physiologist and biomechanist, Nikolai Bernstein. Bernstein (1967) proposed that the human movement system is comprised of a large number of interacting components, all of which will combine to produce movement patterns through generic processes of self-organization and suggested that the fundamental task for movement systems is to go through "the process of mastering the redundant degrees of freedom".

The first application of Bernstein's theory was reported by Arutyun, Gurfinkwl and Mirskii (1968) when investigating the strategies employed in shooting by skilled and unskilled marksmen. Their findings suggested that, contrary to the traditional view, skilled performers actually displayed greater levels of movement variability than their unskilled counterparts. These results were replicated later by Scholz, Schöner and Latash (2000) who hypothesised that higher levels of variability in the shoulder and elbow joints complemented each other to allow the wrist (and therefore gun) to maintain a stable position. Greater movement variability was interpreted as contributing to success in the task as the same high levels of variability were not seen in the shoulder and elbow joints of unskilled shooters, with the consequence that the pistol position remained unstable and therefore performance was inhibited. These studies essentially confirmed

Bernstein’s (1967) anecdotal evidence of novices typically appearing stiff and experts moving in a more fluid, unconstrained manner. According to Bernstein’s theory this was because the novices had removed more than just the redundant degrees of freedom and were no longer able to adapt to the requirements of the task.

Another investigation, this time by Vereijken, Whiting and Newell (1992), also supported this difference between novice and expert athletes by explaining that, to become proficient in any skill, the learner must discover how best to coordinate their body movements in any situation. They suggested that, in the early stages of the acquisition of a movement skill, the complexity of the overall movement is reduced by an initial “freezing” of degrees of freedom, followed later in the learning process by the release of these degrees of freedom and their incorporation into a dynamic, controllable system.

The model of investigation conducted by Scholz, Schöner and Latash (2000) has since been adapted into a range of sport and exercise settings in order to challenge the traditional assumption of invariant movement patterns for skilled performers. In the early 2000s this included papers relating to Basketball (Miller, 2002; Button, Macloed, Sanders and Coleman, 2003 and Robins, Wheat, Irwin, and Bartlett, 2006), Triple jump (Wilson, Simpson, Van Emmerik and Hamill, 2008), Cricket fast bowling (Peterson, Pyne, Portus, Karppinen and Dawson, 2009), Golf (Knight, 2004; Bradshaw et al., 2009; Glazier, 2011; Langdown, Bridge, and Li, 2012 and Tucker, Anderson and Kenny, 2013) and Water Polo (Taylor, Landeo and Coogan, 2014).

A number of the examples shown above concluded that, from a dynamical systems perspective, variability may play a functional role in a number of ways. Far from being a marker of poor performance, the suggestion is that movement variability is a form of “essential noise” (Davis, Shuttleworth, Button, Renshaw and Glazier, 2004), which can perform a number of functional roles. These functional roles include enhancing postural control, aiding the exploration of stability boundaries, transitions between movement patterns and producing a more consistent sporting outcome despite the altering demands placed on the performer (Van Emmerik, Hamill and McDermott, 2005). This, in turn, should allow skilled performers to adapt their movement patterns to the changing constraints of a given task in order to produce a similar outcome despite altered conditions.

Despite this body of evidence, and the huge amounts of available literature focussing on any number of other elements within cycling (see Section 2.2), it is somewhat surprising that there appears to have been little research conducted in this sport using either the dynamical systems theory approach or with the aim of identifying the role of movement variability. Dynamical systems theory seems to be ideally suited to application within the continuous, multijoint nature of the cycling task (Hug, Drouet, Champoux, Couturier and Dorel, 2008) and, in addition, the ability to efficiently adapt pedalling technique to match the changing task perturbations which may be encountered throughout a prolonged cycling event seems like an inherently useful ability. Theoretically, a degree of movement variability could allow cyclists to better maintain consistent outcome measures (e.g. power output, velocity or event finishing time) throughout their performance. This fits nicely with the traditionally held view that "better" performers are more consistent and has been shown to be especially important if the task requires adaptability of complex motor patterns within dynamic performance environments (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006).

The interpretation of movement variability as a positive is conspicuously absent from the field of cycling, as is the use of dynamical systems theory to better understand the underlying motor control/learning processes at play. Therefore, the aim of this thesis is to investigate whether movement variability has a functional role to play within a number of aspects of cycling and if skilled performers are employing more variable movement strategies in the same way as has been suggested in other sports. Wilson et al. (2008) stated that a key component in analyses of movement variability should be exactly this: The examination of the role of variability within the system under investigation. They also suggested that determining whether this variability is beneficial is a difficult task, but it is hoped that this line of study will allow the author to challenge, once again, the traditional view that movement patterns for skilled performers are invariant.

If, as hypothesised, it is discovered that the cycling system (i.e. rider and bicycle) does benefit from a level of intra-individual movement variability, there are a number of possible applications. Firstly, it becomes evident that the 10,000 hours rule which gained such popularity could still be applicable to sport if improvement is judged by the cyclist having greater variability in their movement patterns, and therefore greater adaptability in their technique, rather than their ability to perform a single "correct" technique. From this perspective the 10,000 hours of focussed practice which Gladwell recommended becomes less about the time spent practicing and more about the range of conditions, settings, environmental factors and other perturbations that the athlete experiences during those hours. This, in turn, could be used to influence coaching practice/training approaches with the emphasis being removed from trying to develop a single "correct" technique and instead the focus being on experiencing as many combinations of task constraints as possible. This would reflect the findings of Knight (2004) who suggested that golfers may be able to develop a more reliable swing by exploring different movement patterns, rather that attempting to perform each swing with absolute invarience and Bradshaw, Maulder and Keogh (2007) who stated that it could be more beneficial to place athletes in a multitude of scenarios which offer a range of different task demands.

Applying the dynamical systems approach, as advocated by Davids, Glazier, Araujo and Bartlett (2003), could encourage those athletes who are capable, to develop a range of movement patterns and give them opportunity to learn a variety of possible solutions. This would promote coordinative adaptability (Bradshaw et al., 2009), which should allow them to produce a consistent performance outcome despite the variable conditions or demands. Indeed, there is a growing body of literature, for example Wu et al. (2012) and Moreno and Odoño (2015), advocating the use of variability in training from a motor learning perspective for exactly these reasons.

The second potential application of this PhD is in the area of Injury reduction/avoidance. Kurz, Sterigou, Buzzi and Georgoulis (2005) showed that movement variability may play a functional role in reducing injury through variable loading of the musculoskeletal features of the joint during gait. If it is proven that an amount of intra-individual movement variability can perform the same role during cycling as well as providing the flexibility to be able to adjust to changing environments (Bartlett et al. 2007), then this has implications for those participating in at all levels of the participation spectrum. For those cycling at the competitive end of the sport, a reduction in the occurrence of injuries should result in greater competitive performance and a more predictable adherence to training structures. For those engaging in cycling as a low impact mode of physical activity, and any associated exercise professionals, this would also suggest a level of confidence when trying to increase levels of activity as this can be done without concerns about variable movement patterns causing injuries.

## 1.4 Aims and Hypotheses

Despite evidence of kinetic, kinematic and electromyographic changes in cycling technique in response to differing task constraints (see section 2.3), there has been very limited investigation into the potentially functional role of this intra-individual movement variability within cycling events. With the exception of two published papers (Christiansen, Bradshaw and Wilson, 2008 and Sides and Wilson, 2012) this area has been overlooked in the published literature and, as such, represents a novel area of study for this thesis to explore.

As a result, the aim of this thesis was to answer the question of whether intra-individual movement variability may play a functional role in cycling performance by allowing cyclists to better react to changing task constraints throughout a cycling event. The thesis was specifically designed to address the following research questions:

i) Do more experienced cyclists employ differing levels of intra-individual movement variability compared to their less experienced counterparts?
ii) Does a greater level of intra-individual movement variability have an effect on cycling performance?

An initial hypothesis was that more experienced cyclists would show greater levels of intra-individual movement variability than their less accomplished counterparts, showing that movement variability performs a functional role within cycling and is not a marker of poor motor control as has been traditionally thought. More specifically, it was thought that better performing cyclists would be able to adapt more readily to changing task constraints encountered during a cycling event and would therefore display greater levels of movement variability between successive measurement points throughout the duration of a time trial.

## 1.5 Experimental overview

The investigation of these research questions was conducted through a series of experimental investigations which were designed using a post positivist approach and, accordingly, focus largely on quantitative methods of data collection and analysis, while not discounting the input of the qualitative information provided by participants.

Accordingly, Study 1 demonstrates a highly controlled, laboratory-based investigation with movement variability being measured at a number of points throughout a simulated ten mile (16km) cycling time trial event.

In order to then move investigations into a more ecologically valid, field-based setting, it was important to conduct a number of validation exercises. Study 2 investigated the validity of PowerTap P1 pedals as a potential method of measuring cycling power output compared to a previously validated measurement technique in the form of a cycle ergometer. Similarly, Study 3 investigated whether skin mounted electro-goniometers are a suitable method for replicating the calculations of continuous relative phase performed in Study 1, without relying on the traditional methods of kinematic data collection, which pose huge methodological challenges when studying cycling (see Section 2.5.2).

The two subsequent studies followed a similar theme as an inertial measurement suit (Study 4) and individual inertial measurement units (Study 5) were also assessed in comparison to traditional methods of kinematic data collection. Having established a valid method for recording kinematic measures of joint coupling behaviours (Study 5), investigations were then able to move to a field-based setting (Study 6).

In Study 6, participants were required to complete a time trial effort over a standardised 10 mile (16 km) outdoor course, which was chosen due to the variable nature of the terrain and, more specifically, the presence of two significant climbs. Measures of movement variability were taken at seven successive points across the time trial to allow investigation into how participants reacted to changing task constraints.

Having focussed largely on kinematic measures of movement variability during Studies 1–6, investigations then returned to the controlled setting of the laboratory to investigate muscular recruitment patterns during time trial performance (Study 7). This was designed to help better understand the underlying mechanisms that may lead to increased levels of movement variability and required participants to complete a simulated 10 mile (16km) time trial on a cycle ergometer. As with Studies 1 and 6, measurements were taken at successive points throughout the time trial in an effort to ascertain whether any changes in muscular recruitment patterns occurred which could be attributed to changing task constraints (i.e. greater levels of muscular fatigue) throughout the cycling event.

# 2. REVIEW OF LITERATURE AND METHODS

## 2.1 Motor control and skill acquisition

As outlined above, the focus of this thesis is to identify the role of intra-individual movement variability during performance of a cycling event. However, before focussing on complex sporting skills such as cycling, it is important to understand not only how human movements are produced and controlled but also how they are learned and developed. Herein lies the basis of the parallel fields of motor control and motor learning. Schmidt, Lee, Winstein, Wolf and Zelaznik (2018, p. 21) outlined that, although these fields have emerged from the separate areas of motor behaviour and neurophysiology, and remained largely separate until the 1970s, there has been a combining of ideas, problems and methods which means there is now little benefit in discussing them separately due to their inherently interconnected nature. As such, this chapter aims to give a brief overview of the field of motor control *and* motor learning, while highlighting some important theoretical approaches and key frameworks encountered in each area.

The majority of contemporary motor control and learning literature can be classified into one of two groups: those which follow the ideas of self-organising systems and those which are grounded in motor programme concepts (Magill and Anderson, 2010). This division seems somewhat arbitrary as it has been observed that, although motor control strategies can be grouped and isolated for study, they don’t function independently, with both sensory input and autonomous control being responsible for a resultant movement pattern (Cruse, Dean, Heuer & Schmidt, 1990). Instead, this division could be in reaction to one major challenge when attempting to understand the mechanisms of human movement: the sheer variety of skills which we are able to perform. There has been some suggestion that the way varying levels of sensory input and autonomous function are controlled in discrete skills seem to be different to those methods required for continuous skills (Schmidt, Lee, Winstein, Wolf and Zelaznik, 2018) and Keele (1998) held the view that the division of research into two groups “is due less to competing conceptualisations of the same phenomena than to the kinds of phenomena with which different groups of investigators are concerned” (p. 403).

Keele (1998) suggested that there was a tendency for researchers who use a self-organising system approach to focus on “continuous, often rhythmical skills of longer duration” whereas the motor programme approach is more widely applied to “discrete skills of short duration, where planning and motor programming seem to be critically important and feedback-based adjustments do not”. It is worth noting, however, that the problems encountered when trying to understand both discrete and continuous tasks share many similarities and therefore it is worth briefly explaining both approaches in order to give a greater contextual grounding.

### 2.1.1 Motor programme concepts

Researchers who espouse the idea of a motor programme concept suggest that the central nervous system holds a predetermined set of instructions for how each movement is performed. A motor programme was defined by Keele (1968) as "a set of muscle commands that are structured before a movement sequence begins, and that allows the sequence to be carried out uninfluenced by peripheral feedback." This idea of an "open-loop" system (Schmidt & Lee, 2018) means that once the action is completed the lack of feedback input limits adaptation based on the outcome of the previous performance, so each individual movement requires its own unique set of instructions or motor programme. The idea of a centrally held motor programme has been challenged by a number of authors (MacNeilage, 1970; Schmidt, 1975; Turvey, 1977; Morris, Summers, Maytas & Iansek, 1994; Summers & Anson, 2009), with consistent concerns being raised around the ideas of programme storage and programme novelty.

In simple terms, the "storage problem" (Schmidt, 1975) relates to the idea that if an athlete were to create a unique motor programme for each individual movement and store each of these in the long-term memory, then this would require the athlete to somehow maintain a store of countless millions of individual programmes. Each programme would then need to be almost instantaneously recalled at will in order to perform a given movement pattern. The scale of this problem was demonstrated by MacNeilage (1970) who focussed only on the movements required to create human speech and suggested that this alone would require in the region of 100,000 unique motor programmes in order to produce all the required sounds. He also noted that this estimate did not account for regional accents or slang variants of common words which would undoubtedly increase the required number of motor programmes required.

The second concern with the motor programme notion is referred to as the "novelty problem" (Schmidt, 2003) and is concerned with the degree to which a motor programme is, in fact, unique. An often-cited quote from Sir Frederick Bartlett (1932) demonstrated an early awareness of this problem when he reportedly observed that during tennis "When I make a stroke, I do not, as a matter of fact, produce something absolutely new, and I never repeat something old" (Wagoner, 2013). This, in essence, is the issue raised with motor control programmes in that the performance of a skill will be based on the previous learning but will be slightly different each time and therefore would, under the strict definition of a motor programme, require a unique motor programme to be developed and stored.

In 1975, Schmidt attempted to address both the storage and novelty concerns when he proposed his Schema theory. This introduced the idea of a Generalised Motor Programme which proposed that, instead of having a unique motor programme for every movement, a set of general rules can be applied to a "class" of movements which have consistent features. The most important consistent features were quickly confirmed in terms of the overall duration (Shapiro, 1977), overall force (Hollerbach, 1978) and the muscles involved (Shapiro, 1977) and were often demonstrated using the example of handwriting tasks to show how there are common features in multiple performances of a task, despite different constraints being placed upon it (Raibert, 1977; Hollerbach, 1978).

Schmidt's (1975) theory proposed that, when learning a skill, applying general rules to govern the movement means an individual can either generate a Generalised Motor Programme based on the important consistent features mentioned above or adapt an existing one, depending on how much prior experience the individual has. Despite this potentially reducing both the problems of novelty and storage which were seen with the previous motor programme concept, Schmidt et al. (2018) noted that Generalised Motor Programmes have been examined consistently since their introduction with some notable concerns being raised (p.209).

As acknowledged by Schmidt himself (2003), schema theory is almost completely focussed on how the athlete learned to scale and adjust a Generalised Motor Programme. It never offered answers to the question of how such a programme was acquired in the first place. In addition, a contentious issue highlighted by Schmidt et al. (2018) with regards to Generalised Motor Programmes was that of invariance. Their observations centred around the idea that if there are deviations between the individual performances of a skill, especially when concerned with the relative timing of the skill, then are these deviations meaningful? And what constitutes a meaningful deviation? This is clearly a line of questioning that is extremely relevant to the current thesis and is examined in greater depth throughout this thesis.

### 2.1.2 Self-organising systems concepts

Traditionally viewed in opposition to the concepts discussed above, the self-organising system approach suggests that the motor programme view places too much emphasis on the brain's capacity to pre-plan movements and insufficient emphasis on the dynamics of motor control (Morris et al., 1994; Summers & Anson, 2009). This approach contends that movements are not pre-specified by centrally located motor programmes but, instead, that the evolution of movement patterns occurs as a natural consequence of the dynamic interactions of the central nervous system, the effectors, the environment and the task at hand.

The earliest distinct example of this approach can be seen in Adams' (1971) theory of a "closed loop" system which suggests that, unlike the "open loop" system discussed earlier, feedback from one performance of a task can be built into the plan for the next performance of the task or, critically, used to adjust performance within a continuous task. Indeed, Schmidt et al*.* (2018) noted that closed-loop systems are especially important in situations where a system is required to "control itself" for long periods of time (p.129).

However, as with the models discussed above, which suggest that the management of a movement is handled by direct commands from higher centres, the idea of a closed loop is not without its detractors. Bernstein (1967) suggested that if each individual decision about movement was undertaken at the brain level, then the sheer amount of mental processing required to perform even simple tasks would be prohibitive. Bernstein explained that a movement system has "too many independent states that must be controlled at the same time", which he referred to as degrees of freedom. Because each joint has a number of muscles acting on it, and each of these muscles is made up of hundreds of motor units that also must be controlled, Bernstein suggested that the number of independently moving parts would lead to an impossible situation for the central nervous system if it had to control these degrees of freedom individually via conscious decisions.

Bernstein's work has been cited by many (Brooks, 1986; Keele, Cohen & Ivry, 1990; Schmidt, 1988) as an underpinning for the General Motor Programmes (GMP), discussed above, as GMPs would be a way of reducing the number of degrees of freedom that the system would contain by requiring only the selection of the correct GMP. This is because a GMP would have the capability to influence the activity of the many independent degrees of freedom so that they act as a single unit. In other words, it is suggested that the brain controls the selection of a GMP and initiates it at the proper time, but the programme controls the activity of the individual degrees of freedom involved in the movement, freeing up the brain once the movement starts. This suggestion, although very neat, has been criticised for not answering the question of control as the exact mechanism of how the various degrees of freedom are coordinated remains unexplained by this model (Schmidt et al. 2018).

Beek, Peper and Daffertshofer (2002) cited the investigation of such coordination as having roots in a seminal paper by Kelso (1981). Kelso observed that if an individual is instructed to cycle their index fingers rhythmically in antiphase while gradually increasing the frequency of movement, an involuntary switch to an in-phase pattern occurs at a certain, predictable, critical frequency. This observation prompted the creation of the Haken-Kelso-Bunz (HKB) Model (1985) which presented a theoretical model for this phase transition and referred to the spontaneous formation of movement patterns and pattern changes in a system composed of many components that is open to the exchange of information with its surroundings. In doing so, the HKB model (1985) provides the basis of all models which espouse the belief that human movement is a self-organising system.

The HKB model has been cited as probably the most extensively tested quantitative model in the field of human movement behaviour (Fuchs & Jirsa, 2008) because it was the first to propose that human movement patterns are self-organised, dynamic systems. It has been used as a building block upon which numerous investigations into varying movement patterns have been based (Kelso & Jeka, 1992; Carson, Goodman, Kelso, & Elliott, 1995).

Despite these successes, however, certain shortcomings of the HKB model have also become apparent. Beek et al. (2002) identified that the evolution of the HKB model into a “fundamental formal construct for the experimental study of rhythmically coordinated movements in general” has left it with questionable validity with regard to the assumptions surrounding individual limb movements only having two active degrees of freedom as well as to the proposed coupling between them. In addition, Sporns and Edleman (1993) identified that traditional methods of studying motor control, such as the HKB model, struggle to allow for the high levels of adaptability and flexibility displayed by movement systems when faced with changing biomechanical properties of motor organs during development and when faced with different environmental conditions or tasks.

As such, there are a range of self-organising systems approaches to studying motor control which are increasingly incorporating dynamical systems theory. Dynamical systems theory is a multidisciplinary approach which encompasses elements of mathematics, physics, biology, psychology and chemistry to describe systems which are able to constantly adapt to the varying demands of a task (Williams, Davids, and Williams, 1999) and represents, in a way, a logical extension of the HKB model in an effort to overcome some of the cited shortcoming of the original self-organising systems approach.

### 2.1.3 Summary

Having outlined some of the key developments in both the self-organising systems approach and the concept of motor programmes, it is difficult to argue against Keele’s (1998) suggestion that these two schools of thought do not, in fact, seem to be separate ideas and that they should be viewed more as complementary aspects of the same field.

For example, an initial suggestion when embarking on this PhD investigation was that more accomplished athletes may have developed a “library” of movement patterns which are capable of coping with various perturbations of psychological, physiological and mechanical demands. The storage and novelty problems bring into question the degree to which this is possible and also how much each of these movement patterns is different, but this only strengthens the suggestion that GMPs may exist and are governed by a schema which is developed over time.

In contrast, Bernstein (1967) suggested that that human movement is not governed by a set of motor programmes and instead is a self-organising system. This gave rise to his idea that the organised practice involved in becoming more adept at a given activity is not about learning a series of “correct” motor programmes, it instead trains the athlete to become more efficient at solving the degrees of freedom involved in the particular combination of task constraints faced at the time. This would allow the athlete to dynamically created a stable movement solution sooner and therefore adapt to the changing demands of a task more quickly.

Regardless of which of these is true, it is undeniable that both require an athlete to employ some sort of feedback mechanism in order to select the appropriate motor programme or to dynamically adjust their movement pattern to match the particular combination of variables/inputs they are faced with during the ongoing performance of the skill. Given that the focus of this PhD is cycling, a continuous task, this appears to link more closely to self-organising systems concepts which would allow feedback to play a role in the adaptation of movement patterns throughout a ride in response to changing conditions.

This, therefore, will be the main theoretical standpoint adopted throughout this thesis. Movements will be viewed as dynamically created patterns which emerge organically through the interaction between the cyclist and the task constraints they face. The cyclist’s ability to adapt to those task constraints and efficiently solve the degrees of freedom problem will be viewed as a mark of expertise with invariant outcomes being prized over invariant movement patterns.

## 2.2 Cycling literature

Having discussed the various ways in which it has been theorised that movements are learnt and controlled, there is a temptation here to move on to the sport of interest and try and somehow summarise all the published biomechanical cycling literature. Not only has this been done by numerous authors already (see Gregor, Broker and Ryan, 1991; Fonda and Sarabon, 2010; Hopker and Jobson, 2012; Bini and Carpes, 2014), to try and replicate the total combined knowledge of multiple textbooks here is well beyond the scope of a PhD thesis.

Instead, the aim of this chapter is to summarise the most prevalent measurement techniques and reporting conventions so that they can be followed throughout the coming investigations.

### 2.2.1 Phases of a pedal revolution

Regardless of the purpose of a cycling study, it is useful for authors to be able to compare the data they record by identifying specific times or events during the pedal revolution. The most common way this is achieved is by denoting the start of each revolution as the point at which the pedal is in its highest possible position with the crank positioned vertically (Faria and Cavanagh, 1978; Wozniak-Timmer, 1991; So, Ng and Ng, 2005; Wilson and Bush, 2007; Sides and Wilson, 2012; Bini and Carpes, 2014; Bartaguiz, Dindorf, Dully, Becker and Frohlich, 2023). Having established a zero point, any event throughout the pedal revolution can be described in terms of how many degrees rotation have occurred relative to that standardised starting position. This approach is akin to that which was recommended by Lamb and Stöckl (2014) and Kurz and Stergiou (2002) and allows not only standardisation of each revolution in terms of data points but also gives the opportunity to report events relative to a percentage of a pedal revolution.

Having established a standardised frame of reference for the pedal revolution, the cyclic motion of the pedal is typically divided into different phases, largely dependent on the action being performed at the time. The simplest of these divisions is a crude two-phase split whereby any movement that occurs from 0°–180° is considered part of the "power" phase and the remaining arc from 180° –360° is labelled as the "recovery" phase (Faria and Cavanagh, 1978).

This simple division has been further developed to acknowledge the presence of "dead centres" at the top and bottom of the crank revolution (So, Ng and Ng, 2005). These events during the crank rotation occur at approximately 0° and 180° and denote points where applying a vertical force to the pedal will not result in a rotation of the crank and, instead, a tangential force is required to continue crank progression (see Figure 2-1).

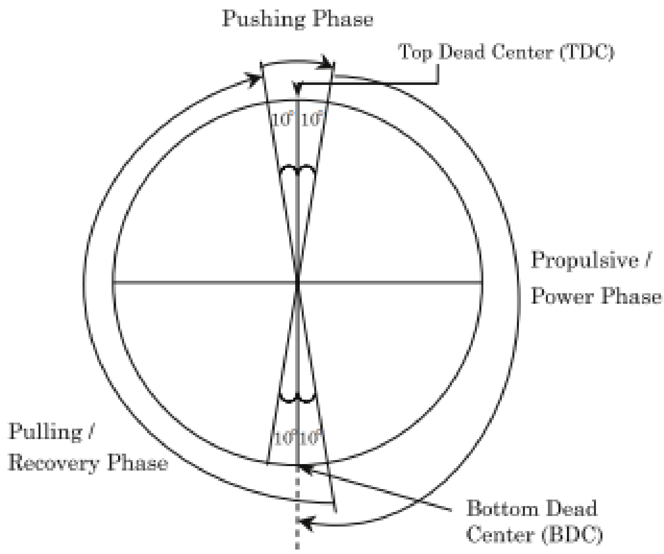



**Figure 2-1. Phases of the pedal revolution**

**(Adapted from So, Ng and Ng, 2005)**

Following greater investigation into both the kinetics and kinematics of crank rotations, this two-phase split with an acknowledgement of top and bottom dead centres has been further divided so that the crank revolution is now, typically, viewed in four quarters. Unlike the simple two-phase split shown above, there is some inconsistency within the literature as to the exact start and finish position of each "quarter". Some authors divide the revolution much like a clock face (Bini and Rossato, 2014; Carpes, Bini and Quesada, 2014) with the 1st quarter running from 0°–90°, the second from 90°–180°, the 3rd from 180°–270° and the 4th and final quarter completing the revolution from 270°–360°. One potential issue with this division is that there are a number of features which have been observed within the crank revolution (e.g. tangential force application to overcome top dead centre) which would, under these definitions, span a quarter boundary. As a result, other authors have adopted a quarter split which is rotated by some 30° (Dorel, Couturier and Hug, 2009; Dorel et al., 2009; Lanferdini, Jacques, Bini and Vaz, 2014). This ensures that the influence of both the top and bottom dead centres are contained within single phases at the top and bottom of the rotation while the remaining phases more closely align with the pattern of pedal force application identified in numerous studies (Soden and Adeyefa, 1979; Peiffer and Abbiss, 2010; García-López, Díez-Leal, Ogueta-Alday, Larrazabal and Rodríguez-Marroyo, 2016).

### 2.2.2 Kinetic data

Since the pioneering work of Hoes, Binkhorst, Smeekes-Kuyl and Vissers (1968) and Soden and Adeyefa (1979), who were among the first to measure the forces applied to a bicycle, there have been many developments in bicycle components in order to minimise resistive forces and the energy cost of pedalling in order to improve performance (Minetti, Pinkerton and Zamparo, 2001). Peiffer and Abbiss (2010) suggested that, despite these developments, changes to the drive train of the bicycle (chain, gears, and crank) have been relatively non-existent and that the biomechanically measured “dead” spots within the normal pedal stroke still occur. This means that the majority of torque is produced with the crank parallel to the ground (90°), with very low or zero forces produced at crank positions of top dead centre (0°) and bottom dead centre (180°).

This quasi-sinusoidal power output has been widely reported (Ericson, 1988; Stapelfeldt, Mornieux, Oberheim, Bellia dn Gollhofer, 2007; Bini, Hume and Cerivi, 2011) and various laboratory-based instruments have been developed to aid in producing such measurements (Hull and Davis, 1981; Newmiller, Hull and Zajac, 1998; Alvarez and Vinyolas, 1996; Dorel, Drouet, Hu, Lepretre and Champoux, 2008).

The result of these investigations is that a coherent picture of a “typical” pattern of power output has been established and can be seen in Figure 2-2.

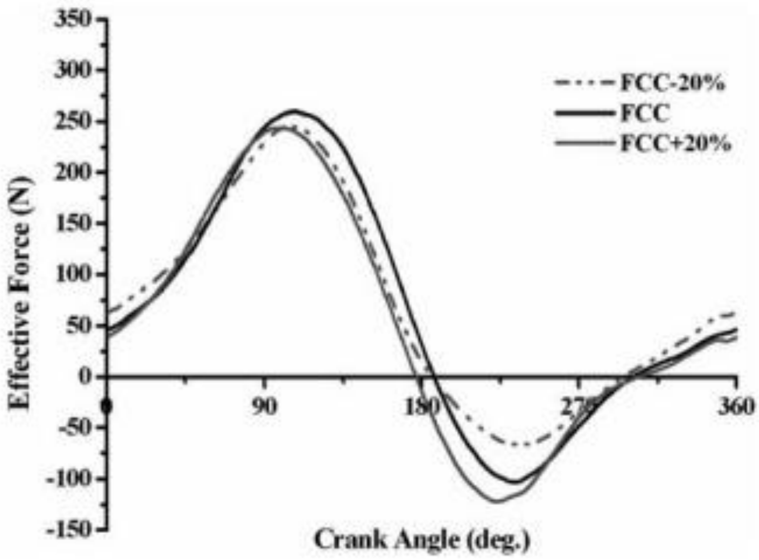



**Figure 2-2. Typical force application throughout a crank revolution**

**(Adapted from Rossato, Bini, Carpes, Diefenthaeler and Moro, 2008).**

This pattern clearly shows a period of negative force which effectively decelerates the pedal and is somewhat at odds with the statement by Bini and Carpes (2014) that the aim of cyclists is to continuously produce maximal power output so that this can be transferred to the cranks and be translated into bicycle speed. The pattern displayed in Figure 2-2 has also been shown to be affected by a number of factors including workload (Bini and Diefenthaeler, 2010), cadence (Bini, Tamborindeguy and Mota, 2010), body position (Diefenthaeler et al., 2006) and fatigue (Amoroso, Sanderson and Henning, 1993). Most relevant to this thesis, however, are the differences that may be seen when recruiting cyclists of differing skill/experience levels.

Although some textbooks have stated that professional cyclists have better pedalling technique than recreational cyclists (Broker, 2003; Cavanagh & Sanderson, 1986), there are conflicting results from experimental studies (Sanderson, 1991; Sanderson, Hennig, & Black, 2000). Coyle et al. (1991) observed that elite cyclists applied higher force during the downstroke than sub-elite cyclists, but sub-elite cyclists had higher pedal force effectiveness. In contrast, other studies have shown higher pedal force effectiveness in elite cyclists than non-cyclists (Mornieux et al., 2008). In both studies, elite cyclists applied higher resultant force and effective impulse during the downstroke phase than sub-elite and non-cyclists, respectively. This could mean a less effective pedalling technique for the elite cyclists if it is assumed that a constant application of power is desirable.

One area of particular interest for this thesis, which appears to be largely absent from the published literature, is not whether this pattern of force application is different between different levels of cyclist but whether the amount of variance from one crank revolution to another varies with differing levels of experience. This discussion will be revisited in Section 2.3.2 of this thesis.

### 2.2.3 Kinematic data

When it comes to kinematic data, the most common method of motion analysis within cycling has been to focus on the movement of the lower limbs (Enoka, 2000). This analysis has typically been limited to the sagittal plane (Ferrer-Roca, Roig, Galilea and Garcia-Lopez, 2012; Carpes et al., 2006) due to this being the plane in which the largest ranges of motion are seen.

It has been established that cycling is unusual in that the range of motion seen at the hip, unlike in other forms of exercise or activity, occurs with the hip always in a position of flexion. For example, the hip extends beyond straight by approximately 35° and flexes about 25° during moderately fast running (Cavanagh, 1986), creating a total range of motion of approximately 60°. In contrast, during cycling the range of motion displayed is around 42°–44° (Bini, Senger, Laferdini and Lopes, 2012) and takes place without ever reaching a point of extension.

Likewise, the knee joint, despite having a total sagittal plane range of motion of approximately (73°–78° (Bini, Senger, Laferdini and Lopes, 2012), never reaches full extension during cycling (Wozniak-Timmer, 1991). Cavanagh and Sanderson (1986) found mean values of 37° knee flexion at 180° in the pedalling cycle and 111° flexion at the 0° crank position. These range of motion values are obviously participant-specific, with Houtz and Fischer (1959) having reported much lower values previously (~40°–65° total knee motion), but will also be affected by bike configuration and rider body position. It has also been shown that these typical ranges of motion will also change as riding conditions change, such as during hill climbing (Arkesteijn, Jobson, hopker and Passfield, 2013) and when the cyclist pedals while out of the saddle (Wozniak-Timmer, 1991), which would suggest a level of functional movement variability being present within cycling technique.

In terms of ankle motion during cycling, Houtz and Fischer (1959) indicated that maximum dorsiflexion occurred at a similar time to maximum hip and knee flexion (~337°–23° crank position) and maximum plantar flexion occurred just past the 180° crank position. These values were somewhat confirmed by Cavanagh & Sanderson (1986) who suggested that the heel should be dropped during the 330°–30° position, and the toes should drop (plantar flexion) across the bottom part of the pedalling cycle; however, there is some debate as to how often this range of motion is actually adopted in the field. Kautz, Feltner, Coyle and Baylor (1991) suggested that this can be largely dependent on the intensity that the cyclist is performing at when measurements are taken. They found that their participants (14 elite male cyclists who completed 40-km time trials in an average of 55.8 min ± 2.9 min) displayed two approaches to coping with the demands of increased workload. Seven of their participants, when pedalling at higher workloads, adopted a more dorsiflexed position throughout the downstroke and applied a greater horizontal force to the pedal around the bottom dead centre position. The other seven participants, however, showed no changes in foot/pedal orientation.

The increase in ankle range of motion shown by some participants throughout the pedal revolution is referred to as “ankling” (Wozniak-Timmer, 1991) and was thought to allow the cyclist to “push” the pedal through the top dead centre with the foot in the dorsiflexed position and “pull” across the bottom dead centre with the foot plantarflexed (Faria and Cavagnah, 1978). Cavanagh and Sanderson (1986) concluded, however, that the ankling pattern described above is “anatomically and mechanically impossible if the rider remains in the seat”.

This conflict of opinion may be partly responsible for the varied values reported when it comes to ankle range of motion. For example, Cavanagh and Sanderson (1986) approximated total ankle range of motion to be around 50°, where Bini, Senger, Laferdini and Lopes (2012) reported much smaller values, in the region of 21°–25°. It could be that there are two distinct pedalling techniques being demonstrated here or it could be interpreted as further evidence of movement variability and a change in technique in response to changing task perturbations.

### 2.2.4 Muscular activation

Assessment of muscle activation in cycling has been mostly conducted using surface electromyography (Bini and Carpes, 2014). This method was, to the best of the author's knowledge, first adopted in cycling by Houtz and Fischer (1959) who studied 14 major surface lower limb muscles and stated that these muscles are activated in an orderly and coordinated way during cycling performance. Their ground-breaking work has been developed by numerous authors since then (Ericson, 1986; Jorge and Hull, 1986; Ryan and Gregor, 1992; Hug et al., 2004a; Hug et al., 2004b; Duc et al., 2006; Hug et al., 2006a; Hug et al., 2006b; Dorel et al., 2007) and the muscles typically sampled are the Gluteus maximus, Rectus femoris, Vastus lateralis, Vastus medialis, Semimembranosus, Semitendinosus, Biceps femoris, Gastrocnemius lateralis and Gastrocnemius medialis, Tibialis anterior, and Soleus (Hug, Bendahan, Le Fur, Cozzone and Grelot (2004).

Such extensive investigation has allowed the composition of normative data regarding the co-ordination of muscular activity throughout the pedal stroke and this information has been published in table format (Ryan and Gregor, 1992. See Table 2-1) and adapted into more visual mediums such as those shown in Figures 2-3.

**Table 2-1. Typical patterns of muscular activation during cycling.**

**(Adapted from Ryan and Gregor, 1992)**

| Muscles | Function | Approximate range of action (°) | Approximate peak activity angle (°) |
|---|---|---|---|
| Gluteus maximus | Hip extension | 340–130 | 80 |
| Vastus lateralis | Knee extension | 300–130 | 30 |
| Vastus medialis | Knee extension | 300–130 | 30 |
| Rectus femoris | Knee extension/Hip flexion | 200–110 | 20 |
| Soleus | Ankle stabilizer | 340–270 | 90 |
| Gastrocnemius | Ankle stabilizer/Knee flexion | 350–270 | 110 |
| Tibialis anterior | Ankle stabilizer/Ankle flexion | All the range | 280 |
| Hamstrings (without biceps femoris) | Knee flexion | 10–230 | 100 |
| Biceps femoris | Knee flexion/Hip extension | 350–230 | 110 |

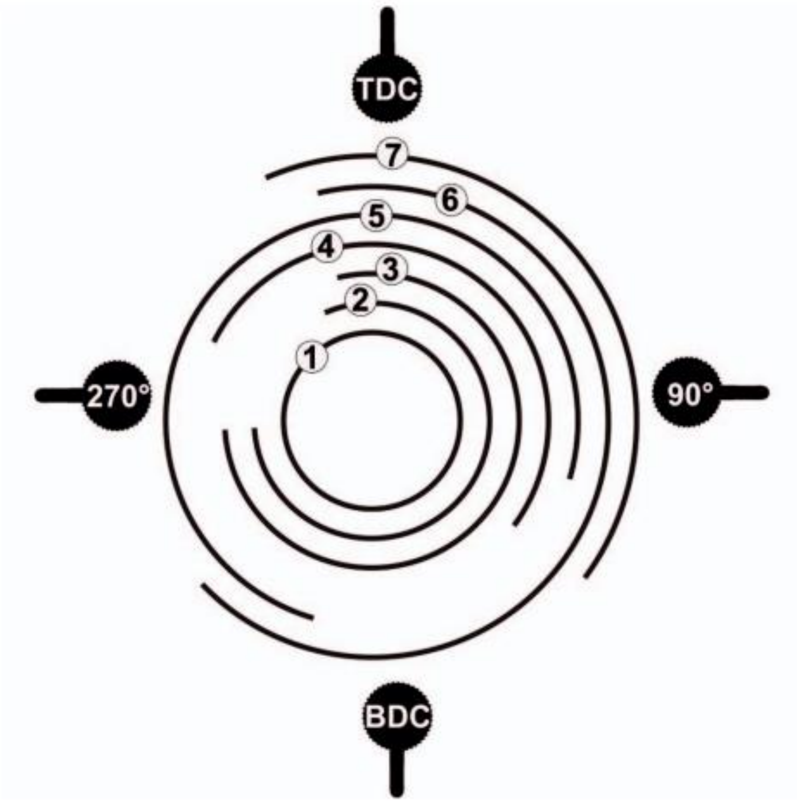



**Figure 2-3. Overview of muscle activity timing during cycling.**

**Here 1= Tibialis Anterior, 2 = Soleus, 3 = Gastrocnemius Medialis, 4 = Vastus Medialis and Lateralis, 5 = Rectus Femoris, 6 = Biceps Femoris and 7 = Gluteus Maximus. TDC = Top Dead Centre and BDC = Bottom Dead Centre. (Adapted from Fonda and Sarabon, 2010).**

The information displayed in Table 2-1 and Figure 2-3 led to the suggestion that that the most important muscle for cycling is the quadriceps (Schmidt, 1998) and that pulling up on the pedals largely depends on the hip flexors. Schmidt (1998) also stressed the importance of the smooth pedal stroke which allows an even distribution of power to the pedals during the course of the entire pedal revolution. As seen in section 2.2.3, whether this actually happens is debatable but it is a clear example of the interconnected nature of the various data types discussed in this chapter.

As useful as diagrams such as Figure 2-3 can be for visualising the co-ordination pattern of muscular recruitment, they lack detail in terms of the pattern of activation which each individual muscle undergoes. Such detail was provided perhaps most clearly in a repeatability study undertaken by Hug and Dorel (2007) and replicated in their comprehensive review which followed (Hug and Dorel, 2009). The “ensemble curves” that they created have been replicated in Figure 2-4.

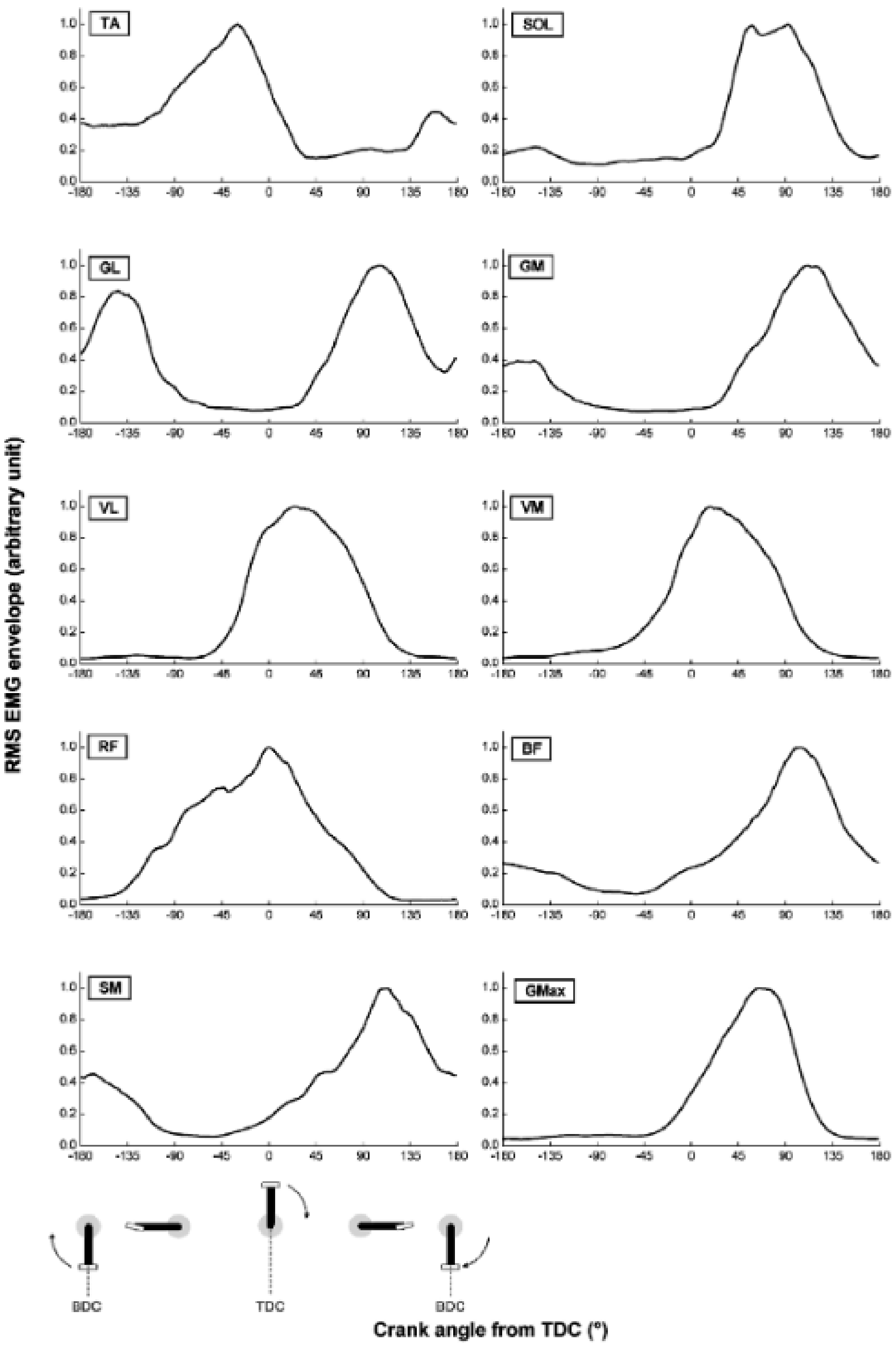



**Figure 2-4. Ensemble curves of muscular activation for 10 different lower limb muscles.**

**(Adapted from Hug and Dorel, 2009).**

To create the figure above, Hug and Dorel (2009) averaged the route mean square traces from 45 consecutive pedal revolutions for each muscle and plotted them normalised against the maximal route mean square value obtained during the cycling bout. This clearly shows the typical pattern of activation each muscle displays when pedalling at a mean power output of 238 ± 23 W and demonstrates nicely that, with the exception of the Gastrocnemius Lateralis, there is one clearly defined peak of activation per muscle during each pedal revolution.

As with the kinematic data discussed above, the typical patterns displayed by Hug and Dorel (2007) have been shown to change in response to varying workload (Macintosh, Neptune and Horton, 2000), cadence (Sanderson and Amoroso, 2009; Candotti et al, 2009), body position on the bicycle (Savelberg, Van de Port and Williams, 2003) and fatigue state (Diefenthaler, Coyle, Bini, Carpes and Vaz, 2012; Dorel et al, 2009; Von Tscharner, 2002). For example, one strategy employed by both expert and novice cyclists when fatigued during a maximal intensity test was to adopt increased activation of gluteal muscles (Dingwell et al., 2008).

Another example of how this typical activation may alter was demonstrated by Arkesteijn, Hopker, Jobson and Passfield (2013). They compared cycling on a treadmill with cycling on a turbo trainer and reported that treadmill cycling induced a larger muscular contribution from Gastrocnemius Lateralis, Biceps Femoris and Gluteus Maximus whereas using a turbo trainer resulted in a greater muscular contribution from Vastus Lateralis, Rectus Femoris and Tibialis Anterior. It is fair to question to what degree cycling on a treadmill accurately replicates the outdoor action, but the results suggest that muscular recruitment during cycling can be altered by the choice of ergometer. This, along with the other examples given here, could be interpreted as the cyclist altering technique, that is to say displaying a level of functional movement variability, in response to changing task constraints. This interpretation, however, is one that is largely absent from the collected cycling literature and is one of the reasons for the focus of this thesis.

### 2.2.5 Summary

As demonstrated throughout Section 2.2, cycling has been the focus of an extensive body of research. The collected knowledge has been summarised on numerous occasions in both review articles (Wozniak-Timmer, 1991; Jeukendrup and Martin, 2001; Faria, Parker and Faria, 2005; Ettema and Loras, 2009; Phillips and Hopkins, 2020; Turpin and Waiter, 2020) and textbooks (Hopker and Jobson, 2012; Bini and Carpes, 2014) and the various elements discussed above have been shown to be undoubtedly interconnected.

There is evidence throughout the collected literature that kinetic, kinematic and electromyographic changes in technique are evident in response to differing task constraints and that this could be interpreted as evidence of functional intra-individual movement variability. This interpretation, however, appears to be very seldom made within the literature with the idea that movement variability may be a hallmark of improved performance being almost entirely absent. This will be discussed further in Section 2.3.

## 2.3 Movement variability in cycling

As demonstrated in Section 2.2, cycling has been studied extensively with existing research covering a wide range of biomechanical topics. Evident within this body of literature is the assumption that individuals share a common optimal pattern of movement and the belief that a single most efficient technique exists for the majority of the population (Brisson & Alain, 1996; Cannon et al., 2007; Ostler et al., 2008; Ettema & Loras, 2009). This may offer an explanation into the relative lack of research on intra-individual movement variability in cycling, which will be explored further here.

### 2.3.1 Muscular recruitment patterns

The idea that individual cyclists move differently to each other (i.e. *inter*-individual movement variability) has only been established in relatively recent years with Hug, Bendahan, Le Fur, Cozzone and Grelot (2004) claiming that, prior to their study, the issue of inter-individual differences had never been addressed in detail. This is a questionable statement as earlier studies had reported a high variability of electromyographic patterns in trained cyclists (Ryan and Gregor 1992). Although it is worth noting that no other indication of the cyclist's experience was given, Ryan and Gregor (1992) monitored EMG signals from ten lower extremity muscles over a range of cycling protocols and evaluated variability between participants by calculating the coefficient of variation (CV%) at 10% intervals of the pedalling cycle. Their results suggested that the single-joint hip and knee extensors (Gluteus maximus, Vastus medialis, and Vastus lateralis) had the lowest CV% values (less than 30%) and attributed this to the role of these muscles as power generators. In contrast, variability was generally higher in the hamstring muscles with two distinct Biceps femoris patterns emerging across their 18 participants. This suggested that inter-individual differences of the EMG patterns were especially apparent for biarticular muscles compared to monoarticular ones but, interestingly, higher levels of variability were recorded in the first 20% of the pedalling cycle for all muscles studied.

Hug et al. (2004) did somewhat confirm these results using surface EMG to determine the pattern of activity of lower limb muscles during two different pedalling exercises in eight professional cyclists. In this instance CV% values were as high as 81% and large inter-individual differences were seen regardless of the muscle in question. Hug et al. (2004) expressed some surprise at these findings given the relative similarity of their participants in terms of oxygen consumption ($\dot{V}O_{2\,max}$ 73.6 ± 5.1 $ml \cdot kg^{-1} \cdot min^{-1}$) and training volume being undertaken (30,000 ± 2,100 $km \cdot year^{-1}$) but nonetheless concluded that the similar expertise displayed by their participants did not manifest in the production of a common muscular recruitment pattern. They further suggested that their results provided evidence that the nervous system has multiple ways of accomplishing a given motor task. This is a viewpoint which echoes that of Van Bolhuis and Gielen (1999) who stated that, at the muscle level, there are multiple synergists as well as various combinations of agonist/ antagonists that can contribute to the same limb trajectory and force production. This is one of the main detractions from motor programme concepts of motor control which have been discussed in other areas of this thesis (e.g. Section 2.1) as it suggests that the nervous system could select a number of different muscle activation patterns to produce a given movement. In turn this has created an area of investigation to address questions around muscle load sharing, which originates from the fact that the number of muscles spanning a joint exceeds the number of degrees of freedom of the joint.

### 2.3.2 Pedal forces

Despite the suggestion that, for a given power output and cadence combination, the effective force profile appears to be fairly typical across cyclists (Gregor et al. 1985; van Ingen Schenau et al. 1992; Sanderson et al. 2000), it has been suggested that substantial differences exist between participants regarding their power generation techniques (Gregor et al. 1991). Hug et al. (2008) aimed to assess this by investigating whether this was as a result of variability in pedal force application patterns to accompany their previously discussed variation in muscular recruitment.

Hug et al. (2008) recruited eleven male experienced cyclists (8.5 ± 3 years of competitive experience with an average of 14,000 ± 4,333 km covered in training the previous season and a Maximum Aerobic Power output of 391.0 ± 22.3 W) and tested their participants at two submaximal power outputs (150 and 250 W). These tests consisted of a 10-min warm-up at 100 W followed by a 6-min task at a constant 150 W workload, immediately followed by a second test performed at 250 W for 3 min. Throughout the whole protocol, participants were asked to maintain a constant pedalling rate fixed at 95 $rev \cdot min^{-1}$ (±5 $rev \cdot min^{-1}$).

Immediate criticism could be levelled at this method due to the lack of condition randomisation and therefore the potential influence of fatigue. Hug et al. (2008), however, considered this protocol as non-fatiguing due to the trained status of the participants and the low workload level (i.e., 150 and

250 W representing about 38 and 63% of MAP, respectively). They also justified their choice of a fixed cadence, despite the findings of Bieuzen, Lepers, Vercruyssen, Hausswirth and Brisswalter (2007) and Emanuele, Horn and Denoth (2012) which advocate a freely chosen cadence, because their chosen cadence represented the mean pedalling rate (94.6 ± 4.2 rev·min$^{-1}$) freely adopted by the participants at the end of the warm-up protocol.

During their protocol, Hug et al. (2008) continuously measured pedal force components and index of mechanical effectiveness using instrumented pedals synchronized with surface electromyography signals measured in ten lower limb muscles. In agreement with Ryan and Gregor (1992) and Hug et al. (2004), this investigation, again, reported high inter-participant variability of EMG patterns at both exercise intensities for biarticular muscles and lower levels in monoarticular muscles. What is interesting, however, is that this was not accompanied by a requisite high inter-participant variability in pedal force application patterns. On the contrary, very low inter-participant variability was recorded in effective force, total force and index of mechanical effectiveness (variance ratios of 0.017, 0.047, and 0.037 respectively at 150 W and 0.019, 0.059, and 0.088 respectively at 250 W) suggesting that there is a level of redundancy in the neuromuscular system.

Ettema, Lorås and Leirdal (2009) also investigated a submaximal workload, adding the manipulation of cadence to produce five conditions ranging from 60—100 rev·min$^{-1}$. Joint powers were calculated using inverse dynamics methods and other kinetic variables were calculated using four different computational models with only the cross-correlation model suggesting that there was a change of technique with increasing cadence. This shows some level of agreement with Hug et al. (2008) with regards low levels of variation of kinetic variables and can perhaps be attributed to the reasonably similar participant groups which both studies recruited with experienced competitive cyclists being investigated in both studies.

DeMarchis, Schmid, Bibbo, Bernabucci and Conforto (2013) followed a similar line of investigation in that they aimed to study muscle coordination and connect it with the inter-individual variability of applied forces but, in contrast to the previous two papers, recruited untrained cyclists (less than 50km cycling per year). Their nine participants performed a single, 2-min sub-maximal cycling task while maintaining a freely chosen pedalling cadence (64.5 ± 5.2 rev·min$^{-1}$) and, in untrained participants, it would appear initially that there is a level of variability present in some force components. DeMarchis et al. (2013) did note, however, that this is only true when analysing the forces in the pedal reference system. When these forces are projected onto the crank reference system, most of the variability is reduced, suggesting that the propulsive action and the force orientation are both carried out similarly among untrained participants.

DeMarchis et al. (2013) went on to highlight the similarities between their findings and those of Hug et al. (2008) as both sample groups produced a negative torque during the second part of the pedalling cycle but also suggested that there may be a different strategy in the control of the tangential force in the recovery phase by elite riders when compared to untrained participants. This comparison is obviously difficult due to the different power outputs between the studied populations, since a higher power output could change the signal to-noise ratio, but suggests there is some merit to a comparison of the variability levels displayed by cyclists of differing abilities.

### 2.3.3 Influence of skill level

The comparison of novice versus elite athletes is a well-established research modality within the field of movement variability. Studies utilising this approach can be seen to study skill performance in basketball (Button, Macleod, Sanders and Coleman, 2003), triple jump (Wilson, Simpson, Van Emmerik and Hamill, 2008), golf (Bradshaw et al, 2009), handball (Wagner, Ptfusterschmied, Klous, Von Duvillard and Müller, 2012) and pistol shooting (Ko, Han and Newell, 2017) to name but a few, but this approach is less well established within cycling. The reasons for this may be due to some of the unique challenges when trying to classify a cyclist's level of expertise (these will be discussed in Chapter 3).

Chapman, Vincenzino, Blanch and Hodges (2008) demonstrated that patterns of leg muscle recruitment varied between novice and highly trained cyclists and then published a follow up paper a year later which attempted to ascertain whether this reflected less skilled muscle recruitment by novice cyclists or a different movement pattern being employed. Despite confirming their earlier findings that there were differences between novice and elite cyclists in the recruitment of leg muscles, Chapman, Vincenzino, Blanch and Hodges (2009) found that joint-angle and velocity were not different between groups when cycling at 55–60, 75–80, 90–95 rev·min$^{-1}$ and preferred cadence. They did concede that there were some minor differences in the absolute range of sagittal plane motion of the ankle but coordination and variability of coordination of sagittal plane hip and knee motion, as well as frontal and transverse plane motions, were not different between groups. Showing a traditional and somewhat dismissive view with regards to movement variability, they concluded that the differences in muscle recruitment reflected less skilled muscle recruitment by novice cyclists and interpreted the slight kinematic variations between groups as further evidence of more skilled control of movement in elite cyclists who had progressed towards a more skilled movement pattern, despite these differences only being apparent in a single plane of ankle motion.

Carpes et al. (2011) also reported muscular activity when comparing cyclists to non-cyclists but their aim was to investigate asymmetry of muscle activation in participants with different levels of experience. Using both incremental and sub-maximal protocols they reported no difference in the magnitude of muscle activation between the preferred and non-preferred leg, in both cyclists and non-cyclists, despite seeing significantly higher gross efficiency in the cyclist group. They suggested that previous reports of pedalling force asymmetries in favour of the preferred leg during pedalling were therefore inaccurate and that cyclists appear to adopt a level of equality in muscle activation regardless of different levels of cycling skill. Despite these findings, they advocated further investigation into the influence of variability of muscle activation on pedalling asymmetry, something which may be considered in the later stages of this thesis.

### 2.3.4 Inter-individual variability

Despite the range of examples shown within Section 2.3, the focus of these studies is very much the variability *between* participants instead of the variability shown by one individual when faced with differing perturbations during the extended performance of a changeable task. In order to get closer to a measure of *intra*-individual variability it is valuable to consider studies which have used the same participants in a range of cycling conditions such as Smith, Davidson, Balmer and Bird (2001) who recorded power output during three indoor and three outdoor time trial events, using eight non-elite but competitive cyclists ($\dot{V}O_{2\,max}$ 5.11 ± 0.70 $l \cdot min^{-1}$).

Smith *et al*. (2001) claimed that this was the first investigation into the reproducibility of mean power recorded during a field-based 40km time trial and this statement alone shows the focus of the paper, as with so much other sports science literature, was not on the intra-individual variability, but instead was trying to obtain a valid measure of performance between two conditions.

In contrast, Bertucci, Grappe and Groslambert (2007) focussed on a comparison of crank torque profile and perceived exertion between the Monark ergometer (818 E) and two outdoor cycling conditions: level ground and uphill road cycling. They recruited seven male cyclists who were described as in their preparative training period for the race season and producing a Maximal Aerobic Power of 322 ± 40 W. These are, unfortunately, the only descriptive characteristics offered relating to the participant's cycling expertise and therefore offer little in the way of benchmarking their experience. All participants completed seven tests in seated position at different pedalling cadences: (a) in the laboratory at 60, 80, and 100 $rev \cdot min^{-1}$, (b) on level terrain at 80 and 100 $rev \cdot min^{-1}$; and (c) on uphill terrain (9.25% grade) at 60 and 80 $rev \cdot min^{-1}$. All tests were conducted for 1 min at maximal aerobic power.

Although the variability within each participant was not strictly the focus of this study, the findings that, at maximal aerobic power, the crank torque profiles when using a Monark ergometer were significantly different to those seen in road cycling conditions could be interpreted to show that the participants were varying their movement pattern to match the particular set of constraints they were faced with in each condition, a central theme of dynamical systems theory.

Similar inferences can be drawn from Kautz, Feltner, Coyle and Baylor (1991) who reported that elite endurance cyclists changed their pedalling technique when faced with an increasing workload at constant cadence, another change in the task constraints. The 14 male cyclists held U.S. Cycling Federation Category 1 or 2 status, had all recently placed in state and/or national level competitions and reported an average recent 40km time trial result of 55.8 min ± 2.9 min. Normal and tangential components of the applied force, crank orientation, and pedal orientation were recorded for 10 consecutive crank revolutions while each participant was riding at approximately 60, 70, 80, 90, and 100% of his respective $\dot{V}O2_{max}$ and maintaining a cadence of 90 rev·min$^{-1}$ at all times.

Kautz et al. (1991) identified two techniques which the cyclists adopted to adapt to the increased workload. Seven participants showed no changes in pedal orientation but predominantly increased the vertical component of the applied force during the down stroke as the workload increased. In contrast, the other participants increased the toe up rotation of the pedal throughout the down stroke and increased the horizontal component between 0° and 90°.

In addition, it was found that negative torque about the bottom bracket during the upstroke usually became positive torque at the higher workloads. This was a small increase with 96.3% of the total work done at high intensity still occurring during the down stroke but, again, suggests that the participants were displaying a level of intra-individual variability in order to adapt the changing task constraints.

Likewise, Bini, Diefenthaeler and Moter (2010) reported changes in cadence, total absolute joint moment and hip, knee and ankle moments as a result of fatigue during cycling. This was accompanied by a change in resultant force and the altered kinematics were attributed to a different mechanical function at the ankle once participants reached a fatigued state. Bini et al. (2010) also suggested that this represented an attempt to overcome decreased contractile properties of muscles during fatigue, clearly suggesting that a new movement pattern was employed in reaction to a changing set of task constraints.

Bini, Hume, Lanferdini and Vaz (2014) also altered the constraints of a cycling task by dictating that their participants ride in either a preferred/self-selected, most forward or most backward position on the saddle. Their participants were a mix of cyclists ($n$ =12) and triathletes ($n$ =9) who performed a range of 1-min test protocols at 90 rev·min$^{-1}$ in order to allow the assessment of force applied on the right pedal, lower limb kinematics and muscle activation with differing saddle positions.

Their analysis showed no large effects from changes in position on the saddle for pedal forces, ankle joint work and ankle kinematics; however, there were large increases in knee joint angle and mechanical work and rectus femoris activation along with smaller hip work at the forward position on the saddle.

### 2.3.5 Pacing strategies

Although none of the studies discussed above specifically focus on variability they can be interpreted as a body of evidence which demonstrates cyclists using a range of different movement strategies depending on the task constraints placed upon them. That is to say, it could be used to argue that there is a level of intra-individual movement variability being shown in order to meet the demands of the task. One of the few areas of cycling where this intra-individual variability has been specifically investigated is when considering the pacing strategies which cyclists employ during an event.

Atkinson, Peacock, Gibson and Tucker (2007) reviewed a number of articles which focussed on precisely this and concluded that an even distribution of power output across a time trial event is optimal, but only if the various factors governing the relationship between cycling power and speed are stable. If, in contrast, gradient or wind velocity vary, they suggested that a variable power strategy would be advantageous. Specifically, they suggested that increasing work rate in headwind and uphill sections and reducing work rate in the opposing areas would result in a decrease in the variability of speed and, therefore, improve overall finishing time. Despite the stated concerns about whether a variable power strategy such as this can be tolerated by elite cyclists, there is a clear suggestion here that a greater level of intra-individual variability (in terms of power output) would produce a more stable outcome measure which has long been seen as the trademark of skilled performance.

Atkinson, Peacock, and Passfield (2007) went on to test the theory of a variable power output strategy by mathematically modelling time trial performances in order to quantify the time savings which could be made as a result. Although this was an entirely hypothetical investigation, a system comprising of a 70kg cyclist and a 10kg bicycle which was modelled to produce a power output of 289W ± 10% was shown to make time savings of 126, 51, and 26 seconds on “hilly”, “windy” and “standard” time trial courses respectively when adopting a variable power output strategy. The authors concluded that this magnitude of time saving could be compared favourably to the predicted benefits of interventions such as altitude training or ingestion of carbohydrate-electrolyte drinks suggesting that there is, indeed, a potentially functional role for variability within cycling.

Seeking to go beyond a theoretical model, Thomas, Stone, Thompson, Gibson and Ansley (2012) conducted an investigation to assess the reproducibility of self-selected pacing strategies by recruiting seventeen well-trained male cyclists ($\dot{V}O_{2max}$ = 4.70 ± 0.33 $L \cdot min^{-1}$) to perform three 20-km time trials on a Velotron Pro cycle ergometer. Their results suggested that the pacing strategy adopted was similar across trials but showed a higher degree of variability for the first and last kilometre. Given the impact that the start and finish phases of a relatively short time trial event can have on overall finishing time (Hettinga, De Koning, Broersen, Van Geffen and Foster, 2006), this may suggest some merit to further investigating whether the greater levels of variability shown in these phases have a positive effect in terms of performance.

Although it could be argued that this discussion of pacing strategies displays support for a level of intra-individual variability within cycling, it does not strictly relate to *movement* variability. Here the unit of assessment is too big with either the entire event or a full kilometre within it being seen as a single performance of the skill in question. This focus is even more prevalent in work by Paton and Hopkins (2006) who reported the typical variation in competition times of elite cyclists in various race series. Their results suggested that elite cyclists displayed a typical coefficient of variation of 0.4% in World Cup road races, 0.7% in Tour de France road races, 1.3% in road time trials, 1.7% in Tour de France time trials and 2.4% in World Cup mountain biking. They went on to acknowledge that team tactics and pack riding could account for the lower variability shown in road races and, accordingly, compared only events where riders act independently of each other.

While there are a number of interesting conclusions to be drawn from this work, the most pertinent with regards the focus of this PhD investigation is that the level of variation shown between races clearly changed depending on the nature of the event. This is especially interesting from a dynamical systems perspective given that the event which shows the greatest variation is mountain biking, the event which would typically involve the most perturbations of terrain, gradient, body position and power output throughout its duration.

In contrast to the approach outlined above, where an entire race is seen as a single skill performance, the aim of this PhD investigation is to investigate intra-individual movement variability within cycling technique by using each pedal revolution as an individual instance of a skill performance. This links with the recommendations of Kautz et al. (1991) who described pedalling technique as the output of a complex biomechanical system and recommended that further investigations should integrate pedalling technique data with the kinematics and dynamics of the lower extremities during cycling. To the author's knowledge this approach has yet to be employed in published literature with very few studies investigating intra-individual movement variability within cycling.

### 2.3.6 Intra-individual movement variability

Christiansen, Bradshaw and Wilson (2008) and Sides and Wilson (2012) are two rare examples of cycling based studies which have mentioned the potentially functional role of movement variability.

Christiansen, Bradshaw and Wilson (2008) reiterated that movement variability has long been considered an undesirable artefact (Bartlett, Wheat & Robins, 2007) citing evidence that greater movement variability can increase energy expenditure (Lay, Sparrow, Hughes, O'Dwyer, 2002). They also acknowledged, however, that movement variability may play a functional role in reducing injury through variable loading of the musculoskeletal features of the joint (Kurz, Stergiou, Buzzi, Georgoulis, 2005). To this end they conducted an investigation designed to, in part, determine the biomechanical differences between seated and standing postures during cycling.

Six well trained male cyclists aged 20-39 years (Height: 178.70 +2.77 cm, Mass: 73.70 +3.95 kg, Leg Length: 84.87 +1.76 cm) completed a number of modified Wingate test protocols using either a seated or standing body position and a range of crank lengths. Each of these tests had a duration of 6 seconds which was justified as similar in duration to the typical sprint efforts seen throughout flat stages of a competitive stage race (Ebert, Martin, Stephens and Withers, 2006). During these trials it was observed that cyclists adopted increased levels of movement variability at the 0° (top) and 180° (bottom) crank arm positions in the pedal revolution. Christiansen, Bradshaw and Wilson (2008) suggested that this would allow for greater adaptation to changing conditions (extrinsic e.g. terrain; intrinsic e.g. fitness, fatigue) and that it would reduce the repetitive stress on the individual joints.

Although this is initially encouraging, it should be repeated that the cycling events in this investigation lasted only 6 seconds. As such, the movement variability shown here does not reflect a dynamic response to changing conditions within a single performance, rather it shows the adoption of a differing technique when met with a new combination of task perturbations. That is to say, this is evidence of variation between performances rather than within a single performance of a long duration skill which led Christiansen, Bradshaw and Wilson (2008) to recommend that future investigations should include other cycling tasks such as time trialling. Addressing this recommendation is one of the main aims of this thesis.

Sides and Wilson (2012) aimed to investigate the nature of lower extremity intra-limb coordination variability in cycling with a view to ascertaining whether variability present in the system is likely to be a functional element in cycling performance or an indicator of a reduction in performance. They also cited a secondary aim of investigating the intra-limb coordinative adaptations that occur in response to a change in cadence and work rate.

In order to achieve this, they recruited six trained and six untrained males who performed nine pedalling bouts on a cycle ergometer at various cadences and work rates (60, 90, and 120 rev·min$^{-1}$ at 120, 210, and 300 W). During these tasks, kinematic data was collected to allow the calculation of two intra-limb joint couplings (hip flexion/extension–knee flexion/extension and knee flexion/extension–ankle plantar-flexion/dorsi-flexion) which were then analysed using continuous relative phase analysis and led to the conclusion that coordination variability is not beneficial to cycling performance. For more information of continuous relative phase analysis, please see Section 3.3.3.

Initial reading of this summary suggests that Sides and Wilson (2012) supported the traditional motor learning theories in viewing variability as noise and indicative of an unskilled performance. This is clearly in contrast to the ethos of dynamical systems theory which considers variability to be an essential element to normal healthy function (Hamill et al., 1999) and would seem somewhat damning for the aims of this PhD investigation. Upon further reading, however, there are a number of details within this study which are worth highlighting for further critique.

Firstly, although the authors should be applauded for recruiting reasonably homogenous participant groups (Trained = 20.82 ± 1.27 years, 72.77 ± 11.00 kg, 1.78 ± 0.07 m. Untrained = 21.24 ± 1.25 years, 74.41 ± 5.90 kg, 1.81 ± 0.06 m), they presented only weekly training duration as a descriptor of cycling status. Although it could be argued that the minimum criteria of 5 h specific cycling training per week is sufficient to denote “trained” status, there is no detail offered as to the composition of this training time. In addition to this, there is a body of literature which questions the validity of quantifying cycling “training dose” simply using volume in the format of duration or distance covered (Jobson, Passfield Atkinson, Barton and Scarf, 2009; Lambert and Borresen, 2010). This suggests that the detail offered by Sides and Wilson (2012) may not be sufficient to reliably classify participants as either “trained” or “untrained”.

The second criticism raised relates to the choice of measurement equipment employed. The authors stated that they used a two-scanner motion analysis system collecting kinematic data at a sampling rate of 100 Hz. Not only does this raise concerns relating to the number of measurement devices, but the sampling rate also seems low compared to the recommendations made by Payton and Burden (2017) and may not accurately record the variability displayed within each pedal revolution. For example, at the highest cadence studied (120 rev·min$^{-1}$) each pedal revolution would take 0.5 seconds. Measuring at 100 Hz gives a measurement every 0.01 seconds or only 50 measures per pedal revolution. This becomes problematic when the authors used the kinematic data to identify the start point of each revolution based on the position of a pedal marker and also interpolated their kinematic values to 100 time points throughout each revolution.

While performing the various cycling tasks, all participants in this study wore sports trainers as opposed to cycling shoes with cleats. Although this undeniably offers a level of control between groups, it could raise questions about the ecological validity of measurements for trained cyclists if they are habitually using clipless pedals, which has been repeatedly shown to change pedalling dynamics (Mornieux, Stapelfeldt, Gollhofer and Belli, 2008; Wheeler Gregor and Broker, 1995).

To their credit, having initially reported CRP values across an entire revolution, Sides and Wilson (2012) took the seemingly logical step of providing a more sensitive analysis by dividing each revolution into separate phases. They performed a simple two-phase split with 12 o'clock to 6 o'clock representing the propulsive phase and 6 o'clock to 12 o'clock representing the recovery phase. Not only does this seem a somewhat crude division when trying to study something as nuanced as movement variability within a revolution, it is also worth noting that it fails to acknowledge the presence of "dead centres" at the top and bottom of the crank revolution (So, Ng and Ng, 2005). These events during the crank rotation occur at approximately 0° and 180° and denote points where applying a vertical force to the pedal will not result in a rotation of the crank and, instead, a tangential force is required to continue crank progression.

In addition, Sides and Wilson (2012) conducted their analysis of variability using only data collected from the trained cyclist group ($n$ = 6) and only included data from the participant's right leg, with no reference to dominance.

One further potential criticism can be raised in relation to the calculated measure of variability presented here. Sides and Wilson report coordination variability (CRPv) which was calculated as the standard deviation at each time point across the 10 revolutions. Although this will, undoubtedly, provide a way of quantifying the amount of variation present, Abdi (2010) suggests that calculating variability in this way is not ideal. This is due to the tendency of standard deviation to unavoidably increase as the range of the measure increases and gave rise to the suggestion that, especially when mean values may be quite different (such as when dealing with different skill level athletes) calculating coefficient of variation CV% may be more appropriate (Bedeian and Mossholder, 2000).

CV% was specifically invented to eliminate the influence of the finite magnitude of a value on variability (Pearson, 1897). It does so by relating the spread of a data set relative to its own mean. This produces a value which is unitless and divorced from any scale of measurement (Simpson, Roe, & Lewontin, 1960) and therefore provides a clearer comparison of the true variance displayed.

In addition to the potential limitations highlighted here, the authors themselves acknowledged that only investigating flexion/extension couplings in the sagittal plane and ignoring movements in the other anatomical axes as well as only using a limited range of workloads may have resulted in an incomplete picture of any differences which may exist. They also advocated caution when considering their results as the participants used a cycle ergometer which limits the ecological validity of the study and recommended future work investigating inter-limb coordination in addition to the intra-limb couplings shown here.

## 2.4 Summary

As demonstrated throughout the literature review chapter, the historical tendency within biomechanics is to either assume that intra-individual variability in movement patterns is merely "noise" (Bartlett, Wheat and Robins, 2007) and discount it, or to actively discourage variability due to an implicit assumption that movement patterns for skilled performers are invariant (Davids, Glazier, Araújo and Bartlett, 2003; Van Emmerick and Van Wegen, 2000; Padulo et al., 2023). However, there is also evidence presented within this chapter that cyclists will change their technique in response to any number of task perturbations. These include the gradient (Arkesteijn, Jobson, Hopker and Passfield, 2013), workload (Macintosh, Neptune and Horton, 2000), cadence (Sanderson and Amoroso, 2009; Candotti et al, 2009), body position on the bicycle (Savelberg, Van de Port and Williams, 2003) and fatigue state (Diefenthaler, Coyle, Bini, Carpes and Vaz, 2012), as well as the style of ergometer being used (Arkesteijn, Hopker, Jobson and Passfield, 2013) if the assessment is conducted in a laboratory setting.

Additionally, it has been shown that the technique alterations mentioned above may be dependent on experience level and that patterns of leg muscle recruitment vary between novice and highly trained cyclists (Chapman, Vincenzino, Blanch and Hodges, 2008). There is evidence that professional cyclists display a different pedalling technique to recreational cyclists (Broker, 2003; Cavanagh & Sanderson, 1986) and that elite cyclists apply higher force during the downstroke than sub-elite cyclists (Coyle et al., 1991) and also show overall higher pedal force effectiveness than non-cyclists (Mornieux et al., 2008).

Many of the findings covered above can be explained by dynamical systems theory, whereby the movement patterns cyclists employ are described in terms of a system which is able to constantly adapt to the varying demands of a task (Williams, Davids, and Williams, 1999). Under this theoretical framework, the differences seen between novice and experienced cyclists can be explained by their respective abilities to produce movement patterns through generic processes of self-organisation. In essence, it is their ability to solve the “degrees of freedom problem” (Bernstein, 1967) which allows a cyclist to better cope when the task requires adaptability of complex motor patterns within dynamic performance environments (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006).

Despite the apparent suitability of dynamical systems theory when studying the continuous, multijoint nature of the cycling task (Hug, Drouet, Champoux, Couturier and Dorel, 2008), and the research discussed throughout this review which shows consistent evidence of cyclists adjusting their technique to match task perturbations, there are very few research studies which have adopted this theoretical viewpoint and even fewer studies have investigated the potential positive roll that movement variabilty could play in overall cycling performance. The two studies discussed here which do take this specific approach (Christiansen, Bradshaw and Wilson, 2008; Sides and Wilson, 2012) both have limitations which have been outlined earlier in this review and it would therefore appear that this is an area of cycling literature which merits further investigation. In essence, the aim of the upcoming investigations is to answer the question of whether intra-individual movement variability may play a functional role in cycling performance.

In order to address this research question, there are a number of methodological considerations to be aware of. The coming sections of this review aim to highlight some of the unique challenges that studying cycling brings with it while it is also intended that the various methodological choices made throughout this thesis will be explained along with potential alternative methods which were ultimately rejected.

## 2.5 Cycling specific methodological considerations

### 2.5.1 Open skill

Because of it’s importance when looking at topics that concentrate on control and co-ordination of movements, movement variability has been most extensively studied in single performance, closed skill applications such as Shooting (Arutyun, Gurfinkwl and Mirskii, 1968; Scholz, Schöner and Latash, 2000), Basketball (Miller, 2002; Button, Macleod, Sanders and Coleman, 2003 and Robins, Wheat, Irwin, and Bartlett, 2006) and, perhaps most extensively of all, Golf (Knight, 2004; Bradshaw et al., 2009; Glazier, 2011; Langdown, Bridge, and Li, 2012 and Tucker, Anderson and Kenny, 2013). All these modes of activity have a common feature in that it is easy to isolate a single instance of skill performance, repeat it outside of the normal competitive environment and concentrate on the importance of trial to trial variability.

Like many of these skills, a cycling task represents a multijoint movement characterised by several degrees of freedom (Hug, Drouet, Champoux, Couturier and Dorel, 2008). In contrast with other movements, however, the constant and cyclic nature of the circular trajectory of the pedal restricts lower extremity displacement and does not lend itself to such dissection into individual units of skill performance. Therefore, when studying intra-individual movement variability, instead of studying repeated performances of the same skill, the focus will be on repetitions of the same action within a single trial (e.g. individual pedal strokes within a time trial). This allows investigation of a temporal/fatigue factor which is not so prevelant in the previously mentioned papers but could be key in understanding how more accomplished cyclists are able to use movement variability in order to mitigate the effect of fatigue and maintain a higher level of power output for longer periods.

### 2.5.2 Capture volume

When studying cycling, another potential issue to overcome is the amount of distance covered during a cycling effort. This makes it difficult to assess the athlete's technique from a kinematic perspective due to the inability to calibrate such an extensive capture volume. One obvious way to combat this difficulty, as alluded to above, is to recreate the cyclist's equipment set up using an ergometer in a controlled environment such as a laboratory setting. There is, however, a readily available body of literature which focusses on the ecological validity of such an approach. For example, studies by Jobson et al. (2007) and Jobson, Nevill, George, Jeukendrup and Passfield (2008) have consistently shown that there is a significant difference in cycling speed and power output between laboratory and road conditions during time trial events and Bertucci, Grappe and Groslambert (2007) show more broadly crank torque profiles are significantly different when comparing lab and outdoor cycling conditions.

Secondary to this is the meticulous nature with which accomplished cyclists attend to their bike configuration. There is a range of literature from the 1960s onwards (Hamley & Thomas, 1967;

Nordeen-Snyder, 1977; Burke, 1994; Iriberri et al., 2008; Fonda, Sarabon and Li, 2014) espousing the importance of performing accurate bike fitting with as little as a 5% change in saddle height affecting knee joint kinematics by 35% and moments by 16% (Bini, Hume and Croft, 2011). It is therefore worthwhile noting that accurately replicating a participant's bike configuration is of paramount importance if an ergometer is to be used.

In acknowledging that these studies bring into question the validity of the ergometer approach, there must also be an awareness that from a pragmatic point of view, these concerns may have to be overlooked in order to provide enough control of conditions to draw meanigful conclusions in the initial stages of this investigation. This in turn raises issues from a dynamical systems theory perspective as the level of control afforded by a laboratory setting may also remove the very stimulli which require an individual to display movement variablity in the first place such as changing road, altitude, weather or competition conditions. It is therefore suggested that this investigation will look to initially make use of laboratory settings but move into the field as soon as is practically possible in order to obtain a true reflection of any movement variability which is present.

### 2.5.3 Recording kinematic measures in the field

When the aforementioned shift to a field-based setting occurs, it brings with it a new set of challenges with regards collecting kinematic data. As mentioned before, it would be impossible to calibrate the entire performance volume to allow for kinematic data to be recorded using the traditional camera-based motion capture techniques, and so alternative solutions must be sought.

The use of wearable sensors provides an excellent alternative and their usage has grown steadily ever since a spring-loaded weight was attached to the body segments to determine its movement characteristics (Lee, Wheeler and James, 2019). For example, Electro-goniometers have long been used for the measurement of lower extremity joint motion (Chao, Askew and Morrey, 1980) and they are often deemed suitable for practical applications within biomechanics because of their limited size (Legnani et al., 2000). The lightweight equipment and non-invasive methods of data collection, coupled with the ability to record to offline data logging systems makes them a potentially excellent choice for field-based assessments within cycling. Indeed, they have already been assessed in terms of their suitability for use in professional bike fitting services (Fonda, Sarabon and Li, 2014) and have been found to be more accurate and valid for use within laboratory studies than manual methods of measuring knee joint range of motion (Shamsi, Mirzaei and Khabiri, 2019).

Likewise, inertial measurement units (IMUs) offer an unobtrusive, lightweight method of data collection in the field. Although initially developed for mo-cap/animation applications within the film and gaming industries, products such as Xsens technologies' motion capture suits quickly became adopted by sports science practitioners who required a portable system in order to research human motion beyond the constraints of the traditional lab environment (Mavor et al 2020). There is a significant body of literature which investigates the validity of such devices (e.g. Van den Noort, Scholtes and Harlaar, 2009; Eckardt, Munz and Witte, 2014; Geissinger and Asbeck, 2020; De Baets et al., 2020). IMUs have been shown to provides accurate measures of accelerations and orientations during multiple functional activities (Cudejko, Button and Al-Amri, 2022), are suitable for rehabilitation applications and sports to detect malposition (Schlage, Kitzig, Stockmanss and Naroska, 2021) and also happen to be relatively cost effective and widely available (Wei, Kurita, Kuang and Gao, 2021).

With such a range of wearable technologies available, it should be possible to find a suitable method of overcoming the challenges inherent within field based kinematic data collection. It should be noted, however, that these wearable technologies and mobile sensor systems have yet to be validated for use within cycling, especially when trying to calculate CRP. This, therefore, will obviously have to be addressed throughout the course of this thesis (see Studies 2-5).

### 2.5.4 Participant groupings

Another issue raised when studying cycling is that of how to quantify the level of accomplishment shown by participants. Initially it was proposed that this investigation would follow a similar structure to that of Scholz, Schöner and Latash (2000) in that it would seek to quantify the level of movement variability present within individuals comparing novices and elite performers. Ideally these groups would be comprised of individuals who are physiologically similar in terms of their generic measures of physical fitness (Lactate threshold, Power Output, $\dot{V}O_{2\ max}$, etc.) but are competing in different categories within the established competitive structure set out by British Cycling (see Table 3-1). In selecting physiologically similar individuals with differing competitive levels it was hoped that a level of control can be sought and therefore it is more likely to be able to attribute differences in performance to technical differences such as enhanced movement variability.

This approach, however, brings its own limitations as it is very difficult to recruit a true "novice" cyclist who would be capable of completing a ten-mile time trial (as required for the first investigation) and it is highly unlikely that a true "novice" cyclist would hold a race license. It is also unlikely that participants of such different experience levels would exhibit similar $\dot{V}O_{2\ max}$ values given the amount of training required to progress through the race licence categories.

Additional difficulties are seen due to the way promotion between race license categories occurs (see Table 3-1) as it is possible for a rider to gain promotion by amassing points from completing a large number of events (but not finishing particularly highly in any of them) or by completing relatively few events but placing highly in those they do enter. It is also possible for a rider to hold, for example, an Elite category license but to have reached this level only ever competing in one particular type of event (e.g. never competing in a time trial event) which, again, questions the validity of using this as a suitable framework for grouping participants into bands of similar accomplishment levels.

**Table 2-2. Competitive cycling category structure adapted from Britishcycling.org.uk, 2015**

| Category | Eligibility | Maintenance |
|---|---|---|
| **4th** | A new junior or senior licence holder. | - |
| **3rd** | Any junior or senior licence holder who has gained 12 points during any one season whilst holding a 4th category licence | Riders are never downgraded to 4th category once a 3rd category licence has been achieved. |
| **2nd** | Any junior or senior licence holder who has gained 40 points during any one season whilst holding a 3rd category licence. | Riders must obtain at least 25 points in events open to that category of rider. |
| **1st** | Any junior or senior licence holder who has gained 200 points during any one season whilst holding a 2nd category licence. | Riders must obtain at least 100 points in events open to that category of rider. |
| **Elite** | Any Senior licence holder who has gained 300 points during the previous season whilst holding an Elite or 1st category licence.<br>A rider who, at the 31 December of the previous year, was listed in the top 10 in the elite men's British Cycling Cross-country MTB Series rankings may also claim an elite licence. | Riders must obtain at least 300 points in events open to that category of rider. |

To demonstrate some of the difficulties outlined above, participants in the initial study were ranked according to the time they took to complete the simulated time trial event. If, for example, all of the 4th category riders had been grouped together, this group would have included the 2nd, 4th, 7th, 8th and 10th ranked riders. This clearly does not represent a homogenous group in terms of time trial performance so alternative ways of grouping participants were sought. Fortunately, the largest difference in finishing time occurred between the 5th and 6th ranked riders, giving an equal split of participants in an upper and lower group. This approach may need revisiting once the investigations move beyond a laboratory setting as other factors such as body size (Jobson et al. 2007) and body position (Jeukendrup and Martin, 2001) play a larger role in overall performance but at the time of analysing the initial study, it appeared to be a logical approach.

## 2.6 Kinematic Analysis Methods

Given the aim of this thesis, it is important to consider those methods that are available to quantify movement variablity from a dyamical systems perspective. Hausdorrff et al. (1999) and Schot, Hart and Mueller (2002) both suggest that methods such as the coefficient of variation (CV%) have traditionally been the predominant measure of movement variation in discrete kinematic analysis. However the sensitivity of such measures has been questioned as they represent the sum of not only the Individual's true biological movement variability but the measurement error also (Rodano and Squadrone, 2002).

These concerns led Bartlett, Bussey and Flyger (2006) and Bradshaw et al. (2007) to develop alternative methods to quanify the true biological variability (BCV%) of human movement and separate it from measurement error. CV% has been reported in previous movement variability studies, for example a study on the variability of the maximal instep soccer kick (Lees and Rahnama, 2014) and were adopted for this thesis also.

At a similar time to Hausdorrff et al's (1999) work, however, Hamill, Haddad and McDermott (2000) identfied that there are a variety of alternative methods available to quantify movement variability and advised that the selection of a method should be determined by the nature of the research question. They discussed a number of methods which can be classified as either discrete or continuous methods and will be briefly outlined below. All of these approaches are cognicent of the idea that joint movements do not happen in isolation due to the interconnected nature of the structures within the human body and therefore deal with the idea of joint or segment couplings. This approach can be seen in any number of gait based kinematic investigations (eg. Rosenbaum, Becker, Wilke and Claes, 1998; DeLeo, Dierks, Ferver and Davis, 2004; Ferber, Davis and Williams, 2005; Herb et al. 2014) and seems appropriate for the in depth analysis of cycling kinematics undertaken throughout this thesis.

### 2.6.1 Discrete methods

Both discrete methods discussed by Hamill et al. (2000) are essentially temporal measures which illustrate the relative timing of key events in a movement cycle, allowing a measure of latency between, for example, the flexion of one joint compared to that of another. This is useful as it is a reasonably simple method which requires no further analysis than calculation of simple joint angles. The disadvantage of these methods, however, is that they only take a meaure of this co-ordination once per movement cycle (Van Emmerick, Rosentein, McDermott and Hamill, 2004). In the case of this particular investigation, this would be the equivalent of only measuring the relative position of two joints once per pedal revolution. The issues with such a reduction in sampling frequency are hopefully apparent but will be discussed in greater detail later in this thesis.

Hamill et al. (2000) explains that the time-series approach allows the determination of a discrete relative phase angle (φ) between two joints or segments at a specific event during a movement cycle. Examples of this approach can be seen in work by Hamill, Bates and Holt (1992) and McClay and Manal (1997) who both used this approach to quantify the relative timing of knee and subtalar joint motions during the support phase of the running stride. In these examples the specific events of interest were the point at which the knee joint reaches maximum flexion and the subtalar joint reaches maximum eversion and this was then calculated as follows:

$$\varphi = \frac{t_1 - t_2}{T} \times 360^{\circ}$$

where T is the support period, $t_1$ is the time to maximum knee flexion, $t_2$ is the time to maximum subtalar eversion. Both $t_1$ and $t_2$ were mearsured from a predetermined zero point (in this case initial foot contact). This calculation results in values between 0° and 360°, where a value of 360° represents two perfectly in phase movements and values between 0° and 359° indicate the amount to which the movements are out of phase. Performing this calulation over a number of strides allowed Hamill, Bates and Holt (1992) and McClay and Manal (1997) to present the variability of this coupling but critically, as mentioned earlier, this approach provides only information at one specific instant in each stride.

A similar issue can be seen with return maps, another discrete measurement tool which was used by McDermott, Van Emmerik and Hamill (2000) to quantify variability in the coordination between stride and respiration during locomotion. When studying the underlying mathematics of this method the similarities with the time series approach are immediatley apparent as discrete relative phase angle is, in this instance, calculated using the formlua below:

$$\varphi = \frac{T_n}{t_n} \times 360^{\circ}$$

In this example, $T_n$ is the time between consecutive heel contacts and $t_n$ is the time from heel strike to the end of inspiration. A return map would then be created by plotting multiple calculations of φ in order to assess the frequency ratios between the two events (in this example breaths and strides). This allows a researcher to assess the preferred ratio between the two events and therefore identify couplings which stray away from this ratio (i.e. display a level of variability) and quantify how close the system is to a transition to a new preferred state.

The advantage of a return map approach over the time-series method is the ability to study systems, such as locomotor-respiratory coupling example presented by McDermott et al. (2000), where frequency ratios other than 1:1 are present. It is also useful for systems where there is a very regular signal (in this example, stride) and a signal that varies based on the frequency of the regular one (in this example, respiration). As neither of these conditions would be present in a cycling-based system it must be concluded that this, along with the issues of single point measurement mentioned above, makes both the discrete methods presented here inappropriate methods of analysis for the current thesis.

### 2.6.2 Continuous methods

In contrast to the discrete methods already outlined, continuous methods offer the ability to evaluate movement coordination, and therefore variability, over a complete movement cycle (Hamill et al. 2000). This is advantageous as the researcher is no longer limited to a single time point within the movement and can chose to either assess movement in terms of relative motion or continuous relative phase.

In order to assess relative motion, the joint angle for each segment involved in the analysis must first be calculated across the entire motion cycle. Once this has been achieved, the relative motion of the joints can be assessed using angle-angle plots and quantified using vector coding techniques (see Sparrow et al., 1987). As with the time-series approach above, the values from this analysis also range between 0 and 360° but here the values are used to describe the relative movement of the joints, rather than the latency between events.

Using a relative motion approach, values of 0° or 180° would suggest the distal joint of a coupling is stationary while the proximal joint is moving. Values of 90° and 270° indicate the opposite. Values of 45° and 225° denote in phase movements in the same direction at both joints with values of 135° and 315° indicate equal movement but in opposite directions. This directional interpretation is advantageous as it provides a greater understanding of the motion the coupling with no need for normalisation procedures. However, as pointed out by Hamill et el. (2000) this method provides no temporal information and therefore offers an incomplete view of the coupling motion.

Continuous relative phase overcomes this issue by replacing the angle plots of a relative motion approach with phase plots which can then be used to calculate the four-quadrant arctangent phase angle of the joints of interest (Hamill et al., 2000). This allows the calculation of the relative phase between two segments at every point in the trajectory (Wheat and Galzier, 2006) and has been detailed in numerous reviews (Hamill et al., 2000; Kurz and Sterigou, 2003; Van Emmerick et al., 2004; Weat and Galzier, 2006).

Lamb and Stöckl (2014) identified that there has been some debate as to whether the signal values for these plots need normalising to avoid the magnitude of values from one segment dominating the continuous relative phase pattern but both they and Kurz and Stergiou (2002) concluded that, in the case of joint kinematics, this is not required because the finite values are unimportant, it is the relative phase which is of interest. Calculation of continuous relative phase, therefore, requires normalisation of values against time, but not normalisation of the original signal values themselves.

Once the phase angles are calculated for joint and the time history is normalised to a fixed number of data points, the continuous relative phase is found by simply subtracting the phase angle of one joint from that of the other at each point in time over the entire movement. For example, the formula to calculate the CRP angle of the thigh/leg coupling is:

$$CRP = \varphi_{thigh}(t) - \varphi_{leg}(t)$$

where $\varphi_{thigh}(t)$ and $\varphi_{leg}(t)$ are the normalised phase angles of the thigh and leg, respectively, at each instant in time of the movement. Continuous relative phase values can, again, range from 0° to 360° where 0° shows the respective movements of the coupled joints perfectly in-phase, while a CRP of 180° indicates that they are perfectly anti-phase and any value between these indicates a relative amount of in-phase or anti-phase movement.

Again, Lamb and Stöckl (2014) identified inconsistencies with this reporting convention with some authors choosing to report values only between 0◦ and 180◦ since the values −180◦ and 180◦ both indicate anti-phase behaviour and others suggesting that the positive and negative values have qualitative meaning and should be preserved. Kurz & Stergiou (2002), for example, support preserving the negative values as they suggested that if the phase angle of the proximal segment is subtracted from the phase angle of the distal segment, then positive continuous relative phase values indicate that the distal segment is ahead of the proximal segment in phase space therefore providing a greater indication of the coupling's interaction.

### 2.6.3 Continuous relative phase analysis

Having briefly outlined these potential methods, it seems that the continuous, multijoint nature of the cycling task (Hug, Drouet, Champoux, Couturier and Dorel, 2008) lends itself best to a continuous relative phase method of analysis. This is because, in a kinematic chain, the motion of one segment subsequently influences the motion of an adgecent segment, and therefore the study of isolated joints does not effectively capture the complexity of the coordinated motion (Bartlet et al. 2007). This is especially true when one end of the kinetic chain is attached to a pedal and Chapman et al. (2009) sugested that the consideration of the coupling relationship between segments may therefore be espiecially crucial in the analysis of motion within the field of cycling.

In addition, continuous relative phase analysis has been deemed to be more sensitive to changes in coordination (Davids et al., 2006) and seems appropriate because of the multiple ways in which cycling could potentially be studied throughout this thesis. Although the focus so far has been on the treatment of kinematic variables, Burgess-Limerick, Abernethy and Neal (1993) identified that information regarding multijoint coordination is also likely to be important in attempting to understand the respective roles and interaction between the bi and monoarticular muscles which are involved in complex human movement. This is an area which may be included in the later stages of this thesis as kinematics and muscular activity are so inherently interconnected.

Limerick, Abernethy and Neal (1993) also suggested that calculations of continuous relative phase should provide a measure which is sensitive to the effects of environmental changes, learning or other independent variables which is obviously important when analysing human movement from a dynamical systems perspective and should aid in the understanding of the control of movement more generally. They went on to state that they believed the use of continuous relative phase analysis provides information that cannot be obtained through conventional angular position vs time presentation and that this may lead to substantive differences in interpretation of kinematic data. They did, however, concede that a strong argument can be made for the use of both types of analysis where inter-joint coordination is relevant to the questions being addressed.

### 2.6.4 Measurement duration

Having established that Continuous Relative Phase was to be the main analysis method for kinematic variables it was then important to ascertain how many individual pedal revolutions needed to be analysed to give a stable measure for each participant. In the first instance kinematic variables were recorded throughout an entire simulated ten-mile time trial event with the intention of having a number of discrete time "windows" from which measures would be taken in order to investigate whether the variables changed over time. These "windows" were fixed at 5, 10, 15 and 20 minutes through the effort giving measures at approximately 25%, 50%, 75% and just before completion of the simulated event. Individual pedal revolutions were identified using the vertical component of pedal motion as a reference and all raw kinematic measures within the revolution were then interpolated to 101 time points. This approach is akin to that which was recommended by Lamb and Stöckl (2014) and Kurz and Stergiou (2002) and allows not only standardisation of each revolution in terms of data points but also gives the opportunity to report events relative to a percentage of a pedal revolution as is the convention in cycling literature.

Once the number of data points in each pedal revolution had been normalised, Continuous Relative Phase values were calculated for two joint couplings (Hip-Knee and Knee-Ankle) and the cumulative standard deviation of these values were plotted starting at 2 revolutions and continuing to 30. As can be seen in the representative figure below, three participant's data was analysed in this way and the standard deviation values seemed to plateau around 8 revolutions. It was therefore decided to analyse 10 pedal revolutions at each time point in order to achieve a stable measurement.

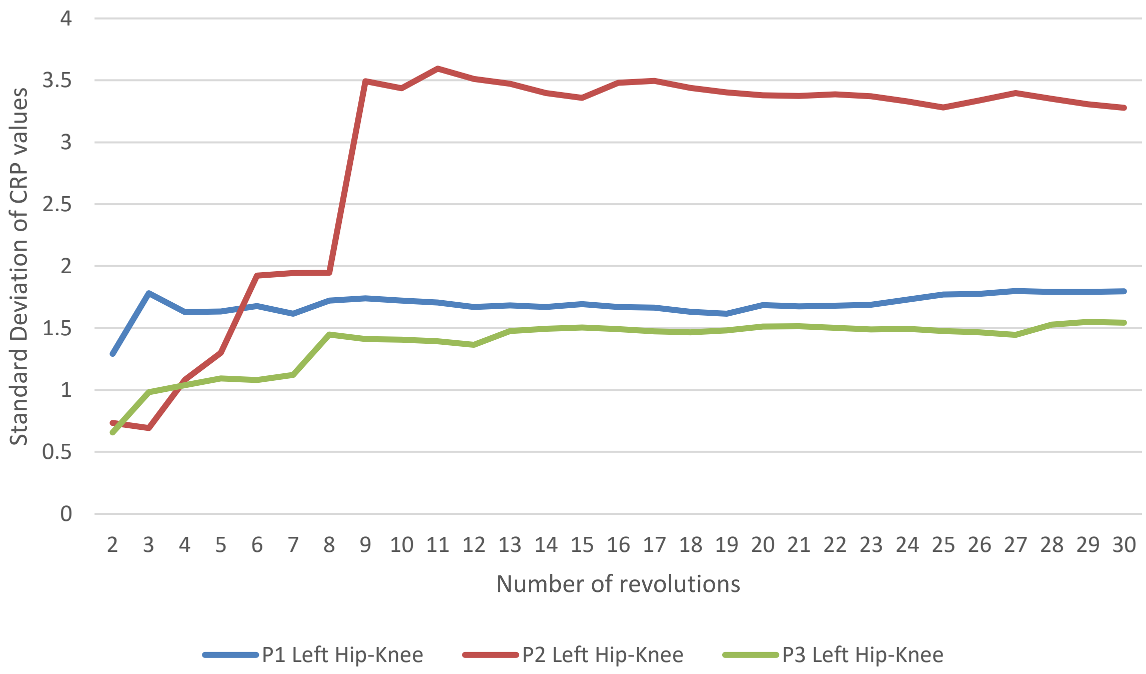



**Figure 2-5. Demonstrating how CRP values stabilise as more revolutions are included for analysis.**

### 2.6.5 Full revolution analysis

The analysis method detailed above gives a mean standard deviation of Continuous Relative Phase across 10 pedal revolutions at each of the 100 time points which data had been normalised to. Initially these 100 Continuous Relative Phase values were combined into a single value to report the mean standard deviation shown across the whole pedal revolution. A representation of the combined values for one coupling produced this way from all participants in the initial study can be seen in Table 3-2 under the heading of "Full Revolution". There were some concerns, however, that this approach would lack the sensitivity required to demonstrate potential differences throughout a pedal revolution and would suffer from the same issues inherent with the discrete measurement methods discussed previously.

### 2.6.6 Simple phase split analysis

To address this issue, Continuous Relative Phase values were calculated using a crude 50-50 split. The suggestion here being that from 0-50% of a pedal revolution represented the phase in which power was being applied to the pedal and 50-100% represented the recovery phase where the leg in question was not actively contributing to power production. This definition is displayed in Wozniak-Timmer (1991) but could be questioned given the body of literature debating whether cyclists actively pull up with the recovering foot when using clipless pedals (eg, Kautz, Feltner, Coyle and Baylor, 1991). Regardless, it served to demonstrate that a level of variation had been masked by only reporting one value per pedal revolution (see Table 3-2) but still did not, in the context of this thesis, give enough detail throughout the various phases of the revolution to fully exhibit the nuanced kinematics at play.

It is worth noting at this point that the methodological decisions outlined so far very much mirror the approach of Sides and Wilson (2012). This is a paper which has been discussed in detail elsewhere in this thesis and also employed a continuous relative phase method of analysis, used a 10-revolution sampling window, selected the same joint couplings, initially reported mean CRP across an entire revolution and subsequently split the revolutions into a propulsive and recovery phase. The methodological decisions taken here were done so independently of this paper as it was not discovered until after this process had been completed.

### 2.6.7 Four phase analysis

In contrast to Sides and Wilson (2012), the decision was taken to improve upon the rather simple dissection of the pedal revolution described above. As such, a further inspection was performed with four "quarters" across the pedal revolution. This classification of a pedal revolution into four sections was employed by Dorel, Couturier and Hug (2009), Dorel et al. (2009) and Lanferdini, Jacques, Bini and Vaz (2014) and effectively separates the power and recovery phases from the top and bottom of the pedal revolution (see Figure 3-2). Given that both the top and bottom points of a pedal revolution have been long been identified as areas where tangential force is at a minimum (Ericsson and Nisell, 1988; Patterson and Moreno, 1990) it seems logical to view them separately to those areas where force production is at it's greatest and the values shown in Table 3-2 would appear to somewhat validate this approach.

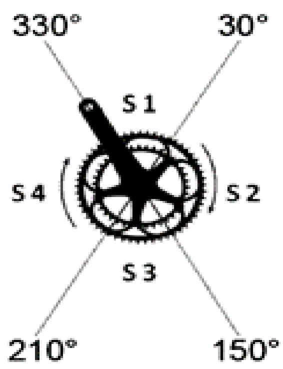



**Figure 2-6. Showing the four phases per pedal revolution.**

**Adapted from Dorel, Couturier and Hug (2009)**

**Table 2-3. Demonstrating the difference in values when calculating CRP via three different methods.**

| | 5min | | | 10min | | | 15min | | | 20min | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full Revolution | Simple Phase Split | "Quarters" Split | Full Revolution | Simple Phase Split | "Quarters" Split | Full Revolution | Simple Phase Split | "Quarters" Split | Full Revolution | Simple Phase Split | "Quarters" Split |
| Top Phase | | | 30.11 (±10.53) | | | 32.81 (±13.82) | | | 28.39 (±8.63) | | | 22.34 (±5.97) |
| Power Phase | | 20.49 (±6.76) | 18.89 (±9.21) | | 21.96 (±7.46) | 18.44 (±6.50) | | 18.68 (±4.57) | 17.49 (±3.76) | | 20.24 (±6.25) | 14.44 (±5.97) |
| Bottom Phase | | | 18.71 (±9.39) | | | 21.54 (±9.31) | | | 16.43 (±4.96) | | | 22.18 (±13.10) |
| Recovery Phase | | 21.42 (±8.19) | 20.86 (±8.64) | | 28.98 (±10.48) | 29.54 (±11.68) | | 23.64 (±7.43) | 23.99 (±11.90) | | 21.64 (±2.35) | 16.83 (±4.64) |
| Full Revolution | 22.62 (±9.08) | | | 25.43 (±8.46) | | | 21.14 (±4.71) | | | 22.83 (±5.79) | | |

In Table 3-2, Left leg Knee-Ankle coupling at all time points are displayed as a representation of the wider data set. This demonstrates how much variance there is when different frames of reference are used to describe a pedal revolution. Taking the data from the 15 minute measurement window, for example, when viewing the pedal revolution in its entirety the result for mean continuous relative phase value is 21.14 (±4.71). Splitting the pedal revolution into the simple power and recovery phases returns mean values of 18.68 (±4.57) and 23.64 (±7.43) respectively. Even this simple division suggests that the overall value for a whole revolution is not sensitive enough to fully demonstrate how the relationship between joints in a couple alters throughout the course of a pedal revolution. As such, whole revolution values will be used to guide gross judgements of variability but further division was required in order to assess the granular nature of any movement variability which may be present in the kinematic data.

## 2.7 Electromyography Analysis Methods

De Luca (1997) described electromyography as a “seductive muse” as it “provides easy access to physiological processes that cause the muscle to generate force, produce movement and accomplish the countless functions which allow us to interact with the world around us”. While this may be true, it is also true that EMG analysis is “too easy to use and consequently too easy to abuse” (De Luca, 1997), leading to incorrect interpretation and use. To avoid abusing this tool, a number of issues need to be addressed, many of which are similar to those raised in the in the previous section relating to kinematic analysis. Instead of refreshing those arguments, the focus here will be on methodological choices which are specific to the electromyographical elements of this investigation.

### 2.7.1 Electrode choice

When conducting EMG analysis, the first choice to consider is the style of electrode used to record muscular signals. At the most fundamental level, a choice needs to be made between using indwelling electrodes which are inserted into the muscle fibre and surface electrodes which are merely attached to the skin to record activity from the underlying muscle.

As noted by Parro (2014), indwelling electrodes may have superior diagnostic value but the process of inserting them is extremely invasive and often painful, making it inappropriate for monitoring human movement. It was also assumed that the use of indwelling electrodes would hugely reduce the likelihood of recruiting voluntary participants for this investigation. Indeed, due to its invasive nature, this technique has been used in very few cycling studies (e.g. Juker et al., 1998, Chapman et al., 2006, Chapman et al., 2007) and in only few muscles (Tibialis posterior, Psoas).

Another reason for not using indwelling electrodes is based on the pioneering work of Henry Pickering Bowditch (1840–1911), Keith Lucas (1870–1916) and Lord Edgar Douglas Adrian (1889–1977). Their work has been widely accepted to explain that the muscle fibres involved in a muscular contraction will adhere to an “all or nothing principle”. That is to say that, when stimulated, each individual muscle fibre contracts with either a maximal response or none at all. If the demands of the task require more muscular force, a greater number of fibres are recruited but the individual contribution of each fibre to overall force production will remain constant.

If we are happy to assume that Lord Adrian’s principle, for which he jointly won the 1932 Nobel Prize for Physiology (Pearce, 2018), is correct, then we must also assume that indwelling electrodes cannot be appropriate for the measurement of sub-maximal contractions. Hug and Dorel (2009) noted that, with indwelling electrodes, the volume of muscle from which signal is recorded is relatively small (few cubic millimetres) and thus may not be representative of the total muscle mass involved in the exercise. It is theoretically possible that using indwelling electrodes means it may be inserted into a muscle fibre that is simply not recruited to perform that task. Conversely, surface EMG has been shown to provide information from a large mass of muscle tissue and is, therefore, more directly correlated to the mechanical outcome (Frigo and Shiavi, 2004).

Additionally, it has been shown that EMG signals progressively and significantly decreased with time with indwelling electrodes, but not the surface electrode equivalent (Reeves, Starbuck and Nester, 2020). It was found that the recorded mean amplitude from indwelling electrodes had reduced by 11% after 25 minutes and 16% after 50 minutes and peak amplitude reduced 22% at 20 minutes and 37% at 50 minutes. None of these changes were evident in the surface EMG signal, bringing into question the suitability of indwelling electrodes for use in experiments of more than 30 minutes.

This is not to say that surface electrodes are without methodological concerns. For example, Allen, Brookham, Cudlip and Dickerson (2013), found that surface electrodes overestimated by 72% and 400% maximal voluntary contraction in external and internal axial humeral rotation trials, respectively. They recommended caution when interpreting surface recordings as indicators of indwelling recordings for exertions where the muscle studied is not a primary mover. In addition to this, there is a greater likelihood of “crosstalk” when using surface electrodes.

Crosstalk occurs when an electrode records data from a source other than the muscle of interest and can lead to artificially inflated values for muscular recruitment. Although some literature shows this as a significant issue (Farina, Merletti, Indino, Nazzaro and Pozzo, 2002; Farina, Merletti, Indino and Graven-Nielsen, 2004) this is still an area of debate with literature reviews on the subject still being published (e.g. Mesin, 2020.) and other studies discounting it entirely with Solomonow et al. (1994) concluding that “the crosstalk problem in surface recording is negligible for most biomechanical studies”.

Given the likely duration of a ten-mile time trial, the possible discomfort for participants and the chance of erroneous data when conducting sub-maximal muscular contractions, it was agreed that this investigation would employ surface electrodes only.

### 2.7.2 Intra electrode distance

One proposed method of addressing crosstalk in surface electrodes is to reduce the interelectrode distance when recording surface electromyography. This has been an ongoing area of investigation with comprehensive guidelines published before the turn of the 21$^{st}$ century (Hermens et al., 1999) and continued additions/critiques being published very recently (e.g. Farago, Macisaac, Suk and Chan, 2022; Xu et al., 2022; Smit et al., 2022).

Farina et al. (2002) evaluated crosstalk between vastus lateralis, vastus medialis, and rectus femoris muscles by selective electrical stimulation of one muscle and recording from the stimulated and another muscle with linear surface arrays of eight electrodes. Single-differential and double-differential detection systems were used with interelectrode distances in the range 10–40 mm. Their results suggest that crosstalk increased with increasing interelectrode distance and was statistically higher for single than for double-differential recordings.

Castroflorio et al. (2004) investigated if the sensitivity of surface electromyography was affected by the inter-electrode distance of the bipolar recording and the effect of inter-electrode distance on the estimated amplitude and spectral EMG variables. They found that increasing the inter-electrode distance resulted in a significant reduction of the estimation variability and noted that amplitude EMG variables were particularly affected by inter-electrode distance. They therefore recommended that this should be fixed when subjects or muscles are compared in the same or different experimental conditions.

Afsharipour, Soedirdjo and Merletti (2019) furthered this discussion and focussed on the three issues of electrode size, inter-electrode distance and the effect of the size of the electrode grid. Their recommendations were that small electrodes (< 3 mm) with small interelectrode distances (< 5 mm or < 10 mm as a questionable compromise) be used for surface EMG as this was a balance between the need for small inter-electrode distance and the fact that this will require greater signal amplification as the signal strength will be weaker.

In accordance with all recommendations above, the electrodes used for all EMG investigations in this thesis were from the Delsys Trigno Avanti range which features 1mm contacts with a fixed 10mm inter-electrode distance. They are capable of onboard filtering using a Butterworth bandpass and Route Mean Square Envelope Calculations with a 100ms window.

### 2.7.3 Feedback system

Most commercially available EMG systems can be classified as either hard-wired/“on-line” or data logger/”off-line” systems (Payton and Burden, 2017) with each of these options offering their own relative strengths and limitations.

A data logger style system allows for data collection away from a fixed position or static computer station. This is advantageous when studying actions such as cycling which cover a large distance (see section 3.2.2) and, by definition, would require the participant to go beyond the range of any wireless transmission range during the performance of their event.

Traditionally, however, data loggers have not allowed the production of a “live” view of the recorded EMG signal and therefore the potential for incomplete recordings is increased. Additionally, these types of systems have a limited amount of internal storage, which inevitably results in a compromise somewhere in the recording process. Typically, this manifests in either reduced sampling rates, reduced recording durations or a limited number of electrodes used. Although the first two of these concerns have been largely addressed in recent years, the data logger system available for this thesis is limited to a maximum of four sensors transmitting via Bluetooth to a mobile phone.

On-line systems, where data is transmitted directly to a base station that is usually attached to a computer with an internet connection, don’t suffer from these limitations. They offer the theoretical ability to record an infinite amount of data with as many sensors as are available but make it impossible to collect data beyond the range of the wireless transmission or, in the case of a truly “hardwired” system, beyond the length of the cable.

Due to the differing testing environments which may potentially be employed during this thesis a decision will be made during the planning stages of each study as to which system to employ. This will always be the system which allows the greatest amount of data to be recorded, assuming that it is feasible to use it in a safe and accurate way during the proposed protocol.

### 2.7.4 Normalisation of muscular amplitude values

Regardless of the feedback system selected, the main variable reported to ascertain how hard a muscle is working is the peak amplitude of the EMG signal. It has long been suggested that some form of normalisation should be applied to these measures to facilitate comparison between participant activation levels (Bolgla and Uhl, 2007; Lehman and McGill, 1999; Mirka, 1991), between two different muscles or ipsilateral sides of the same participant (Lehman and McGill, 1999) and to allow for comparison of results against previously published studies (Soderberg and Knutson, 2000). Several methods have been proposed for the purpose of EMG amplitude normalisation in cycling but there seems to be little agreement on which is most suitable (Fernandez-Pena, Lucertini and Ditroilo, 2009; Norcross, Blackburn and Goerger, 2010).

Traditionally, normalisation has been achieved by expressing the recorded amplitude as a proportion or a percentage of the peak amplitude recorded during an isometric maximal voluntary contraction (iMVC) of the same muscle (Burden, 2007). There are numerous examples of this approach (eg. Arokoski et al., 1999; Lobbezoo et al., 1993; Smith et al., 2004) and it has been demonstrated to be reliable (Dankaerts et al., 2004; Kollmitzer et al., 1999) with recommendations by both ISEK (Merletti et al., 1999a) and the SENIAM project (Merletti et al., 1999b). Despite this, there are a number of criticisms to outline here.

Inherent within the use of iMVCs is the assumption that participants can actually perform an effort which elicits a maximal isometric muscular contraction. This may not be true, especially if they are not trained and well-motivated (Fernandez-Pena, Lucertini and Ditroilo, 2009). Additionally, despite Allen et al. (1995) concluding that most participants were able to maximally activate their muscles during iMVCs they warned that the ability to consistently do so varied. Ekstrom, Soderberg and Donatelli (2005) concurred that no one muscle test produced an accurate iMVC for all individuals. More problematic is that outputs from this normalisation method in excess of 100 per cent have been recorded (e.g., Jobe et al., 1984, reported peak amplitude at 226% of iMVC) suggesting that it may not actually be a valid representation of a participant's maximal contractile ability.

In response to this criticism, normalisation against sub-maximal isometric contraction was advocated by De Luca (1997) and adopted by Hunt et al. (2003) and Dankaerts et al. (2004). The use of peak amplitude values taken from contractions that are less than 80 per cent iMVC to provide a more stable reference value was found to be more reliable in between-days repeated measures, but it was concluded that correctly determining the relative sub-maximal loads for every muscle is difficult (Dankaerts et al., 2004).

Burden (2007) raised another potential issue with the use of iMVCs when he questioned whether, as most tasks in sport and exercise involve non-isometric contractions, it is appropriate to use iMVCs, regardless of intensity, to normalise amplitude from dynamic contractions. This is a view shared by Clarys and Cabri (1993) and Prilutsky et al (1998) who had previously suggested that a dynamic activity would be a more suitable reference value and Rouffet and Hautier (2007) who underlined that, when dealing with sports movements, the EMG profile should be the expression of the dynamic involvement of specific muscles.

This conflict of methods endures as some authors (e.g. Burden and Bartlett, 1999 and Burden et al., 2003) showed that the use of Isokinetic MVCs showed only minor differences compared to Isometric MVCs, while others have begun investigating sport specific approaches to normalisation. For example, Hunter et al. (2002) compared four normalisation protocols to be used within cycling. Three conditions were designed to elicit an iMVC and the fourth was a dynamic pedalling action against a constant load, which was repeatedly increased until the subject could no longer complete a full revolution of the pedal. Their results revealed that iMVCs were greatest when performed on an isometric leg extension dynamometer and, therefore, concluded that this was a more appropriate method of normalisation than a cycling specific activity.

In contrast, Fernandez-Pena, Lucertini and Ditroilo (2009) presented a maximal isokinetic protocol (MIP) of normalisation in cycling that required 10 performances of a 6-second, maximal effort pedalling trial at a fixed cadence of 80 rev·min$^{-1}$. Having compared the MIP results against a range of sub-maximal workloads they concluded that it represented a suitable normalisation procedure because the contribution of the tested muscles was similar for maximal and submaximal conditions, the pedalling frequency, posture and joint angle ranges of the cyclist matched in both conditions and the type and relative timing of muscular contractions were also similar in both.

Initially this would seem to present an ideal normalisation procedure, especially when considering that this allows normalisation values for all muscles of interest to be assessed at the same time, rather than using an iMVC method which requires a separate test each muscle. However, as the authors note, there are some limitations. Firstly, both the MIP and submaximal trials were performed at 80 rev·min$^{-1}$ despite it being shown that a cadence of 100–115 rev·min$^{-1}$ is more often related to maximal power output (Baron, 2001; Baron et al., 1999; Sargeant et al., 1981). This leads the authors to recommend that this normalisation is only suitable for submaximal cycling exercises performed at the same cadence as the MIP.

Additionally, one of the great strengths that Fernandez-Pena, Lucertini and Ditroilo (2009) claimed with their method is that it could be performed on exactly the same equipment as the following submaximal test. This initially sounds useful but, in reality, restricts investigations to being conducted on an ergometer with an isokinetic mode and not, as required in the later stages of this thesis, in the more ecologically valid setting of a field test using the participant's own bike (see Section 3.2.3).

Ultimately the decision was taken to not perform normalisation tests for this investigation due to the range of reasons explained above, the lack of agreement on a suitable method and mainly because the focus of this investigation is on the *variability* of peak amplitude and not the actual finite values themselves. As shown earlier, the amplitude from surface EMG electrodes does not suffer from the progressive and significant decreases that indwelling electrodes do (Reeves, Starbuck and Nester, 2020); thus, comparing within a prolonged performance within a single participant should be valid and was adopted as the major method of analysis for this investigation.

Additionally, because the emphasis is on the *variability* of muscular recruitment and not the finite levels, results can be reported using the co-efficient of variation (CV%). This provides a degree of normalisation (Bedeian and Mossholder, 2000) as CV% was specifically invented to eliminate the influence of the finite magnitude of a value on variability (Pearson, 1897). It does so by relating the spread of a data set relative to its own mean and this produces a value which is unitless and divorced from any scale of measurement (Simpson, Roe, & Lewontin, 1960). This, therefore, negates the need for normalising EMG values at the recording stage as the variability in muscular recruitment can be expressed as a percentage and effectively normalised at the reporting stage.

### 2.7.5 Measures of fatigue

Hug (2011) stated that a potential strategy to counteract the effects of fatigue consists of modifying the timing of activation with the muscles involved. If this is the case, then it is important to discuss whether fatigue can be accurately assessed using EMG, or else we run the risk of building judgements of variability off measures which are, themselves, inherently flawed.

There are a range of studies which have focused on alterations in EMG activity level in the lower limb muscles during sub-maximal fatiguing pedalling exercises (Petrofsky, 1979; Housh et al., 2000; Hautier et al., 2000; Billaut et al., 2005) and have mostly used measures of amplitude of muscular activity and frequency of muscular activation as indicators of fatigue. The exact terms given to these variables differs between authors, but the historical consensus has been that an increased amplitude of muscular activation represents an additional recruitment of muscle fibres to compensate for the decrease in the force of contraction that occurs in fatigued muscle fibres (Edwards and Lippold, 1956) and a reduced frequency of activation demonstrates the slowing of muscle fibre action potential conduction velocity (Linstrom et al., 1970). These frequency-based variables have been shown to be particularly important when measuring fatigue as they are more sensitive to changes than amplitude values obtained via a root mean square plot (Merletti, Knaflitz and De Luca, 1990).

This established view has been challenged, however, as studying a muscle in isolation does not address the ability to alter the coordination of multiple muscles in response to fatigue rather than a participant being hindered by changes within a specific muscle (Hug, 2011). Authors who prescribe to this school of thought suggest that an increase in the amplitude of EMG activity is not necessarily linked to muscle fatigue and could have been induced by having to compensate for a different muscle. Likewise, they suggest that the absence of any change does not necessarily indicate that there is no decrease in the production of force as the contractile properties of the muscle may have been altered by fatigue.

An example of the difficulties interpreting EMG results can be seen when considering the results of Dorel et al. (2009) who reported a 29% increase in the EMG activity level for gluteus maximus and a 15% increase for biceps femoris during a constant load pedalling exercise. Without measurement of data from every lower limb muscle involved in the movement, it is possible to interpret this increase as either a systemic or a local level change. That is, it could be a result of a change of muscle coordination strategy to take more of the load in the glute/hamstring complex to compensate for fatigue in other muscles or a change of local muscle fibre recruitment as a direct result of local fatigue in these muscles. It is also possible that both mechanisms are at play here, meaning that either interpretation is, at least to some degree, flawed.

Lepers et al. (2002) attempted to address this difficulty in interpretation by employing alternative methods of studying muscular fatigue during a 5-hour exercise cycle at 55% of the maximal aerobic power. These were designed to focus more closely on the neural (M-Wave, voluntary activation, maximal activity level) and contractile (muscular twitch) properties of a muscle group to make interpretation of fatigue easier. Their results suggested that the contractile properties of the Vastus Lateralis are significantly altered after the first hour, whereas the central drive was more impaired toward the latter stages, but practical considerations have stopped these methods being widely adopted as it is very difficult to obtain this level of information from multiple muscle groups simultaneously.

Instead, authors have focused on muscle coordination changes (Farina et al. 2004) and investigation of muscular activation at specific points throughout the pedal revolution (von Tscharner, 2002) in order to quantify fatigue. These approaches will certainly be considered in the later stages of this thesis and an approach which takes a system level approach (i.e. focusses on co-ordination rather than individual muscle contractions) seems appropriate given the theoretical underpinning of this thesis.

## 3. STUDY ONE: Intra-individual variability of sagittal plane kinematics during indoor TT

### 3.1 Introduction

Cycling is a worldwide pastime with more than 5 million people over the age of 16 cycling at least once a month in England alone (Cycling UK, 2019). As such, cycling has received significant scientific attention with the most common method of motion analysis being to focus on individual lower extremity joints (e.g. Ericson et al., 1988; Caldwell et al., 1999), specifically in the sagittal plane due to the lack of motion observed in the frontal or transverse planes (Umberger and Martin, 2001).

Although this approach can provide valuable information about joint motion, it does not consider that the motion of one segment subsequently influences the motion of an adjacent segment, and therefore does not effectively capture the complexity of the coordinated motion of components of the body (Bartlett et al., 2007). The acknowledgement of the coupling relationship between segments has been well established in gait based kinematic investigations (eg. Rosenbaum, Becker, Wilke and Claes, 1998; DeLeo, Dierks, Ferber and Davis, 2004; Ferber, Davis and Williams, 2005) but has only more recently been recognised as crucial in the analysis of human movement within the field of cycling by Chapman et al. (2009).

Aside from this, there are also some traditional assumptions inherent within the literature which has studied intra-individual movement variability. Firstly, it has been historically assumed that intra-individual movement variability is either detrimental to normal function or purely evidence of random noise within the neuromuscular or measurement system (Davids, Glazier, Araújo and Bartlett (2003), Van Emmerick and Van Wegen (2000), Hamill, van Emmerik, Heiderscheit, and Li (1999) and Newell and Corcos (1993). This has led to the hypothesis that this “noise” may result in an inability to convey consistent results and, therefore, that it should be discounted.

Linked to this is the second assumption that movement patterns for skilled performers are invariant (Bartlett, Wheat and Robins, 2007). Although this assumption has significant support from the field of motor learning research, which emphasises decreased variation in performance as a hallmark of the learning process, there is growing evidence that intra-individual movement variability may perform a functional role in task performance (Van Emmerik, Hamill, and McDermott, 2005). This is especially true when the task requires adaptability of complex motor patterns within dynamic performance environments (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006) and may enable greater adjustment for both intrinsic and extrinsic factors which may influence an athlete’s performance.

The idea of movement variability as a functional element of skill performance has its groundings in dynamical movement systems theory which aims to describe systems which are able to constantly adapt to the varying demands of a task (Williams, Davids, and Williams, 1999). Evidence of such adaptations in skilled performers have been established in shooting (Arutyun, Gurfinkwl and Mirskii, 1968; Scholz, Schöner and Latash, 2000), Basketball (Miller, 2002; Button, Macloed, Sanders and Coleman, 2003 and Robins, Wheat, Irwin, and Bartlett, 2006), triple jump (Wilson, Simpson, Van Emmerik and Hamill, 2008), cricket fast bowling (Peterson, Pyne, Portus, Karppinen and Dawson, 2009), golf (Knight, 2004; Bradshaw et al., 2009; Glazier, 2011; Langdown, Bridge, and Li, 2012 and Tucker, Anderson and Kenny, 2013) and water polo (Taylor, Landeo and Coogan, 2014).

A number of these authors concluded that, from a dynamical systems perspective, variability may play a functional role in producing a more consistent sporting outcome despite the altering demands placed on the performer (Van Emmerik, Hamill and McDermott, 2005) and therefore should be viewed as a form of "essential noise" (Davis, Shuttleworth, Button, Renshaw and Glazier, 2004).

Despite this body of evidence, there appears to have been little research conducted using either the dynamical systems theory approach or focussing on intra-individual movement variability within cycling with, to the best of the author's knowledge, only one study specifically focussing on this approach (Sides and Wilson, 2012).

Although initial reading of their findings suggests that Sides and Wilson (2012) support the traditional motor learning theories in viewing variability as indicative of an unskilled performance, there are some potential limitations with their study relating to the participants recruited, the data collection methods and the way in which the data was analysed which could raise questions about the validity of their findings. This, coupled with the lack of research in the area and their recommendations for future research to expand the investigation of intra-individual movement variability, provides the rationale for the present study which aims to investigate if lower extremity intra-individual movement variability varies in cyclists of differing performance levels and if this plays a functional role in the completion of a simulated indoor time trial event.

## 3.2 Methods

*Participant information*

Ten trained cyclists volunteered to take part in the study (see Table 4-1). Participants all held a current British Cycling Race License (Category 1 $n$ = 1, Category 2 $n$ = 2, Category 3 $n$ = 2, Category 4 $n$ = 5) and Mean training load was self-reported as 10.85 ± 4.21 hours or 156.00 ± 48.35 miles per week. Participants maintained their normal diet and daily activity patterns throughout the testing period and provided written informed consent before taking part in the study. Local ethical approval was provided by the University of Winchester.

**Table 3-1. Participants' descriptive characteristics**

| | Age (Years) | Height (Metres) | Mass (Kg) | Maximum one minute Power Output (W) | Maximum one minute Power Output ($W \cdot Kg^{-1}$) | $\dot{V}O2$ max ($ml \cdot Kg \cdot min^{-1}$) |
|---|---|---|---|---|---|---|
| **Mean** | 31.9 | 1.8 | 72.10 | 365.5 | 5.13 | 73.21 |
| **Standard deviation** | 10.3 | 0.1 | 9.40 | 69.2 | 0.53 | 12.24 |

*Testing procedure and instrumentation*

*Graded exercise test*

Initial testing consisted of a graded exercise test (GXT) to establish $\dot{V}O_2$max values for each participant to ensure physiological similarities across the sample (See Table 4-1). An electromagnetically braked cycle ergometer (SRM, Germany) was used to conduct a continuous incremental cycling GXT where workload was increased by 5 W per 15 seconds. Initial workload was adjusted according to participant’s self-reported estimate of maximal power output so that the total duration of the GXT was between 8 and 10 minutes. Criteria for termination of the maximal GXT was primarily based on volitional exhaustion.

Throughout the GXT, online respiratory gas analysis was performed using a breath-by-breath automatic gas exchange system (MetaLyzer 3B, Cortex, Germany) following volume and gas calibration. HR was monitored using a wireless chest strap telemetry system (Polar Electro T31, Kempele, Finland) as well as ratings of perceived exertion every minute using the Borg 6-20 RPE scale.

*Time trial events*

Subsequently, participants visited the laboratory on 3 occasions, separated by a minimum of 48 h to allow full recovery from the previous trial. During each testing session, reflective markers (Qualisys, Gothenburg, Sweden) were attached to the Greater Trochanter, Lateral epicondyle of the femur, Lateral malleolus and 5$^{th}$ metatarsal on both sides of the participant’s body as well as a reflective marker on each pedal. Participants subsequently undertook a self-directed warm up followed by a simulated 10-mile (16-km) time trial and self-directed cool down. Time trials were conducted from a standing start and participants were given free choice of gearing and cadence throughout.

All trials were conducted in an air-conditioned laboratory using a standard Wattbike Pro cycle ergometer (Wattbike Ltd., Nottingham, UK), with PowerTap P1 pedals (CycleOps, Madison, WI, USA). Participants used their own cycling shoes and those who normally rode with cleats incompatible with the PowerTap pedals had their cleat position replicated with 3 bolt Kéo cleats (Look cycle international, Nevers, France). The ergometer was set to, as closely as possible, replicate the dimensions of each participant's own bicycle and participants were given access to any data they would normally ride with to monitor their cycling effort (cadence, power output etc.).

A 12-camera motion capture system (Qualisys Oqus 300+, Gothenburg, Sweden) sampling at 500 Hz recorded three-dimensional kinematic data at the hip, knee and ankle throughout each trial via Qualisys Track Manager (Version 2019.2). Perceived exertion was recorded throughout each time trial event using Borg's RPE scale. This was conducted at 2-minute intervals after an initial 5 minutes of riding had been completed. Time trial completion time was retrieved from the Wattbike using Wattbike Expert software version 2.60.20 (Wattbike Ltd., Nottingham, UK).

*Data analysis*

One time trial was selected per participant for analysis. This was the last performance to allow the first two to act as familiarisation sessions unless, due to technical errors with marker adhesion, there was insufficient kinematic data to make this feasible. In this case, the most complete recording was used for analysis.

Sagittal plane joint angle and joint angular velocities at the hip, knee and ankle were recorded for 10 complete pedal revolutions at 5 minute intervals throughout the time trial. One revolution was identified as the time between the pedal reaching the top dead centre (0°) on two consecutive occasions. This was defined as the point where the pedal marker reached its maximal value in the z-axis of the global co-ordinate system. Joint angle and angular velocity were then interpolated to 100 data points using a cubic spline technique.

The interpolated data was then used to calculate Continuous relative phase (CRP) in a similar way to Sides and Wilson (2012) to provide intra-limb couplings at: (i) knee flexion/extension–ankle plantarflexion/dorsiflexion (KA) and (ii) hip flexion/extension–knee flexion/extension (HK).

CRP was defined as the difference between the normalised phase angles of the coupling throughout the revolution, measured in degrees (°). CRP was reported on a linear scale of 0°-180° with 0°

corresponding to a perfectly in-phase coupling, meaning that the phase angles for the two motions are identical, and 180° representing a perfectly anti-phase coupling.

*CRPv Testing*

In order to replicate the analysis methods of Sides and Wilson (2012) initial testing involved the calculation of continuous relative phase variability (CRPv) which was defined as the standard deviation at each data point across the 10 revolutions for each participant. This process was repeated for data sampled at 5min, 10min, 15min and 20min throughout the time trial effort.

Each revolution was subsequently divided into four phases as performed Dorel, Couturier and Hug (2009) to produce separate top, drive, bottom and recovery phases (see Figure 4-2) and mean CRPv values per phase were calculated for each.

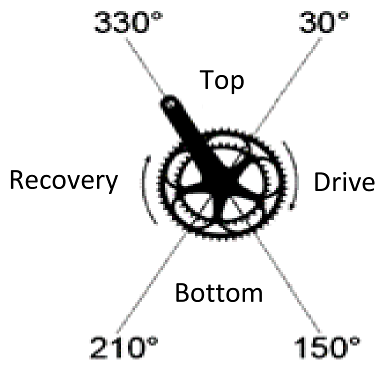



**Figure 3-1. The four phases per pedal revolution.**
**(Adapted from Dorel, Couturier and Hug (2009)**

*Whole group CRPv testing*

The first rounds of analysis were conducted using the whole participant group to correlate each participant's mean CRPv per pedal phase with the time taken to successfully complete the time trial ($Time_{TT}$). This was conducted using Pearson's Product moment correlation co-efficient and was repeated for each coupling (HK and KA) of each leg (Left and Right) at each time point (5min, 10min, 15min and 20min) throughout the time trial.

Subsequently, a three-way Analysis of Variance was conducted to test for differences between time points (5min, 10min, 15min and 20min), legs (left and right) and couplings (HK and KA) as well as the interactions between these factors. This was repeated for each phase of the revolution (top, drive, bottom and recovery) to assess whether the amount of movement variability displayed by participants varied throughout the time trial.

*Split group CRPv comparisons*

Following the initial testing, the group was split into “upper” and “lower” groups at the point of the largest difference in $Time_{TT}$ (between the 5th and 6th ranked riders). This gave an equal split of participants between groups (*n*= 5 in each). The statistical procedures outlined for whole group testing were then repeated considering the upper and lower groups separately.

In addition, a series of one-way independent samples ANOVAs were conducted to investigate differences between upper and lower groups in terms of CRPv values in each pedal phase (top, drive, bottom and recovery) and over time (5min, 10min, 15min, 20min).

*CV% testing*

To offer an additional measurement of variability, the coefficient of variation (CV%) of CRP values was calculated using the formula below:

$$\text{Co-efficient of variation} = (\text{standard deviation}/\text{mean})*100$$

This produced a percentage value (CV%) which represents the amount of variance each participant displayed in their joint couplings between the measurement time points (5min, 10min, 15min and 20min) throughout the simulated time trial. Conducting this additional calculation was designed to overcome the influence of the finite magnitude of a value on variability (Pearson, 1897) and negate the tendency of standard deviation to unavoidably increase as the range of the measure increases. CV% is a unitless value and is divorced from any scale of measurement (Simpson, Roe, & Lewontin, 1960) and is therefore suggested as a clearer comparison of the true variance displayed.

A Pearson’s product moment correlation coefficient was calculated to test for the relationship between CV% and the time taken to complete the simulated 10-mile time trial ($Time_{TT}$) for all riders.

This process was repeated using the same pedal revolution divisions described above and, as before, initial testing was conducted using the whole participant group to correlate each participant’s coefficient of variation in continuous relative phase values (CV%) against the time taken to successfully complete the time trial ($Time_{TT}$). This was conducted using Pearson’s Product moment correlation co-efficient and was repeated for both Hip-Knee and Knee-Ankle joint couplings. This was specifically designed to ascertain whether a relationship existed between the amount of variation a cyclist showed between measurement points and the time taken for them to complete the time trial. It was theorised that the ability to be more variable in their movements should aid a cyclist's overall performance when faced with a task where the constraints can be altered.

All statistical testing was performed using IBM SPSS statistics version 24 (IMB Corporation, New York, NY, USA), with a significance level set at $p < 0.05$.

### 3.3 Results

Mean and Standard Deviation of CRPv values for the whole group can be seen in Table 4-2. The same data for the upper and lower groups is displayed in Tables 4-3 and 4-4 respectively.

**Table 3-2. Mean (± Standard Deviation) CRPv values (◦) across 10 pedal revolutions for whole group data.**

| | | 5 minutes | | | | 10 minutes | | | | 15 minutes | | | | 20 minutes | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Left leg | | Right leg | | Left leg | | Right leg | | Left leg | | Right leg | | Left leg | | Right leg | |
| | | HK | KA | HK | KA | HK | KA | HK | KA | HK | KA | HK | KA | HK | KA | HK | KA |
| Pedal phase | Top | 2.35 (±0.80 ) | 29.01 (±10.41) | 4.26 (±2.05) | 28.46 (±10.32) | 3.53 (±2.09 ) | 32.43 (±14.60) | 3.87 (±2.21) | 26.37 (±10.16) | 2.22 (±0.47) | 28.33 (±9.45) | 4.39 (±2.00) | 41.79 (±17.45) | 2.58 (±0.23) | 23.43 (±5.97) | 2.82 (±1.38) | 33.93 (±7.85) |
| | Drive | 1.68 (±0.62) | 19.17 (±9.65) | 3.03 (±2.21) | 20.43 (±11.22) | 2.66 (±1.75) | 19.07 (±6.57) | 2.55 (±1.15) | 18.23 (±10.84) | 1.79 (±0.55) | 17.28 (±4.07) | 2.96 (±1.70) | 21.66 (±15.08) | 2.33 (±0.79) | 15.08 (±6.44) | 2.05 (±0.85) | 19.16 (±11.35) |
| | Bottom | 2.27 (±1.00) | 17.88 (±9.46) | 3.82 (±2.24) | 14.85 (±7.89) | 3.03 (±1.28) | 22.22 (±9.61) | 3.44 (±1.98) | 13.37 (±4.05) | 2.60 (±0.80) | 17.15 (±5.01) | 4.15 (±2.63) | 13.09 (±4.14) | 3.04 (±1.35) | 25.07 (±12.34) | 2.95 (±2.18) | 17.31 (±7.32) |
| | Recovery | 2.60 (±2.02) | 19.91 (±8.47) | 6.43 (±7.91) | 23.85 (±9.78) | 3.55 (±1.84) | 29.64 (±12.38) | 5.33 (±7.83) | 22.75 (±7.62) | 2.96 (±1.30) | 23.12 (±12.79) | 6.42 (±7.32) | 30.52 (±13.91) | 2.28 (±0.44) | 17.24 (±5.06) | 5.60 (±8.30) | 29.00 (±13.23) |

**Table 3-3. Mean (± Standard Deviation) CRPv values (°) across 10 pedal revolutions for Upper group data.**

| | | **5 minutes** | | | | **10 minutes** | | | | **15 minutes** | | | | **20 minutes** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Left leg** | | **Right leg** | | **Left leg** | | **Right leg** | | **Left leg** | | **Right leg** | | **Left leg** | | **Right leg** | |
| | | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** |
| **Pedal phase** | **Top** | 2.36 (±0.86) | 31.55 (±13.39) | 4.88 (±2.42) | 22.59 (±4.85) | 3.46 (±3.16) | 27.53 (±13.48) | 2.63 (±1.00) | 18.50 (±7.54) | 1.80 (±0.03) | 24.50 (±0.30) | 5.74 (±1.84) | 36.50 (±20.61) | 2.45 (±0.28) | 24.98 (±11.26) | 1.69 (±0.09) | 24.15 (±0.41) |
| | **Drive** | 1.67 (±0.46) | 17.65 (±7.40) | 3.86 (±2.77) | 19.19 (±7.60) | 2.58 (±2.62) | 16.97 (±7.11) | 2.55 (±1.22) | 13.89 (±6.22) | 1.58 (±0.49) | 18.62 (±1.55) | 4.06 (±1.67) | 20.12 (±9.97) | 2.81 (±0.24) | 18.02 (±11.17) | 1.39 (±0.11) | 15.58 (±5.83) |
| | **Bottom** | 1.95 (±0.60) | 20.57 (±12.77) | 4.25 (±2.81) | 16.45 (±9.51) | 2.83 (±1.70) | 21.80 (±11.61) | 2.52 (±1.05) | 11.50 (±2.56) | 2.12 (±0.78) | 20.09 (±5.85) | 4.83 (±3.07) | 13.42 (±2.17) | 3.66 (±2.35) | 34.62 (±13.77) | 1.62 (±0.12) | 21.38 (±16.38) |
| | **Recovery** | 2.09 (±1.06) | 19.36 (±9.86) | 5.07 (±4.00) | 24.34 (±13.07) | 2.85 (±1.24) | 22.26 (±13.55) | 1.97 (±0.80) | 18.56 (±6.67) | 2.58 (±1.59) | 13.53 (±5.37) | 4.83 (±3.98) | 27.32 (±18.11) | 2.27 (±0.84) | 13.21 (±3.84) | 1.37 (±0.04) | 17.24 (±1.74) |

**Table 3-4. Mean (± Standard Deviation) CRPv values (°) across 10 pedal revolutions for Lower group data.**

| | | **5 minutes** | | | | **10 minutes** | | | | **15 minutes** | | | | **20 minutes** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Left leg** | | **Right leg** | | **Left leg** | | **Right leg** | | **Left leg** | | **Right leg** | | **Left leg** | | **Right leg** | |
| | | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** | **HK** | **KA** |
| **Pedal phase** | **Top** | 2.34 (±0.84) | 26.46 (±6.94) | 3.64 (±1.63) | 34.33 (±11.40) | 3.59 (±1.12) | 36.35 (±15.71) | 4.86 (±2.51) | 32.66 (±7.23) | 2.43 (±0.43) | 30.24 (±11.58) | 3.56 (±1.83) | 46.03 (±15.49) | 2.66 (±0.20) | 22.39 (±1.94) | 3.27 (±1.40) | 37.84 (±5.05) |
| | **Drive** | 1.69 (±0.81) | 20.70 (±12.22) | 2.21 (±1.27) | 21.67 (±14.89) | 2.72 (±0.97) | 20.75 (±6.35) | 2.55 (±1.24) | 21.70 (±13.11) | 1.90 (±0.62) | 16.61 (±5.00) | 2.07 (±1.21) | 22.88 (±19.39) | 2.00 (±0.90) | 13.12 (±2.47) | 2.32 (±0.88) | 20.59 (±13.26) |
| | **Bottom** | 2.60 (±1.28) | 15.20 (±4.50) | 3.40 (±1.71) | 13.26 (±6.57) | 3.19 (±1.02) | 22.56 (±9.13) | 4.18 (±2.35) | 14.87 (±4.64) | 2.84 (±0.80) | 15.68 (±4.67) | 3.62 (±2.43) | 12.82 (±5.53) | 2.63 (±0.50) | 18.70 (±7.57) | 3.49 (±2.43) | 15.68 (±1.28) |
| | **Recovery** | 3.11 (±2.72) | 20.46 (±7.97) | 7.79 (±10.97) | 23.37 (±6.61) | 4.11 (±2.17) | 35.55 (±8.42) | 8.01 (±10.09) | 26.10 (±7.16) | 3.15 (±1.35) | 27.92 (±13.08) | 7.69 (±9.53) | 33.08 (±11.07) | 2.29 (±0.16) | 19.93 (±4.09) | 7.29 (±9.52) | 33.71 (±12.85) |

*Relationship testing*

Of the 64 correlations run to test for a relationship between CRPv and $Time_{TT}$ for the whole group data, only the right leg Hip-Knee coupling at fifteen minutes showed a statistically significant ($p<0.05$) correlation. These results were r = -0.777, p = 0.014 for the top phase and r = -0.666, p = 0.050 for the drive phase, showing a statistically significant large negative correlation between CRPv and $Time_{TT}$ at these points. All other correlations were non-statistically significant at an alpha level of $p<0.05$.

Once participants were split into upper and lower groups, the correlation of right leg Hip-Knee coupling at 15 minutes with $Time_{TT}$ remained statistically significant in the top phase of the revolution for the upper group (r = -0.975, p = 0.025) but was no longer significant for the lower group. The correlation of right leg Hip-Knee coupling at 15 minutes for the drive phase was no longer statistically significant for either group.

In addition, the lower group showed statistically significant correlations between $Time_{TT}$ and the following couplings:

Right Leg Knee-Ankle at 5 minutes in the top phase (r = -0.966, p = 0.008)

Right Leg Knee-Ankle at 5 minutes in the bottom phase (r = 0.922, p = 0.026)

Left Leg Knee-Ankle at 15 minutes in the top phase (r = -0.950, p = 0.050)

Left Leg Knee-Ankle at 20 minutes in the recovery phase (r = 0.988, p = 0.042)

All other correlations were statistically non-significant for both the upper and lower groups.

*Difference testing*

For the whole group testing, there was a significant difference ($p<0.005$) between HK and KA couplings during all pedal revolution phases with the KA coupling showing consistently higher levels of CRPv across all time points than the HK coupling.

Once participants were split into upper and lower groups, this remained the case for the lower group while only the drive phase showed a significant difference (p= 0.013) between couplings for the upper group.

Whole group data showed a significant difference (p=0.014) between legs during the drive phase with the right leg showing consistently greater levels of variability compared to the left at 5, 15 and 20 minute time points. This difference was no longer statistically significant within either group following the split of data, despite there also being no statistically significant differences between the two groups during the drive phase.

When comparing CRPv levels between the two groups, there was a statistically significant difference in the right leg Knee-Ankle coupling at 10 minutes during the top phase ($p=0.024$, Upper group = 18.50$^{o}$ ± 7.54, Lower group = 32.66$^{o}$ ± 7.23) and again at 20 minutes ($p=0.015$, Upper group = 24.15$^{o}$ ± 0.41, Lower group = 37.84$^{o}$ ± 5.05). There were no other statistically significant differences between the groups.

There were no significant differences ($p>0.05$) shown in CRPv over the course of the time trial when comparing between time points. This was the case for whole group, upper group and lower group data.

*CV% Relationship testing*

The correlation coefficients and significance values for the relationship between CV% and $Time_{TT}$ can be seen in Table 4-5.

**Table 3-5. Correlation results for CV% of CRP values against $Time_{TT}$.**

| Analysis Mode | Joint Coupling | Phase | r | P |
|---|---|---|---|---|
| Full revolution | H-K | | -0.375 | 0.285 |
| | K-A | | -0.126 | 0.728 |
| Two-phase | H-K | Power | -0.218 | 0.544 |
| | | Recovery | -0.096 | 0.793 |
| | K-A | Power | -0.144 | 0.691 |
| | | Recovery | -0.489 | 0.152 |
| Four-phase | H-K | Top | -0.017 | 0.962 |
| | | Drive | 0.019 | 0.958 |
| | | Bottom | 0.59 | 0.073 |
| | | Recovery | -0.072 | 0.843 |
| | K-A | Top | -0.378 | 0.281 |
| | | Drive | 0.082 | 0.821 |
| | | Bottom | -0.04 | 0.907 |
| | | Recovery | -0.505 | 0.136 |

As seen in Table 4-5, all observed correlations were non-statistically significant at an alpha level of $p<0.05$. All relationships were negative with the exception of the Hip-Knee joint coupling during the drive and bottom phases and the Knee-Ankle coupling during the drive phase when the revolution was split into four phases.

### 3.4 Discussion

The aim of the current study was to investigate if lower extremity intra-individual movement variability varies in cyclists of differing experience and if this plays a functional role in the completion of a simulated indoor time trial event.

Skill level was originally to be inferred by grouping participants according to the different categories they were competing at within the established competitive structure set out by British Cycling. Participant's varying fitness levels could then be controlled by recruiting participants who were physiologically similar in terms of generic measures of physical fitness. Although it could be argued that the group was reasonably physiologically homogenous (Power output = 5.13 ± 0.53 $W \cdot Kg^{-1}$, $\dot{V}O_{2\,max}$ = 73.21 ± 12.24 $ml \cdot Kg \cdot min^{-1}$) grouping the 4$^{th}$ category riders together, for example, would have created a group which included the 2nd, 4th, 7th, 8th and 10th ranked riders in terms of finishing time. This clearly shows that performance levels in a simulated time trial cannot be predicted by race license category and therefore grouping participants according to this criteria was deemed unsuitable. Instead, this investigation used the time taken by each participant to complete the simulated time trial effort was used as an indicator of skill level.

*Relationship testing*

The general lack of statistically significant correlations between CRPv couplings and $Time_{TT}$ shows that there is little in the way of an established relationship between the level of intra-individual movement variability employed by participants and the performance outcome. The two significant correlations which were found for the whole group, however, were both negative ($r = -0.777$, $p = 0.014$ and $r = -0.666$, $p = 0.050$) suggesting that a greater level of movement variability may be linked to a shorter duration for the time trial event.

This is in direct contradiction of Sides and Wilson (2012) who concluded that movement variability is not beneficial to cycling performance. Instead, they posit that out-of-phase motion has previously been considered to reflect a less stable coordinative state (Scholz, 1990) and that this may be indicative of the reduced effective force application as highlighted by Sanderson and Black (2003).

Once participants were split into upper and lower groups in order to further investigate the behaviours of different skill levels, the upper group only showed one statistically significant correlation (r = -0.975, p = 0.025) with the lower group showing four statistically significant correlations, none of which had been present in the whole group analysis. Of these four, two showed a positive relationship (Right leg Knee-Ankle at 5 minutes in the bottom phase and Left leg Knee-Ankle at 20 minutes in the recovery phase) and two showed a negative relationship (Right Leg Knee-Ankle at 5minutes in the top quarter and Left leg Knee-Ankle at 15minutes in the top quarter).

Given the lack of consistency in terms of the direction of the relationship and the coupling, leg or time point in which the statistically significant correlations occur, it is very difficult to reliably infer whether there is any functional role of intra-individual movement variability from this data.

*Difference testing*

*Comparing between couplings*

For the whole group testing, there was a significant difference (p<0.005) between HK and KA couplings during all pedal revolution phases with the KA coupling showing consistently higher levels of CRPv across all time points than the HK coupling. This was expected as it has long been established that maximum knee and hip extension occur simultaneously (Houtz and Fischer, 1959; Wozniak Timmer, 1991) at approximately 180$^{o}$ of the pedal revolution but peak ankle dorsiflexion occurs around 90$^{o}$ and peak plantarflexion at approximately 285$^{o}$ (Cavanagh, 1986).

Interestingly, once participants were split into upper and lower groups, the significant difference between HK and KA couplings remained for the lower group while only the drive phase showed a significant difference (p= 0.013) between couplings for the upper group. This could potentially be explained if the upper group were performing more of an "ankling" motion.

Ankling is a technique which involves pushing the pedal across the top of the pedalling cycle (0$^{o}$) with the foot in the dorsi-flexed position and pulling across the 180$^{o}$ point of the cycle with the foot plantar-flexed (Faria and Cavanagh, 1978). This has been demonstrated to occur more in elite cyclists than novices (Chapman et al*.,* 2009) and would potentially produce a more in-phase motion in terms of a Knee-Ankle coupling, explaining the lack of significant differences between couplings in the upper group's data.

*Comparing between legs*

Whole group data showed a significant difference (p=0.014) in the CRPv levels between legs during the drive phase with the right leg showing consistently greater levels of variability compared to the left at 5, 15 and 20 minute sampling windows. This initially suggests that leg dominance has some influence on the movement patterns, but this difference is no longer present within either group following the split of data. Given that there was also no statistically significant differences between the two groups in terms of CRPv levels during the drive phase it must be recommended that this is an area for further investigation as it was by both Carpes, Mota and Faria (2010) and Sides and Wilson (2012) who identify intra-limb co-ordination and symmetry as under researched and worthy of further investigation.

*Comparing between time points*

It was initially thought that the level of CRPv shown by participants may change over time based on work by Amoroso, Sanderson and Henning (1993), Sanderson and Black (2003), and Bini, Diegenthaeler and Mota (2010) all of whom reported changes in the kinetics or kinematics of the cycling action as a result of fatigue. In the present study participants reported a mean RPE of 18.6 ± 1.7 (a rating of extremely hard to maximal exertion) upon completion of the time trial so it is fair to assume that a level of fatigue was present but this did not manifest in any significantly different levels of CRPv across time points. This was true regardless of whether whole group, upper or lower group data was being investigated. This is perhaps not overly surprising given the suggestion that the effect of fatigue on movement variability cannot be generalised across athletes (Trezise, Bartlett and Bussey, 2011) but it should be noted that this suggestion comes from a dual case study of sprinters so it's application here is questionable.

*Comparing between groups*

The final comparison of CRPv levels between the upper and lower groups showed there was a statistically significant difference in the right leg Knee-Ankle coupling at 10minutes during the top phase ($p=0.024$, Upper group = $18.50^{o}$ ± 7.54, Lower group = $32.66^{o}$ ± 7.23) and again at 20minutes ($p=0.015$, Upper group = $24.15^{o}$ ± 0.41, Lower group = $37.84^{o}$ ± 5.05). These results do somewhat agree with Sides and Wilson (2012) in that the lower group shows greater levels of variability in both cases. With only two of sixty four comparisons resulting in a significant difference, however, it would seem ill advised to make general statements based on the strength of these results alone.

*CV% relationship testing*

The lack of any statistically significant correlations between CV% and $Time_{TT}$ shows that there is little in the way of an established relationship between the level of intra-individual movement variability employed by participants and the performance outcome. The general trend, however, shows that the relationships reported are mostly negative in nature. Despite the majority of these relationships failing to reach the $r = \pm0.400$ threshold which would allow them to be deemed as moderate relationships (Schober, Boer and Schwarte, 2018), their negative nature is does suggest that a greater level of movement variability could potentially be linked to a shorter duration for the time trial event.

This is in direct contradiction of Sides and Wilson (2012) who concluded that movement variability is not beneficial to cycling performance. Instead, Sides and Wilson (2012) agree with previous statements that variability of motion is considered to reflect a less stable coordinative state (Scholz, 1990) and that this may be indicative of the reduced effective force application as highlighted by Sanderson and Black (2003).

*Summary and Limitations*

In summary of the findings above, there some limited evidence of differences in levels of intra-individual movement variability employed by different levels of cyclist during an indoor cycling effort. In much the same way as Sides and Wilson (2012), it should be noted that this investigation is limited to only flexion/extension couplings in the sagittal plane at the expense of movements in the other anatomical planes but, considering the findings from a dynamical systems perspective highlights certain methodological limitations with the current study which may go some way to explaining the lack of differences reported here.

As mentioned previously, there is growing support for the notion that intra-individual movement variability may perform a functional role in task performance (Van Emmerik, Hamill, and McDermott, 2005), especially when the task requires adaptability of complex motor patterns within dynamic performance environments (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006). By using a cycle ergometer in a laboratory setting it is possible that the dynamic element of the performance environment has been controlled to such a degree that there isn't enough demand placed on the system in order to require a variable response. That is to say, removing the task perturbations such as variations of road surface, weather conditions, gradient etc. may have unintentionally limited the amount of intra-individual movement variability the cyclists need to exhibit in order to complete the task. As a result, this study may not give a true representation of the functional role intra-individual movement variability can play.

Linked to this is also the inherent lack of ecological validity attached to the use of a cycle ergometer when attempting to replicate the cycling action. Jobson et al. (2007) and Jobson, Nevill, George, Jeukendrup and Passfield (2008) have shown a significant difference in cycling speed and power output between laboratory and road conditions during time trial events and Bertucci, Grappe and Groslambert (2007) show more broadly crank torque profiles are significantly different when comparing lab and outdoor cycling conditions.

As a result, future research should aim to investigate the intra-individual movement variability employed by cyclists of differing levels during outdoor cycling in order to understand further it's role within this sport.

**3.5 Conclusion**

The results presented here suggest two significant negative linear correlations between the level of movement variability displayed by participants and the time taken for them to complete the time trial. In addition, statistically significant differences in the level of movement variability displayed by differing levels of cyclist were seen at two time points. This suggests that there is a link between the level of intra-individual movement variability displayed by a cyclist and the time in which they were able to complete a 10-mile simulated time trial task in laboratory conditions. That this relationship is only evident in some cases could be due to a lack of task perturbations in the laboratory setting and therefore further research is needed to understand the influence of the environmental factors which are present during road cycling before the potentially functional role of intra-individual movement variability can be fully understood.

These findings help to partially answer the overall thesis research question as they allow us, to a certain extent, to confirm that intra-individual movement variability can play a functional role in cycling. However, we cannot fully support this conclusion due to the testing environment being different to the competitive environment in which cycling would normally take place.

Before investigations could move into a typical competition environment it was important to ensure that valid methods of data collection were being used. The investigations which were completed to ensure this are detailed in the following chapter.

# 4. VALIDATION OF METHODS

Due to the results of the indoor investigation (Study 1), where some evidence of a relationship between greater levels of movement variability was found, it was deemed important to progress investigations into a more ecologically valid testing environment which would more accurately replicate typical competitive conditions encountered during cycling events. The potential for using the same equipment in field testing was therefore investigated in the next series of studies.

## 4.1 STUDY TWO: Validity of PowerTap P1 pedals during laboratory-based cycling time trial performance

The first of these validation studies concerned the validity of the PowerTap P1 pedals and was published in *Sports.* It can be retrieved using the weblink https://www.mdpi.com/2075-4663/6/3/92 and has been reproduced in its entirety here for the reader's ease. The published version is also presented in Appendix I.

### 4.1.1 Introduction

Laboratory based testing must be conducted upon the assumption of accurate and reliable data collection. To this end, a number of cycle ergometers have been validated for use within laboratory settings including the Wattbike (Wattbike Ltd, Nottingham, UK) which has been shown to be both valid and reliable across a range of testing protocols.

For trained cyclist populations, the Wattbike has been reported to have a coefficient of variation (CV) of 2.6% (Hopker, Myers, Jobson, Bruce and Passfield, 2010) and to afford "highly reproducible" results during 30-s sprint and 4-min performance test protocols (Driller et al., 2014). In addition, the Wattbike demonstrates high levels of intra-day and inter-day reliability (Driller et al., 2014) and no significant difference between measures of power output recorded in test–retest conditions (Wainwright, Cooke and O'Hara, 2016). As such, the Wattbike is considered to be an accurate and reliable tool for training and performance assessments but there is a growing acknowledgement that laboratory-based research may not possess adequate levels of ecological validity (Bertucci, Grappe and Groslambert, 2007; Mieras, Heesh and Slivka, 2014; Prins, Terblanche and Myburgh, 2007; Stevens and Dascombe, 2015; Jobson et al., 2007; Palmer, Dennis, Noakes and Hawley, 1996; Smith, Davidson, Balmer and Bird, 2001; Coakley and Passfield, 2017).

Researchers have reported differences of up to 8% between indoor cycling performance and an equivalent outdoor event (Jobson et al., 2007; Palmer, Dennis, Noakes and Hawley, 1996; Smith, Davidson, Balmer and Bird, 2001; Coakley and Passfield, 2017). This would suggest that, despite the validity of the Wattbike, laboratory protocols do not accurately replicate ''real-world'' performance and, as such, it has become increasingly important to be able to measure power output during outdoor cycling events using a range of devices designed to be fitted to the athlete’s own bicycle rather than relying only on laboratory-based measures.

The Schoberer Rad Messtechnik (SRM) device, which consists of a number of rotational strain gauges housed between the crank spindle and chain ring interface, has become the “gold standard” device for such mobile power measurement applications due to its high validity and reliability (Abbiss et al., 2009; Gardner et al., 2004; Jones and Passfield, 1998; Martin et al., 1998) and the ability to collect valid and reliable data during actual sporting performance while using the cyclist’s own bicycle. This is not to say that it is without limitations as the SRM device remains prohibitively expensive for most recreational-level participants and there are also potential compatibility issues due to the wide range of bottom bracket standards currently employed by bicycle manufacturers. In addition, the device itself requires a certain level of mechanical competency to install correctly and requires manufacturer-based servicing for battery replacements (Novak and Dascombe, 2017). These issues, along with the suggestion that when using this style of device there may be potential distortion of the crank arms, which would lead to systematic error in torque measurement (Kyle, 1990), have led to the development of alternative mobile power measurement devices.

One example of this is power measuring pedals, such as Garmin Vector pedals (Garmin, Schaffhausen, Switzerland), which, instead of containing strain gauges in the crank arms, house them within each pedal body. Not only does this allow power measurement to be differentiated between right and left – something that was only possible with additional computation modules when using the SRM device – it also removes the potential influence of crank distortion. In addition, pedals-based devices are almost universally compatible, regardless of the individual bicycle componentry, which affords the potential to transfer between bicycles, with limited mechanical experience required for installation or maintenance.

Garmin Vector pedals have been compared with the SRM device and have been shown to report non-statistically significant differences in power output (Novak and Dascombe, 2017) and to give reproducible results across a range of power outputs and various cycling efforts such as sub-maximal incremental tests, sub-maximal 30-min continuous tests and sprint tests (Bouillod, Pinot, Soto-Romero, Bertucci and Grappe, 2017). It has been noted, however, that they increasingly overestimate at higher power outputs, whilst underestimating during sprints with a low gear ratio and during a 2-hour road cycling session on hilly terrain (Bouillod, Pinot, Soto-Romero, Bertucci and Grappe, 2017). This would suggest that data from Garmin Vector pedals should be treated with some caution.

One, largely unresearched, alternative to the Garmin Vector pedals is the P1 pedals system by PowerTap (Madison, USA). The PowerTap P1 pedals have four pairs of strain gauges per pedal to measure applied force at the pedal body in both the vertical and horizontal planes and Hall effect sensors attached to the pedal axle, which results in a claimed 40 measurement points per pedal stroke (PowerTap, 2018). In addition, the PowerTap P1 pedals have a temperature sensor at the point of force measurement. This allows for automatic accommodation for changes in temperature in an effort to avoid measurement error due to changes in environmental conditions during data collection and is something which, to the best of the author's knowledge, is not present in any of the other devices mentioned here.

Despite the popularity of power measuring pedals and the number of papers examining the validity of the Garmin Vector pedals, there has been little published on the validity of the PowerTap P1 pedals with, to the authors' knowledge, only one paper comparing PowerTap P1 pedals with the SRM device (Czajkowski, Bouillod, Dauriannes, Soto-Romero and Grappe, 2016). These researchers evaluated the pedals during both sub-maximal incremental test and sprint test protocols in a small (n=5) experimental cohort. Though such protocols can provide valuable insight, it has been observed that 'constant work' or 'time trial'-type tests, where the cyclist is required to complete a set distance in the shortest time possible, provide more appropriate simulations of the bioenergetics of most competitive events lasting several minutes or more (Hopkins, Schabort and Hawley, 2001).

The aim of this study, therefore, was to assess the validity of the PowerTap P1 pedals by comparing them with the previously validated Wattbike cycle ergometer during self-paced, simulated time trials.

### 4.1.2 Methods

*Participants*

Ten trained cyclists (9 male, 1 female) (mean ± SD: 31 ± 10 yr; 1.80 ± 0.10 m; 72 ± 9 kg, Maximum Power Output 366 ± 69 W) volunteered to take part in the study. All cyclists held a current British Cycling Race Licence and maintained their normal diet and daily activity patterns throughout the test period. All participants gave written informed consent before taking part in the study, which had local ethics committee approval.

*Procedure*

Participants visited the laboratory on 3 separate occasions, separated by a minimum of 48 hours to allow full recovery from the previous trial. Each visit consisted of a self-directed warm up followed by a simulated 10-mile (16-km) time trial and self-directed cool down. Time trials were conducted from a standing start and participants were given free choice of gearing and cadence throughout.

All trials were conducted in an air-conditioned laboratory using a standard Wattbike Pro cycle ergometer (Wattbike Ltd, Nottingham, UK), with PowerTap P1 pedals (CycleOps, Madison, USA), which were zeroed before each ride, in line with manufacturer recommendations. Participants used their own cycling shoes and those who normally rode with cleats incompatible with the PowerTap pedals had their cleat position replicated with 3 bolt Kéo cleats (Look cycle international, Nevers, France). The ergometer was set to, as closely as possible, replicate the dimensions of each participant's own bicycle.

*Data Analysis*

Power output and cadence were recorded for the duration of the time trials by a Garmin Edge 1000 head unit (Garmin, Schaffhausen, Switzerland) and the ergometer's display unit for the PowerTap pedals and Wattbike respectively. The Garmin data was then exported to third party open source analysis software, Golden Cheetah, and Wattbike data was analysed using Wattbike Expert software (Wattbike Ltd, Nottingham, UK), where it was displayed as a single value per second.

Technical issues during some testing sessions meant that a small number of incomplete data sets were recorded by the Wattbike. Affected trials were removed from the study, which did not alter the number of participants tested but did result in only 20 of the 30 trials performed being analysed.

Mean, maximum, and minimum power outputs and mean, maximum, and minimum cadences were calculated, checked for normality and compared between equipment using paired samples T-tests. Effect sizes were calculated for these tests by calculating the mean difference between the two measures and then dividing the result by the pooled standard deviation.

A Bland and Altman 95% limits of agreement (LoA) analysis quantified the agreement (bias and random error) between measurement equipment. In accordance with recommendations for carrying out LoA analysis (Atkinson, and Nevill, 1998), the data was checked for heteroscedasticity via a Levene's test and LoA analysis was followed by intra-class correlation coefficients (ICC) via the two-way mixed model to quantify the consistency of the power and cadence measurements between PowerTap P1 pedals and Wattbike.

All statistical testing was performed using IBM SPSS statistics version 24 (IMB Corporation, New York, USA), with a significance level set at $p<0.05$

### 4.1.3 Results

Levene's test revealed a lack of heteroscedasticity ($p>0.05$) and the results of paired samples T-tests showed no statistically significant differences between the PowerTap P1 pedals and the Wattbike in any of the measured variables: mean power output, minimum power output, maximum power output, mean cadence, minimum cadence or maximum cadence ($p>0.05$).

For the purpose of clarity, limits of agreement (LoA) results are reported in the format: Bias ± SD (Upper CI, Lower CI), where the bias represents the mean difference between the measurement methods and the lower and upper confidence intervals were calculated as Bias ±1.96 x SD. This is followed by a value for intraclass correlation coefficient (ICC).

Limits of Agreement analyses resulted in values of: 2.35 ± 18.3 W (CI −33.5 and 38.2) and an ICC of 0.973 for mean power output (Fig. 5-1); –3.95 ± 41.8 W (CI −86.0 and 78.1) and an ICC of 0.944 for maximum power output (Fig. 5-2) and −18.65 ± 57.2 W (CI −130.7 and 93.4) and an ICC of 0.816 for minimum power output (Fig. 5-3);. Cadence analysis showed 0.25 ± 3.8 rev·min$^{-1}$ (CI −7.2 and 7.7) and an ICC of 0.864 for mean cadence (Fig. 5-4); 1.05 ± 2.6 rev·min$^{-1}$ (CI −4.1 and 6.2) and an ICC of 0.960 for maximum cadence (Fig. 5-5); and −1.00 ± 23.9 rev·min$^{-1}$ (CI −47.8 and 45.9) and an ICC of 0.619 for minimum cadence (Fig. 5-6).

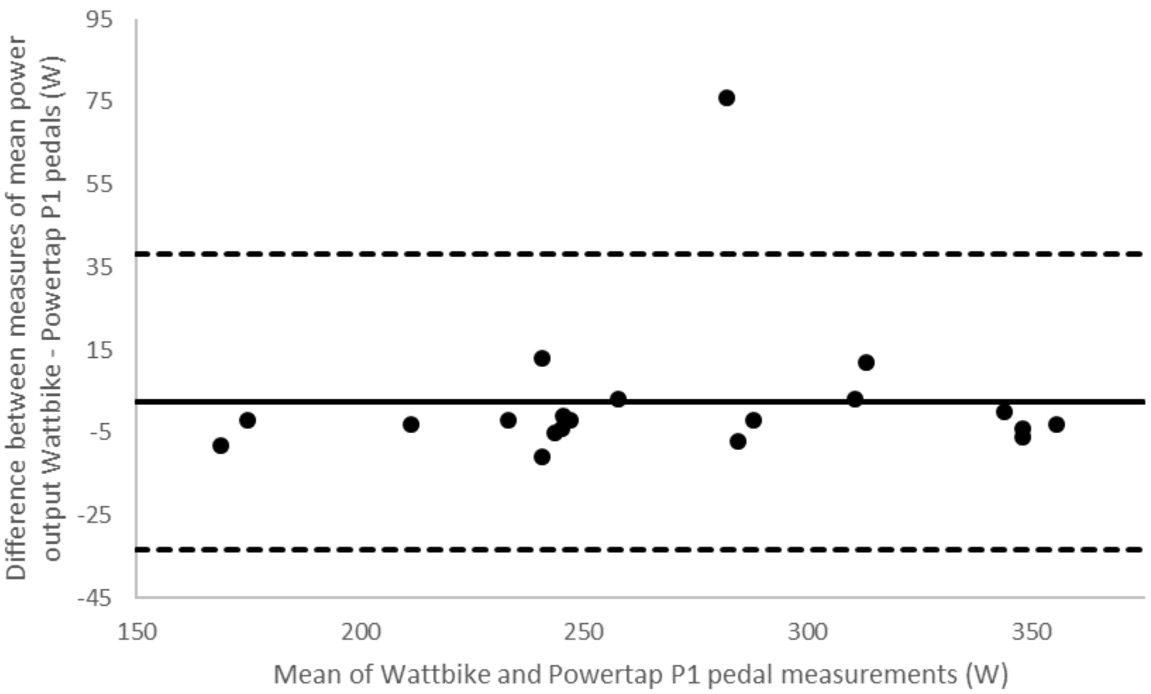



**Figure 4-1. Bland-Altman plot for mean power output. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in power output reported between the two measurement methods).**

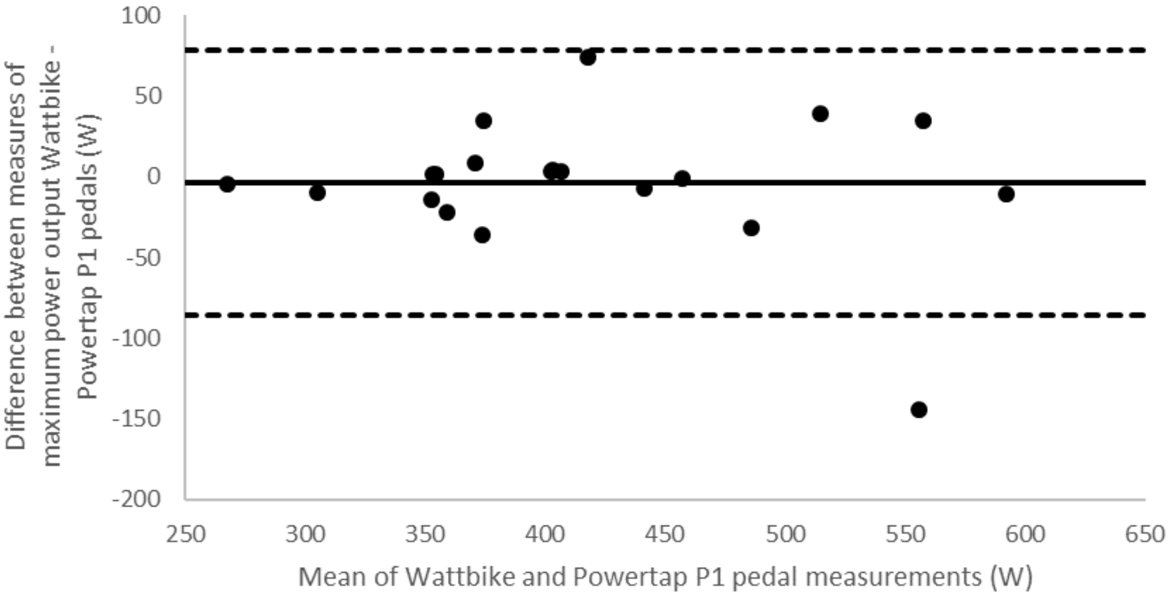



**Figure 4-2. Bland-Altman plot maximum power output. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in power output reported between the two measurement methods).**

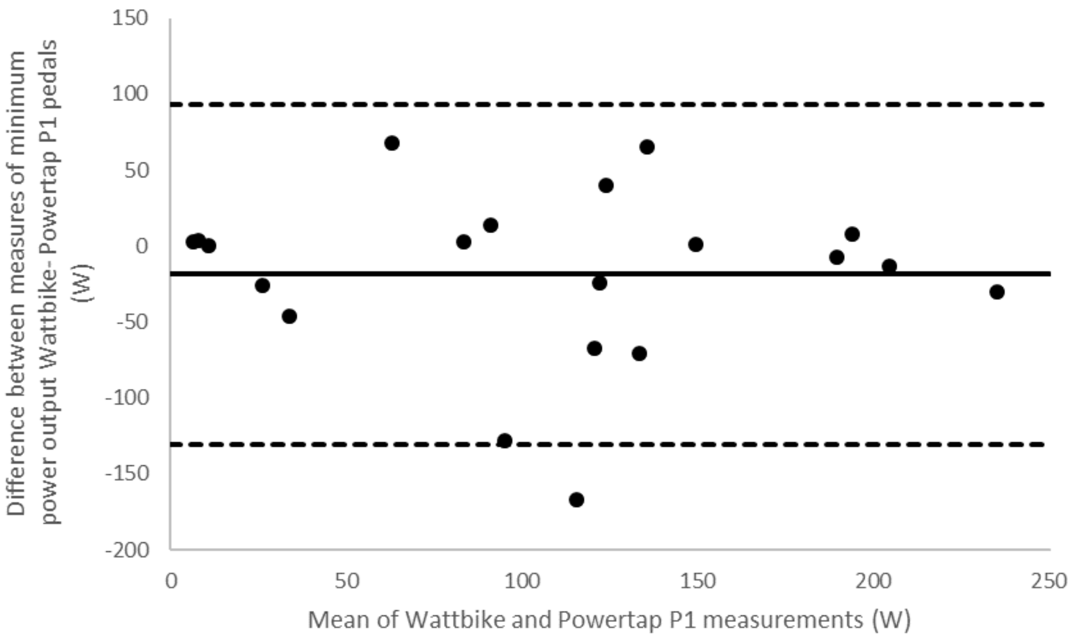



**Figure 4-3 Bland-Altman plot for minimum power output. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in power output reported between the two measurement methods).**

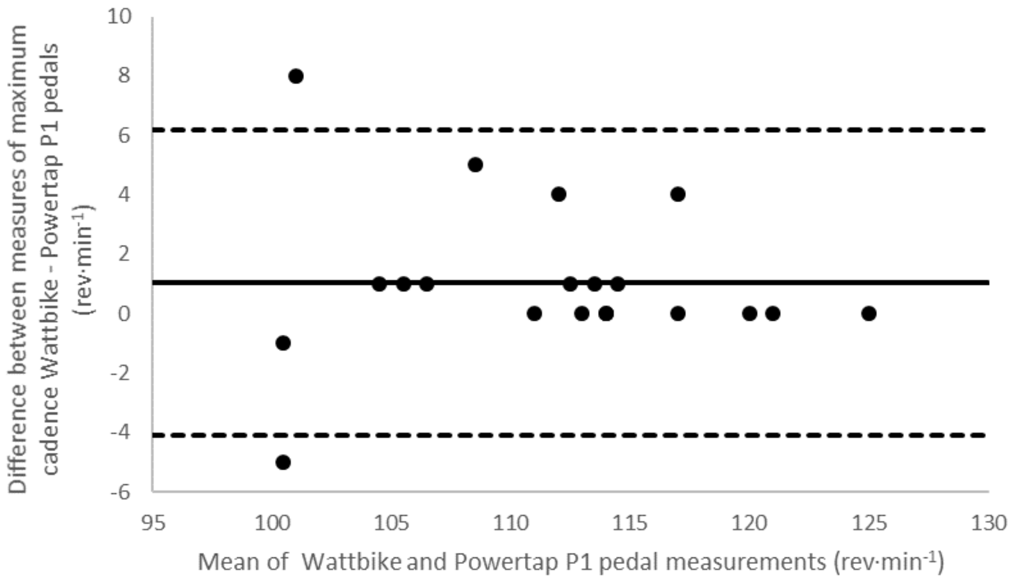



**Figure 4-4. Bland-Altman plot for mean cadence. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in cadence reported between the two measurement methods)**

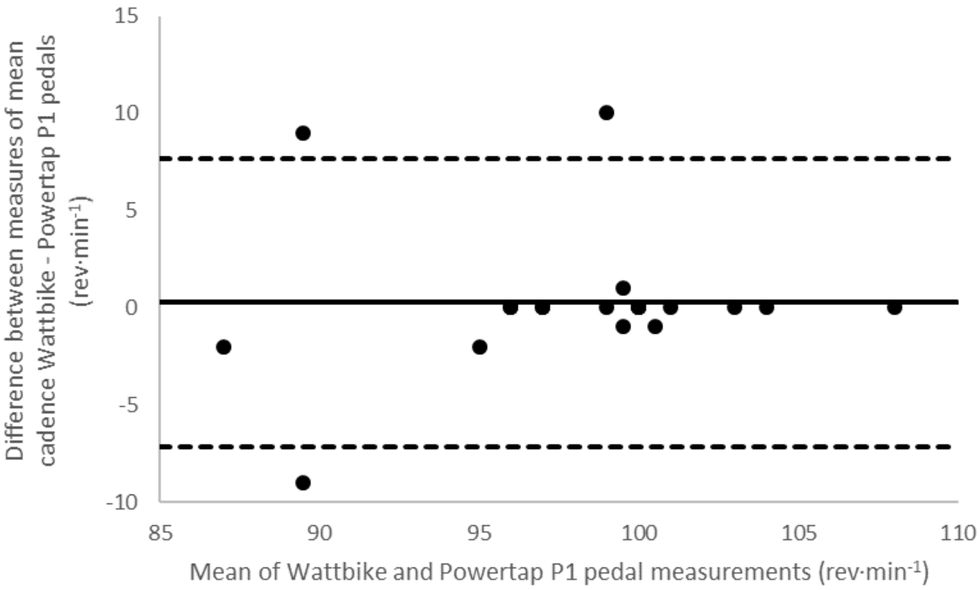



**Figure 4-5. Bland-Altman plot for maximum cadence. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in cadence reported between the two measurement methods)**

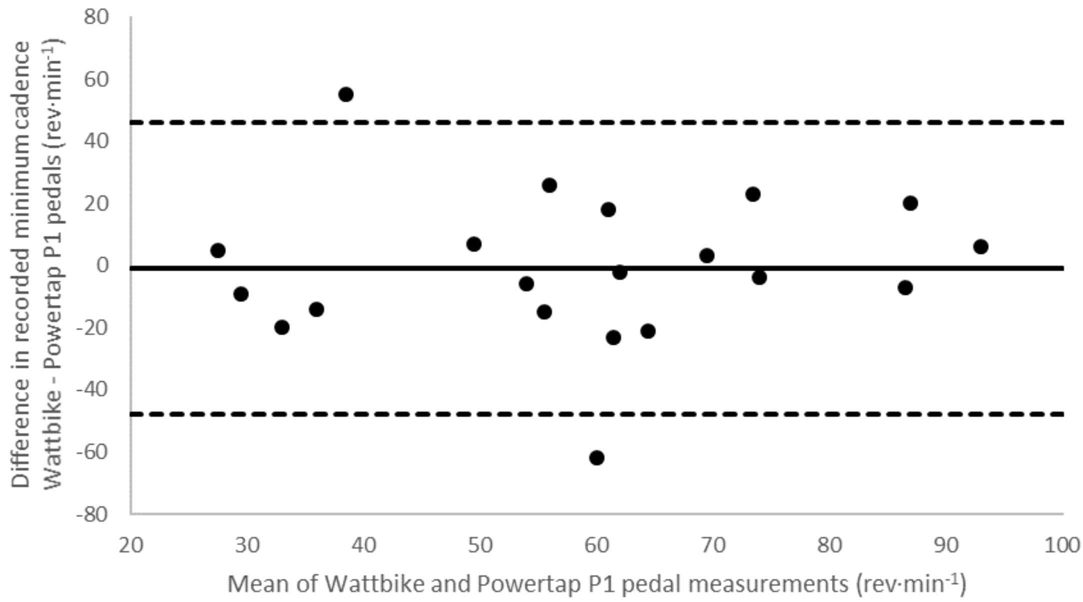



**Figure 4-6. Bland-Altman plot for minimum cadence. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in cadence reported between the two measurement methods)**

**4.1.4 Discussion**

The aim of this study was to assess the validity of measurements by PowerTap P1 pedals during simulated time trial performances. Difference testing suggested no statistically significant differences between the PowerTap P1 pedals and the Wattbike ergometer for any of the recorded variables.

The PowerTap P1 pedals underreported maximum power output values by 3.95 W, while overestimating mean power output values by 2.35 W in comparison to the previously validated Wattbike (Hopker, Myers, Jobson, Bruce and Passfield, 2010). This represents a −0.94% difference for maximum power output and 0.88% difference for mean power output, both of which are lower than the −1.5% difference which has previously been reported by other authors (Czajkowski, Bouillod, Dauriannes, Soto-Romero and Grappe, 2016). Although it is worth noting that the previous paper conducted both sub-maximal incremental test and sprint test protocols instead of the simulated time trial used here, it would still appear that there is a greater level of agreement between the Wattbike and PowerTap P1 pedals investigated in this paper than there was between the PowerTap P1 pedals and the SRM device investigated before (Czajkowski, Bouillod, Dauriannes, Soto-Romero and Grappe, 2016).

In contrast, the PowerTap P1 pedals appear to have underreported minimum power output by an average of 18.65 W, a 16.03% difference between the two measurement methods. Although, this appears to be a large difference, it is statistically non-significant and this variable is likely to be of little interest to cyclists in the field.

The levels of agreement shown in this study compare favourably with previously reported values gathered during both submaximal incremental and continuous 30-minute testing protocols to compare the data produced by Garmin Vector pedals and the SRM device. During incremental tests, non-significant differences in mean power output between devices were found (Bouillod, Pinot, Soto-Romero, Bertucci and Grappe, 2017), with LoA analysis highlighting a bias of 13.7 ± 12.4 W and 0.6 ± 6.2 W between the SRM and Stages systems and the SRM and Vector pedals, respectively. The 30-minute continuous test more closely resembles the time trial effort evaluated in the current study and also produced no significant difference between the mean power outputs recorded. It was noted, however, that the Garmin Vector underestimated mean power output by 16.5% compared to the SRM. Given that a 0.88% difference for mean power output was recorded in the current study, it would appear that the PowerTap P1 pedals agree more closely with the Wattbike than do Garmin Vector pedals with the SRM.

Further support for the validity of the PowerTap P1 pedals is provided by consideration of ICC results. ICC values less than 0.50, between 0.50 and 0.75, between 0.75 and 0.90, and greater than 0.90 are suggested to be indicative of poor, moderate, good, and excellent levels of agreement between measures, respectively (Koo and Li, 2016). As such, it can be suggested that there are excellent levels of agreement between the PowerTap P1 pedals and the Wattbike for maximum cadence (0.960), maximum power output (0.944) and mean power output (0.973). These are followed by good reliability for mean cadence (0.864) and minimum power output (0.816) and moderate reliability for minimum cadence (0.619).

The differences between systems seen in this study in terms of minimum power output may be the result of a lack of synchronisation at their point of measurement as the PowerTap P1 pedals claim 40 measurement points per pedal stroke (PowerTap, 2018) compared to 2 measurement points by the Wattbike (Hopker, Myers, Jobson, Bruce and Passfield, 2010). Alternatively, the discrepancy may be the result of differences in how the two systems measure force. The Wattbike calculates force via the use of chain tension over a load cell, whereas the PowerTap P1 pedals have four pairs of strain gauges per pedal to measure applied force at the pedal body in both the vertical and horizontal planes. Regardless of the reason for this variation in measurements, these results suggest that caution should be employed when investigating minimum power output values using the PowerTap

P1 pedals although the authors would repeat that this variable is likely to be of little interest to cyclists or researchers using the devices in the future.

It must be acknowledged that the sample size for the current study could be viewed as a potential limitation (n=10). It is worth noting, however, that mean calculated effect sizes for this study were 0.11 for power output variables and 0.08 for cadence variables. With such small differences between measures, it was calculated that 896 participants would be required for power output variables and 1693 for cadence variables before the level of difference seen here became statistically significant at an alpha level of $p < 0.05$.

In addition, although all participants were experienced cyclists who held a British cycling race licence it would be fair to say that none would consider themselves to be time trial specialists. This may have led to issues with pacing strategy and power production during the testing protocol as it has previously been identified that 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 (Coakley and Passfield, 2017). In the current study this is not a significant concern due to the concurrent nature of the measurements and the results discussed above would suggest that the PowerTap P1 pedals are a viable alternative to the SRM device for mobile power measurement applications.

#### 4.1.5 Conclusion

There are no statistically significant differences between PowerTap P1 pedals and a Wattbike when measuring maximum, minimum, and mean power output or when measuring maximum, minimum, and mean cadence during a laboratory-based time trial. In addition, there are good to excellent levels of agreement between the PowerTap P1 pedals and Wattbike (ICC > 0.80) for all variables except minimum cadence. This study suggests that PowerTap P1 pedals are valid for measurement applications within a laboratory setting but further investigation is needed during real cycling locomotion in the field to assess their usage in outdoor applications.

## 4.2 STUDY THREE: Validity of skin mounted electro-goniometers as a method of calculating CRP during indoor TT efforts.

Having validated the power measuring pedals (Study 2) the focus then moved to establishing a valid method of collecting kinematic data in a field-testing environment.

The initial findings from this study were reported as a non-debated E-poster at the annual conference of the European College of Sport Science (ECSS) 2020 and then expanded to a full write up which has been published in *Sensors* and can be retrieved at https://www.mdpi.com/1424-8220/22/12/4371/htm. It has been duplicated here for the reader's ease and is also presented in Appendix II.

### 4.2.1 Introduction

Historically, cycling kinematics research has tracked joint and segment positions in an effort to calculate joint ranges of motion (Carpes, Bini and Quesada, 2014). These joints are then, most commonly, analysed in isolation (Bailey, Maillardet and Messenger, 2003; Dingwell, Joubert, Diefenthaeler and Trinity, 2008; Bini, Diefenthaeler and Mota, 2010; Cockroft, 2011). Although this is the most widely replicated approach, it has been criticised for not effectively capturing the complexity of coordinated motion (Bartlett, Wheat and Robbins, 2007).

As an alternative, it has been suggested that the continuous, multi-joint nature of the cycling task (Hug, Drouet, Champoux, Couturier and Dorel, 2008) lends itself best to a continuous relative phase (CRP) method of analysis, whereby the influence of one segment's motion upon an adjacent segment can be more readily acknowledged. This is achieved by calculating the joint angle at each joint across the entire motion cycle and then using angle-angle plots. These plots can then be quantified using vector coding techniques to establish the relative motion of two adjacent joints (Sparrow, Donovan, Van Emmerik and Barry, 1987).

CRP values can range from 0° to 360°, where 0° shows the respective movements of the coupled joints perfectly in-phase, and 180° indicates that they are perfectly anti-phase. Any value between these indicates a relative amount of in-phase or anti-phase movement.

Inconsistencies with this reporting convention have been identified (Lamb and Stöckl, 2014) with some authors choosing to report values only between 0° and 180°, given that the values −180° and 180° both indicate anti-phase behaviour, whilst others utilise both the positive and negative values because they have qualitative meaning that should be preserved. For example, it has been suggested that preserving the negative values is important because if the phase angle of the proximal segment is subtracted from the phase angle of the distal segment, then positive continuous relative phase values indicate that the distal segment is ahead of the proximal segment in phase space, therefore providing a clearer of the coupling's interaction (Kurz and Stergiou, 2022).

The level of detail offered by CRP analysis allows more detailed evaluation of the interactions along the kinematic chain and has been suggested to be especially important where one end of the segmental chain is effectively fixed, in the case of cycling through its attachment to the pedal. The consideration of the coupling relationship between segments has been therefore suggested to be especially crucial in the analysis of cycling motion (Chapman, Vicenzino, Blanch and Hodges, 2009). Additionally, CRP analysis has been deemed to be more sensitive to changes in coordination (Davids, Bennett and Newell, 2006) and could offer greater insight into the changing techniques employed in response to learning, environmental changes such as wind speed or road surface or other independent variables (Burgess-Limerik, Abernathy and Neal, 1993).

CRP has traditionally been measured using motion capture systems in a laboratory setting (Miller, Meardon, Derrick and Gillette, 2008; Seay, Van Emmerik and Hamill, 2011; Hein et al., 2012). This requires the duplication of a cyclist's equipment using an ergometer due to the amount of distance covered during a cycling bout and the inability to calibrate such an extensive capture volume for kinematic analysis. There is, however, a readily available body of literature that focusses on the lack of ecological validity of such an approach. Studies have shown that there is a significant difference in cycling speed and power output between laboratory and road conditions during time trial events (Jobson et al, 2007; Jobson, Nevill, George, Jeukendrop and Passfield, 2008), whilst others have shown that crank torque profiles are significantly different when comparing laboratory and outdoor cycling conditions (Bertucci, Grappe and Groslambert, 2007). This has prompted calls to move towards a testing environment where riders can use their own bikes to accurately replicate ''real-world'' performance (Carpes, Bini and Quesada, 2014), an approach which may be facilitated by the use of electro-goniometers during field testing.

Electro-goniometers have long been used for the measurement of lower extremity joint motion (Chao, An, Askew and Morret, 1980) and their physical characteristics make them suitable for practical applications within biomechanics (Legnani, Zappa, Casolo, Adamini and Magnani, 2000). The lightweight equipment and non-invasive methods of data collection, coupled with the ability to record to offline data logging systems makes them a potentially excellent choice for field-based assessments within cycling. Indeed, they have already been assessed in terms of their suitability for use in professional bike fitting services (Fonda, Sarabon, and Li, 2014) and have been found to be more accurate and valid for use within laboratory studies than manual methods of measuring knee joint range of motion (Shamsi, Mirzaei and Khabiri, 2019).

The aim of this study, therefore, was to investigate whether electro-goniometers offer a valid method for the calculation of CRP values during cycling performance. If this is the case, investigations into cycling technique can move to a more ecologically valid setting, whilst considering the interconnected nature of joint movements which occur during the movement.

### 4.2.2 Method

*Participants*

Seven participants (4 male, 3 female, age: 29 ± 7yrs, height: 1.76 ± 0.10m, mass: 71.97 ± 11.57kg) volunteered to take part in the study. Participants were recreationally active and free from injury at the time of testing but were not trained cyclists. All participants gave written informed consent before taking part in this study, which had local ethics committee approval in accordance with the rules of the Declaration of Helsinki of 1975, revised in 2013.

*Procedure*

Participants were invited to adjust the cycle ergometer (Wattbike Pro cycle ergometer, Wattbike, UK) to their comfort. This configuration was maintained throughout the testing session. Reflective markers (Qualisys, Sweden) were attached to the participant's right leg at the greater trochanter, lateral femoral condyle and lateral malleolus. A marker was also attached to the lateral side of the participant's shoe, with placement determined by palpation to establish the positioning of the base of the 5th metatarsal. Bi-axial electro-goniometers (Biometrics, UK) were attached at the hip, knee and ankle. The electro-goniometer at the hip was aligned vertically with the strain gauge running immediately posterior to the greater trochanter marker and the terminals positioned equidistant superior and inferior to the marker. The electro-goniometer at the knee was positioned on the medial aspect of the knee, aligned vertically with the strain gauge running directly over the medial femoral condyle and the terminals equidistant superior and inferior to this landmark. The electro-goniometer at the ankle was attached so that the superior terminal was aligned vertically above the medial malleolus, the strain gauge ran over the medial malleolus and the inferior terminal was positioned horizontally on the participant's shoe so that the electro-goniometer recorded an angle of 90$^o$ with the participant standing in the anatomical reference position. Goniometers were "zeroed" before application and applied to achieve values as close to 0$^o$, 0$^o$ and 90$^o$ respectively.

Participants performed exercise bouts of 30s at four prescribed cadences (60, 80, 100, 120 rev·min$^{-1}$) on the stationary ergometer (Wattbike, UK), with freely chosen resistance. Participants were given free choice of riding posture but asked to maintain the same position across all conditions.

*Data Analysis*

Measures were synchronously recorded by the bi-axial electro-goniometers (Biometrics, UK) and a 12-camera motion capture system (Qualisys, Sweden), with both systems recording at 500Hz. Raw marker trajectories were used to calculate sagittal plane joint angle and joint angular velocity which were recorded at the hip, knee and ankle and analysed for 10 complete pedal revolutions per participant per condition. Data was interpolated to 100 time points and used to calculate mean Continuous Relative Phase (CRP) per pedal revolution at two intra-limb couplings: (i) knee flexion/extension–ankle plantarflexion/dorsiflexion (KA) and (ii) hip flexion/extension–knee flexion/extension (HK).

Following checks for normal distribution, a combination of repeated measures T-tests and Wilcoxon signed rank tests were used to check for significant differences between measurement systems, followed by intra-class correlation coefficients (ICC) via the two-way mixed model to quantify the consistency of the CRP values produced by the two systems.

All statistical testing was performed using IBM SPSS statistics (IMB Corporation, USA), with an alpha level set at $p<0.05$.

**4.2.3 Results**

When comparing the mean CRP values produced by the two systems (Table 6-1), there were statistically significant differences ($p<0.05$) at 80 and 100 rev·min$^{-1}$ for the Hip-Knee coupling and at 120 rev·min$^{-1}$ for the Knee-Ankle coupling.

The goniometers appeared to report consistently higher mean values at the Hip-Knee coupling across all cadences. This is also true for 80, 100 and 120 rev·min$^{-1}$ for the Knee-Ankle coupling with the goniometers apparently underreporting at 60 rev·min$^{-1}$, compared to the previously validated camera system (Table 6-1).

**Table 4-1. Comparisons between Mean Continuous Relative Phase values produced across a complete pedal revolution.**

| Coupling | Cadence (rev·min$^{-1}$) | Mean CRP Value (Mean ±SD) | Sig. | ICC |
|---|---|---|---|---|

| | | Camera System | Goniometers | | |
|---|---|---|---|---|---|
| Hip-Knee | 60 | 3.57 (±1.94) | 5.55 (±1.05) | 0.080 | -0.413 |
| Hip-Knee | 80 | 3.33 (±2.36) | 6.81 (±1.84) | 0.043* | -0.272 |
| Hip-Knee | 100 | 2.48 (±1.76) | 7.19 (±1.73) | 0.028* | -0.103 |
| Hip-Knee | 120 | 7.81 (±6.57) | 13.59 (±5.23) | 0.191 | -0.418 |
| Knee-Ankle | 60 | 11.43 (±4.83) | 8.71 (±3.36) | 0.066 | 0.749 |
| Knee-Ankle | 80 | 12.31 (±6.13) | 13.17 (±6.67) | 0.691 | 0.664 |
| Knee-Ankle | 100 | 12.26 (±6.70) | 18.95 (±13.11) | 0.176 | 0.346 |
| Knee-Ankle | 120 | 11.29 (±5.10) | 29.22 (±16.25) | 0.009* | 0.376 |

* Denotes a significant difference between systems at p<0.05.

Intra-class correlation coefficients were created via the two-way mixed model to quantify the consistency of the CRP values produced by the two systems (see Table 6-1). The majority of these coefficients were below 0.5, suggesting poor levels of reliability between systems. The only exceptions to this were seen at 80 and 100 rev·min$^{-1}$ at the Knee-Ankle coupling, where values of 0.749 and 0.664 respectively were recorded. This would suggest, at best, a moderate level of agreement between systems and predicated further investigation into the basic joint position data produced by each system to ascertain the reason for such discrepancies.

Comparing positional data between systems revealed significant differences (p<0.05) at all cadences when comparing mean maximum hip angle and mean minimum hip angle (Table 6-2). The only exception to this was at 80 rev·min$^{-1}$ (p=0.197) where there was no statistically significant difference between the two systems; however, the large standard deviation value (±18.95) in the goniometer dataset does offer some cause for concern.

**Table 4-2. Comparison of Mean Maximum and Mean Minimum hip angle recorded across 10 pedal revolutions.**

| **Cadence ($rev \cdot min^{-1}$)** | 60 | | 80 | | 100 | | 120 | |
|---|---|---|---|---|---|---|---|---|
| **Measurement System** | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer |
| **Maximum Hip angle (°)** | 73.25 (±2.10) | 84.08 (±13.70) | 73.56 (±2.00) | 82.22 (±17.30) | 73.37 (±2.42) | 82.88 (±15.85) | 71.80 (±2.75) | 83.52 (±16.89) |
| **Sig.** | <0.001* | | <0.001* | | <0.001* | | <0.001* | |
| **Minimum Hip angle (°)** | 33.49 (±5.21) | 40.79 (±17.71) | 33.87 (±5.65) | 36.30 (±18.95) | 33.21 (±5.60) | 37.11 (±19.25) | 31.02 (±5.92) | 39.24 (±17.70) |
| **Sig.** | 0.010* | | 0.197 | | 0.044* | | <0.001* | |

* Denotes a significant difference between systems at $p<0.05$.

When comparing the mean maximum knee angle, there was further evidence that the two systems did not agree, with statistically significant differences ($p<0.05$) being seen at all cadences (see Table 6-3). This is also the case when comparing the mean minimum knee angle (see Table 6-3). Again, statistically significant differences ($p<0.05$) were recorded at all cadences.

**Table 4-3. Comparison of Mean Maximum and Mean Minimum knee angle recorded across 10 pedal revolutions.**

| **Cadence ($rev \cdot min^{-1}$)** | 60 | | 80 | | 100 | | 120 | |
|---|---|---|---|---|---|---|---|---|
| **Measurement System** | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer |
| **Maximum Knee angle (°)** | 138.75 (±8.66) | 165.24 (±6.36) | 138.52 (±9.39) | 166.99 (±6.07) | 138.61 (±8.87) | 170.04 (±5.36) | 140.26 (±9.74) | 173.62 (±8.19) |
| **Sig.** | <0.001* | | <0.001* | | <0.001* | | <0.001* | |
| **Minimum Knee angle (°)** | 70.75 (±4.17) | 113.25 (±13.35) | 70.42 (±4.44) | 116.62 (±14.08) | 69.81 (±4.40) | 117.41 (±13.29) | 70.17 (±4.92) | 121.00 (±15.70) |
| **Sig.** | <0.001* | | <0.001* | | <0.001* | | <0.001* | |

* Denotes a significant difference between systems at $p<0.05$.

Levels of reported ankle flexion/extension were also statistically significantly different ($p<0.05$) between the two measurement systems at all cadences with regards to both maximum and minimum mean reported values (see Table 6-4).

In summary, positional data suggested that the goniometer systems consistently over-reported both maximum and minimum values for hip and knee flexion/extension, while simultaneously under-reporting the corresponding values at the ankle.

**Table 4-4. Comparison of Mean Maximum and Mean Minimum ankle angle recorded across 10 pedal revolutions.**

| **Cadence (rev·min$^{-1}$)** | 60 | | 80 | | 100 | | 120 | |
|---|---|---|---|---|---|---|---|---|
| **Measurement System** | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer |
| **Maximum Ankle angle (°)** | 120.65 (±11.98) | 102.31 (±9.61) | 117.97 (±5.67) | 102.18 (±8.70) | 118.11 (±6.15) | 104.41 (±13.20) | 119.68 (±5.31) | 114.49 (±48.72) |
| **Sig.** | <0.001* | | <0.001* | | <0.001* | | <0.001* | |
| **Minimum Ankle angle (°)** | 100.90 (±13.35) | 83.59 (±7.17) | 95.39 (±7.38) | 83.23 (±7.17) | 94.91 (±6.92) | 83.23 (±6.80) | 94.80 (±5.26) | 79.22 (±12.10) |
| **Sig.** | <0.001* | | <0.001* | | <0.001* | | <0.001* | |

* Denotes a significant difference between systems at p<0.05.

### 4.2.4 Discussion

Results from this investigation suggest that bi-axial electro-goniometers are not a valid method for recording CRP values during simulated cycling efforts. There were statistically significant differences ($p<0.05$) between measurement systems in two of four tested cadences for the Hip-Knee coupling and a further significant difference was reported at 120 rev·min$^{-1}$ for the Knee-Ankle coupling. The lack of agreement between systems is further supported by ICC values, which mostly fall below 0.5, showing poor levels of agreement between systems (Koo and Li, 2016) when calculating CRP.

The discrepancy between systems could be due to the fact that signal values were not normalised. There has been some debate as to whether or not normalisation would avoid the magnitude of values from one segment dominating the CRP pattern (Lamb and Stöckl, 2014). However, multiple studies (Lamb and Stöckl, 2014; Kurz and Stergiou, 2002) concluded that, in the case of joint kinematics, normalisation is not required because the finite values are unimportant, it is the relative phase that is of interest. Calculation of CRP, therefore, appears to require normalisation of values against time, as done here, but not normalisation of the original signal values themselves.

As shown above, further investigation into the reason for the lack of agreement revealed statistically significant differences ($p<0.05$) between systems at the fundamental level of measured angular position. The two systems only agreed in terms of the minimum angle recorded at one joint (the hip), in one condition (80 rev·min$^{-1}$). All other comparisons returned significantly different results. Discrepancies at this level make it almost inevitable that there will be differences between reported CRP values, based, as they are, on differing fundamental measures.

The reason for such discrepancies in basic measures of angular position could, in part, be attributed to poor experimental control in terms of goniometer placement. Although every effort was made to replicate the exact placement described in the Methods section above, the lack of anatomical landmarks to use for reference means it is possible that there was some variation in placement between participants.

Even if placement was perfectly replicated between participants, it has been suggested that the human body lacks even surfaces and right angles on which to attach sensors of this nature in order to accurately calculate joint angles (Seel, Raisch and Schauer, 2014). The suggestion being that the lack of flat surfaces means the orientation of a measurement device cannot possibly be aligned with any physiologically meaningful axis. This is especially apparent at the knee where, despite traditionally being described as a single planar hinge joint, there are degrees of freedom relating to flexion/extension, abduction/adduction and internal/external rotation (Favre, Jolles, Aissaoui and Aminian, 2008). Although abduction/adduction and internal/external rotation angles very rarely exceed a range of ±10° (Perry and Davids, 1992), it is possible that this is enough to affect the measurement of angular position when using a system such as the electro-goniometers used here, which assume entirely planar motion.

Related concerns with the placement of the electro-goniometers include the influence of soft-tissue movement artifacts, the suggestion that surface mounted markers may not adequately represent true anatomical locations and the assumption that markers attached to the skin surface are rigidly connected to the underlying bones (Ramesay and Wretenberg, 1999; Stagni, Fantozzi, Cappello, and Leardini, 2005). It has been reported that skin marker trajectories showed up to 31mm error, when compared to a prosthesis-embedded anatomical frame, and up to a 192% root mean square error in abduction/adduction estimations taken from markers placed on the thigh and shank. Although the reflective markers used in this investigation were placed on bony anatomical landmarks (greater trochanter, lateral femoral condyle and lateral malleolus) to remove the influence of such artifacts, it should be noted that it is not possible to mount the electro-goniometers in such a way. The electro-goniometers, therefore, may have been subject to the type of soft tissue movement artifacts described above and this could contribute to the lack of agreement between systems in terms of fundamental angular position and CRP.

A potential limitation of the current study relates to the way in which the measures were produced. Although care was taken to match the sampling frequencies of the systems at 500Hz and the same 10 revolutions were analysed per participant per condition, the systems themselves were not synchronised. It is possible that this may have contributed to the differences seen between systems, but it is worth noting that, even at the highest cadence (120 rev·min$^{-1}$), the chosen sampling rate still provides approximately 250 measures per pedal revolution.

In the current investigation, CRP was reported as a mean value for an entire pedal revolution. The poor agreement between systems shown at this level meant that it was deemed more worthwhile to investigate the root of the discrepancies between systems rather than delve further into the divisions of a pedal revolution, but this is something which would be recommended once a valid measurement system has been established. Reporting a single CRP value, averaged across a complete pedal revolution may not offer enough detail throughout the various phases of the revolution to fully exhibit the nuanced kinematics at play. Therefore, it is suggested that future studies should split the pedal revolution into separate power and recovery phases. This approach has been adopted previously (Sides and Wilson, 2012) and has, at times, been extended to an even more detailed analysis of four “quarters” across the pedal revolution (Dorel, Couturier and Hug, 2009; Dorel et al., 2009; Lanferdini, Jaques, Bini and Vaz, 2014). The purpose of such a split would be to effectively separate the power and recovery phases from the areas at the top and bottom of the pedal revolution, which have long been identified as areas where pedalling kinematics are altered due to tangential force being at a minimum (Ericson, Nisell and Nemetth, 1988; Patterson and Moreno, 1990).

### 4.2.5 Conclusion

Although it has been suggested that the use of CRP analysis provides information that cannot be obtained through conventional angular position vs. time presentation, the results from this study would suggest that bi-axial electro-goniometers are not a suitable method for recording such values. Further investigations are recommended to establish a valid alternative to traditional motion capture systems so that investigations into joint-couple motions during cycling may move to a more ecologically valid setting that accurately replicates the “real world” performances of athletes.

## 4.3 STUDY FOUR: Validity of Inertial Measurement Suit

### 4.3.1 Introduction

Given the findings of Study 3, which strongly suggested that electro-goniometers were not suitable for calculating CRP at the Hip-Knee and Knee-Ankle joint couplings during cycling, it was evident that an alternative method of collecting valid kinematic data at the hip, knee and ankle was needed. This would hopefully allow the investigation to move outdoors, into a more ecologically valid scenario, to investigate intra-individual movement variability in a "real world" setting without relying on the "gold standard" data collection of a camera-based motion capture system.

One potential alternative method was found in the form of a device which was developed and manufactured by a local research and development company who preferred not to be named in this thesis due to the relatively early stages of the business. Their device was a base-layer style garment which was designed to be worn underneath the athlete's normal clothing to allow for non-invasive monitoring of golf swing movements during practice and competition events. Data capture was achieved via 18 Inertial Measurement Units (IMUs) which are embedded within the garment and record positional data at a rate of 1000Hz. The company had already undertaken significant in-house validation against motion capture systems using a range of golfing athletes at varying levels of expertise. Although, to the best of the author's knowledge, none of this work had been published, the company were confident that the suit was capable of accurately measuring 90,000 pieces of data per second and had developed their own interactive map which featured a 3D avatar to allow for real time feedback of measured variables.

If this wearable garment were to prove a valid way of capturing kinematic data in a field-testing environment the benefits would be huge for both the athlete and coach but also for the biomechanist. Firstly, the suit had been specifically designed to measure human movement outside of the laboratory setting, meaning that it would not require the re-purposing of laboratory-based equipment and would allow cyclists of all skill levels to monitor their movement regardless of the setting in which training or performance was to take place.

Secondly, the lightweight equipment and non-invasive IMUs, coupled with the fact that it would allow cyclists to continue wearing their own preferred cycling clothing over the top, made this a potentially excellent choice for field-based assessments within cycling. There is a significant body of literature which investigates the validity of such devices (e.g. Van den Noort, Scholtes and Harlaar, 2009; Eckardt, Munz and Witte, 2014; Geissinger and Asbeck, 2020; De Baets et al., 2020) and IMUs have been shown to provides accurate measures of accelerations and orientations during multiple functional activities (Cudejko, Button and Al-Amri, 2022).

In addition, the immediacy with which the IMU garment provides data would mean a huge reduction in the analysis and processing time required for a biomechanist to obtain specific kinematic variables. The automatic reporting functions, coupled with the manufacturer's cloud-based data sharing platform, would also allow a cyclist to use the system for in-person training with their coach or transmit their data directly to a coach anywhere in the world to provide real-time feedback.

Given the raft of potential benefits described above, the IMU suit appeared to be an ideal solution to provide kinematic measures of cycling in a field-based setting. The suit had already been highly tested for golf swings but no investigations on its validity when measuring cycling movements had been conducted. The aim of this investigation was therefore to fully replicate the methods of Study 3 in order to validate the IMU suit for use in cycling applications.

Although it was originally intended that this would be a full validation study, initial findings made it clear that the suit was not going to be a suitable option (see Section 7.3) so only pilot testing results will be discussed here.

**4.3.2 Pilot testing method**

For the pilot testing a single participant was required to wear the IMU motion capture suit and then have reflective markers (Qualisys, Gothenburg, Sweden) attached to the Greater Trochanter, Lateral epicondyle of the femur, Lateral malleolus and 5$^{th}$ metatarsal on the dominant (left) side of the participant's body. All markers were placed on the suit and attached using double sided tape then secured using Kinesio tape. The participant then performed 4 cycling bouts of 30 seconds each at 60, 80, 100 and 120 rev·min$^{-1}$ on a Wattbike pro ergometer (Wattbike, Nottingham, UK). Cycling bouts were synchronously recorded by both the suit and the camera system (Qualisys, Gothenburg, Sweden).

Due to the commercially sensitive nature of the processing algorithms employed by the suit, the data from the suit was processed by the manufacturer and returned in the form of Microsoft Excel sheets displaying sagittal plane knee and hip angles.

**4.3.3 Pilot testing results**

At lower cadences (60 and 80 rev·min$^{-1}$) the initial values reported by the suit seemed generally promising in that the range of motion and peak angles seemed believable. Representative data is displayed in Figures 7-1 and 7-2.

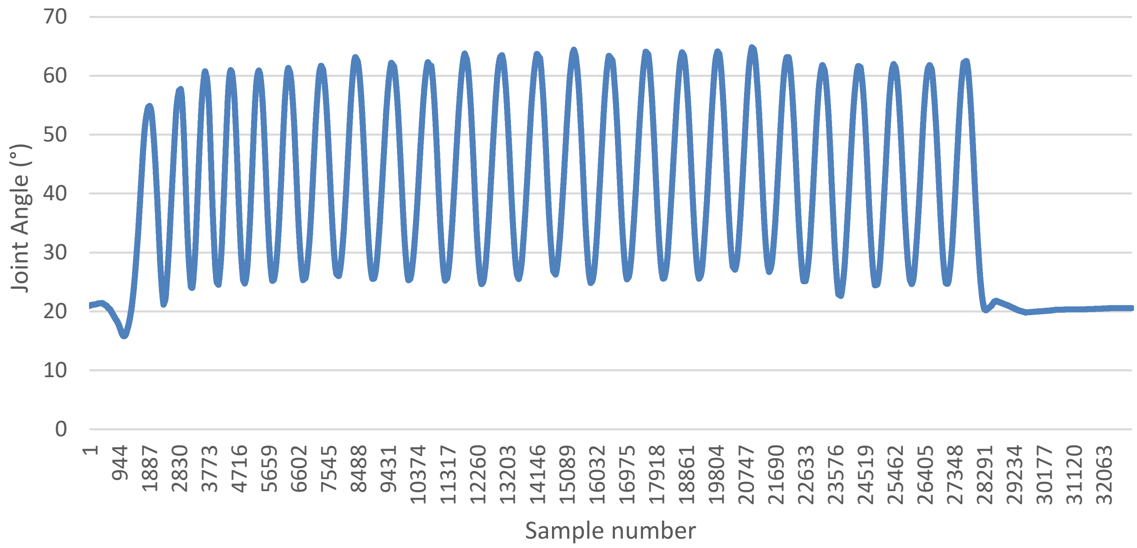



**Figure 4-8. Left hip joint angle at 60 rev.min$^{-1}$.**

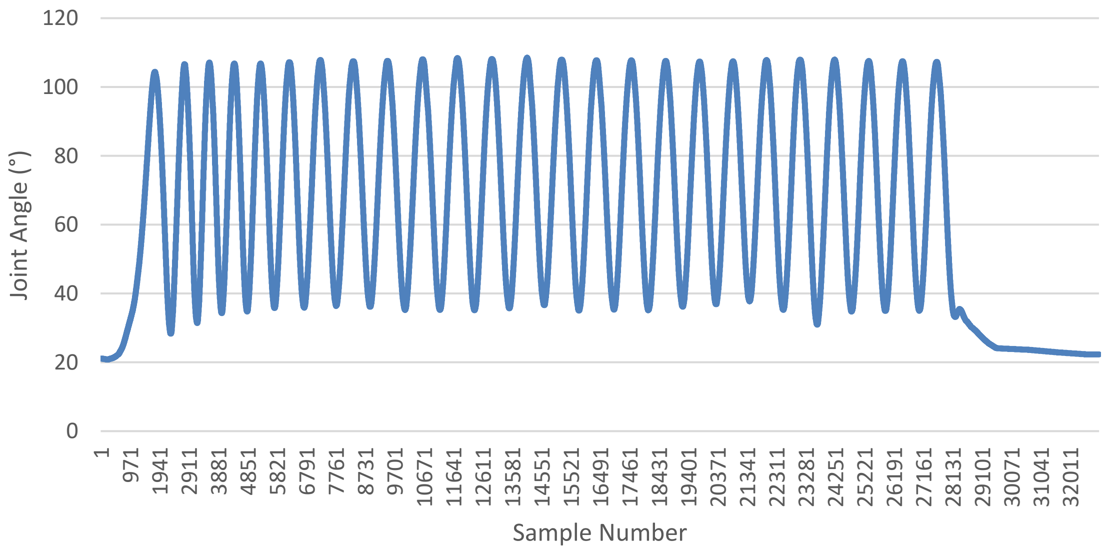



**Figure 4-9. Left knee joint angle at 60 rev.min$^{-1}$**

However, once the higher cadences were reached (100 and 120 rev·min$^{-1}$) it became apparent that the data from the suit was subject to a significant amount of drift. This resulted in the reporting of anatomically impossible hip angles as seen in the example Figures 7-3 and 7-4.

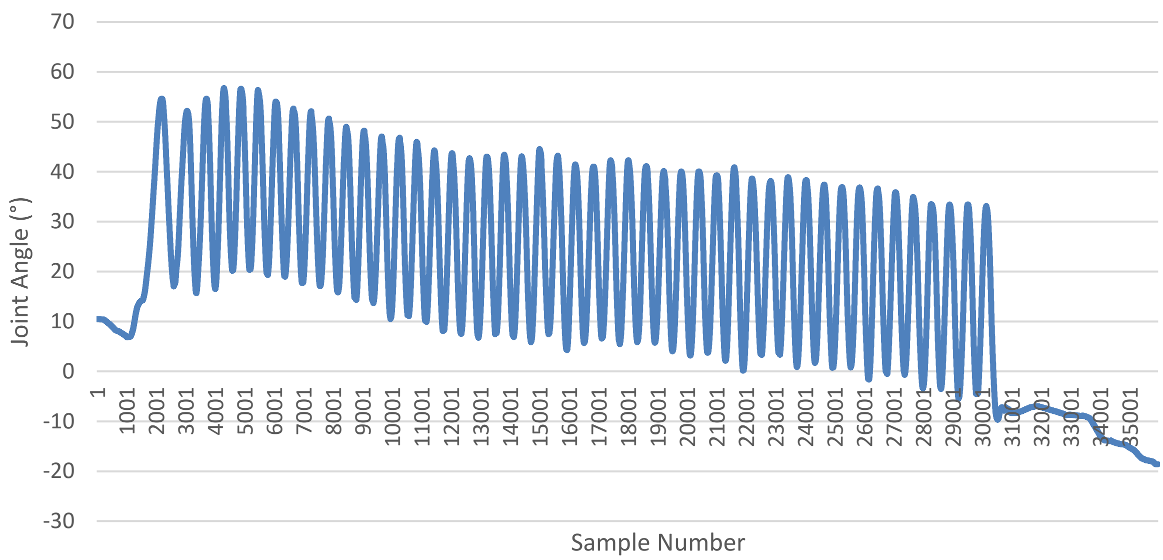



**Figure 4-10. Left hip joint angle at 80 rev.min$^{-1}$.**

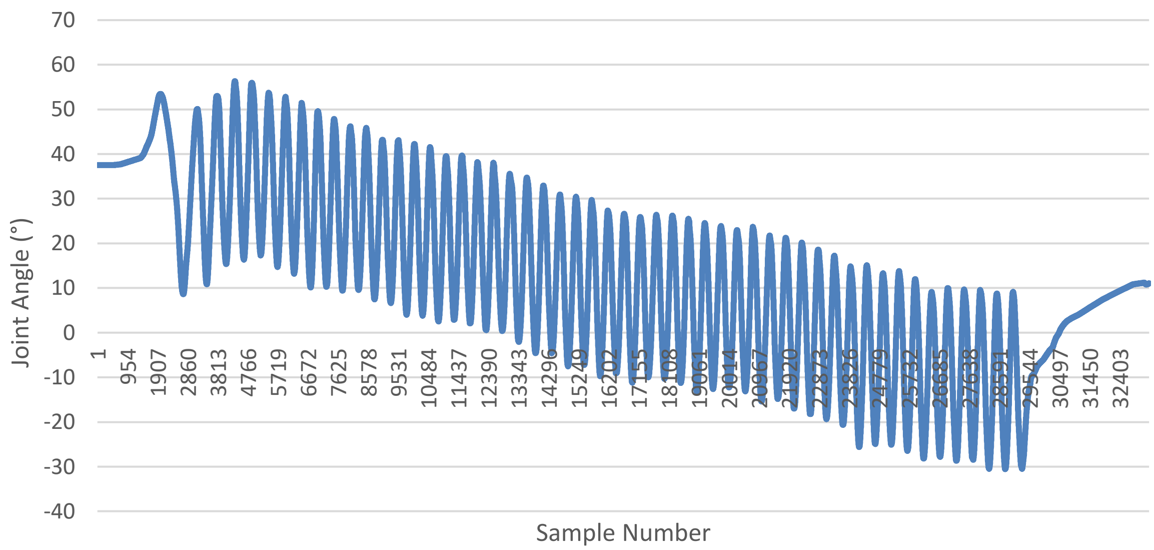



**Figure 4-11. Left hip joint angle at 120 rev.min$^{-1}$.**

### 4.3.4 Pilot testing discussion

Upon seeing the initial results, it was agreed that no further analysis would be conducted, and the manufacturer of the suit was approached for an explanation of the drift. They offered a number of potential reasons.

Firstly, they suggested that the magnetic field produced by the Wattbike could be interfering with the IMUs ability to measure accurately. This would seem reasonable as one component of all IMUs is reliant on magnetic field measures. However, the manufacturer's representative at the testing session checked the magnetic field around the ergometer before testing commenced and was satisfied that it fell within the workable boundaries for their device. In addition, the Wattbike calculates force via the use of chain tension over a load cell so it is unclear where this alleged magnetic interference may have originated from.

Secondly, the manufacturer suggested that the drift may have been due to the time elapsed between calibration events. This, again, makes sense as the suit is designed to record individual golf swings which are, by their nature, very short duration. However, the manufacturer also suggested that the suit only needed calibration at the start of each testing session. Regardless, the suit reported a peak hip angle which drifted by approximately $45^{o}$ ($56.31^{o}$ – $11.30^{o}$) and also shifted the reported minimum hip angle from a positive to a negative value within a single 30 second recording of cycling movements. This alone clearly makes it unsuitable for recording an outdoor time trial effort which is expected to be in the order of 30 minutes of duration.

The manufacturer's final suggestion was that, due to the processing algorithms which had been programmed into the suit's bespoke software, it was unable to mathematically cope with the thigh segment moving beyond the global horizontal plane. This is a movement which is completely absent from the performance of a golf swing for which the suit had been validated and therefore, apparently, caused a mathematical argument that the software was unable to solve when processing 3D kinematic values. Having not been given access to any of the data processing it is not possible to comment on the validity of these claims.

Due to the timing of this investigation coinciding fairly closely with the suit's commercial launch and a perceived lack of interest in expanding beyond golf at the time, the manufacturer was unwilling to put any time, effort or resources into resolving any of the issues described here and the partnership came to an end at this point.

### 4.3.5 Pilot testing conclusion

It was clear from the level of drift apparent in the data recorded using the suit, and the resultant reporting of anatomically impossible values for hip angle, that it was not going to provide a suitable option for recording joint kinematics during outdoor cycling time trial efforts and it was abandoned at this time in favour of other IMU based solutions (see Study 5).

## 4.4 STUDY FIVE: Validity of Xsens Dot Inertial Measurement Units.4.4.1 Introduction

Having established that the methods investigated in Studies 3 and 4 would not be suitable for the determination of CRP, the decision was taken to test the validity of an alternative IMU system for use in cycling data capture. Such a system has been developed by Xsens Technologies B.V. (Enschede, Netherlands) which was founded in 2000 and is viewed as "the leading innovator in 3D motion tracking technology and products" (Rana and Mittal, 2020). Although initially developed for mo-cap/animation applications within the film and gaming industries, Xsens products quickly became adopted by sports science practitioners who required a portable system in order to research human motion beyond the constraints of the traditional lab environment (Mavor et al., 2020). This has led to a significant body of literature which investigates the validity of such devices with numerous studies available which have done this in a variety of human motion settings (e.g. Van den Noort, Scholtes and Harlaar, 2009; Eckardt, Munz and Witte, 2014; Geissinger and Asbeck, 2020; De Baets et al., 2020). Although the body of work presented gives confidence in the company's ability to produce valid and reliable Inertial Measurement Unit (IMU) based motion capture systems, it should be noted that the collected literature largely relates to the company's flagship "Awinda" system and none of it focusses directly on human movement during cycling.

In 2020, Xsens released a new product under the name of Xsens DOT which was designed to be a more affordable IMU system costing ~£500 and featuring just 5 units compared to Xsens' flagship MTw Awinda full body system which requires 17 sensors and costs in the region of £3000. It was also designed to promote community development of custom applications with a "simple-to-use Software-Development-Kit (SDK) and comprehensive documentation".

Naturally, the scientific community immediately produced a number of studies to assess the validity of the new system with conclusions that it provides accurate measures of accelerations and orientations during multiple functional activities (Cudejko, Button and Al-Amri, 2022). It was also shown that the Xsens Dots were suitable for rehabilitation applications and sports to detect malposition (Schlage, Kitzig, Stockmanss and Naroska, 2021), have great potential to improve limb exercises monitoring and RoM measurement in home-based physical therapy. Another cited benefit was also that the system was cost effective and can be made available widely for immediate application (Wei, Kurita, Kuang and Gao, 2021).

Despite the overwhelmingly positive evidence above, there is a notable absence of validation studies in sporting applications and, more specifically, none have been found in cycling at this time. This may, in part, be due to the short period of time that Xsens Dots have been commercially available and, therefore, the aim of this study was to continue on from the previous two investigations of this thesis (Studies 3 and 4) in an effort to provide a valid method for measuring joint angles and calculating continuous relative phase during field-based cycling activities.

If Xsens Dots are proven to be a valid method for such measurements, then this would be advantageous for a number of reasons. Firstly, it would provide an affordable alternative to the full-body, suit-based, products that were investigated earlier in this thesis (see Study 4). Second, the lack of a suit allows more flexibility to attach sensors in anatomically relevant positions allowing for variation in participant anthropometry. Third, the lack of suit would allow cyclists to perform field testing while wearing their preferred clothing and equipment, contributing to higher overall ecological validity. Finally, the ability to tailor the specific calculations for each application make for a more efficient use of researchers' time. Rather than being restricted to the pre-determined variables produced as standard from a manufacturer's app, researchers could produce only variables which are relevant to the task of interest.

### 4.4.2 Method

*Participant information*

For this validation, the decision was taken to replicate the methods adopted in Studies 3 and 4. To this end, 8 participants (5 male, 3 female, mean ± SD: 32 ± 8 yr; 1.85 ± 0.27 m; 68 ± 14 kg) who were recreationally active but were not trained cyclists were recruited to take part in the study. All participants were free from injury at the time of testing and provided written informed consent before taking part in this study.

*Testing procedure and instrumentation*

Participants were invited to adjust the cycle ergometer (Wattbike Pro cycle ergometer, Wattbike, UK) to their comfort. This configuration was maintained throughout the testing session. Reflective markers (Qualisys, Sweden) were attached to the participant's right leg at the greater trochanter, lateral femoral condyle and lateral malleolus. A marker was also attached to the lateral side of the participant's shoe, with placement determined by palpation to establish the positioning of the base of the 5th metatarsal.

In addition, inertial measurement units (Xsens Dot, Xsens technologies, Netherlands) were attached at the midpoint of the thigh and shank segments and on the superior aspect of the foot. The thigh sensor was placed on the lateral aspect, mid-way along the line between the greater trochanter and lateral femoral condyle markers oriented so that the x axis of the sensor's local co-ordinate system ran along the longitudinal axis of the segment. Similarly, the shank sensor was also placed on the lateral aspect, mid-way along the line between the lateral femoral condyle marker and lateral malleolus markers, again oriented so that the x axis of the sensor ran along the longitudinal axis of the segment. The foot sensor was attached to the superior aspect of the participant's shoe, as close to the border between intermediate and lateral cuneiforms as was possible to determine via palpation. The sensor was oriented such that the x axis of the sensor ran along the longitudinal axis of the foot and was as horizontal as possible given the underlying structure and footwear.

Participants performed exercise bouts of 30 s at four prescribed cadences (60, 80, 100, 120 rev·min$^{-1}$) on the stationary ergometer (Wattbike, UK), with freely chosen resistance. Participants were given free choice of riding posture but asked to maintain the same position across all conditions.

Position and orientation data was synchronously recorded by the IMUs and a 12-camera motion-capture system (Qualisys, Sweden), with both systems reporting at 120 Hz.

*Data analysis*

Raw marker trajectories were used to calculate sagittal plane joint angle and joint angular velocity, which were recorded at the hip, knee and ankle and analysed for 10 complete pedal revolutions per participant per condition. The same variables were calculated from the IMUs by exporting Euler angle outputs and converting them to joint angles using a custom-built Excel spreadsheet (Microsoft Excel, Microsoft corporation, Washington, USA).

Both data sets were interpolated to 100 time points and used to calculate mean continuous relative phase (CRP) per pedal revolution at two intra-limb couplings: (i) knee flexion/extension–ankle plantarflexion/dorsiflexion (KA) and (ii) hip flexion/extension–knee flexion/extension (HK).

This process was repeated with each pedal revolution being split into a crude "power" and "recovery" phases (0-180$^{o}$ and 180-360$^{o}$ respectively) in a similar manner to Sides and Wilson (2012) and this was further extended to subsequently divide each revolution into four phases as performed Dorel, Couturier and Hug (2009) to produce separate top, drive, bottom and recovery phases (see figure 8-2).

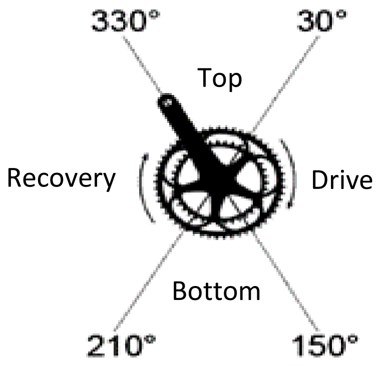



**Figure 4-12. Showing the four phases per pedal revolution.**
**Adapted from Dorel, Couturier and Hug (2009)**

All analyses were initially run including all 40 revolutions per participant (n=320 total comparisons) before being split according to cadence (60, 80, 100 and 120 rev·min$^{-1}$) and analysed again (n=80 comparisons per cadence).

IBM SPSS statistics (IMB Corporation, Armonk, NY, USA) was used to calculate intra-class correlation coefficients (ICC) via the two-way mixed model to quantify the consistency of the CRP values produced by the two systems for full revolution, simple half and half splits and four phase values.

### 4.4.3 Results

Intra-class coefficient values are displayed in Tables 8-1 and 8-2, overleaf. All correlations considered either good or excellent have been denoted in the following tables using an asterisk.

Using the guidelines from Koo and Li (2016), this requires ICC results to be between 0.75 and 0.90 to be denoted as "good" and >0.9 to be considered as "excellent". Conversely, ICC results of <0.5 indicate poor levels of agreement and results between 0.5 and 0.75 suggest only moderate levels of agreement between systems.

**Table 4.4. Levels of agreement between the Camera system and IMUs at the Hip-Knee coupling.**

| Data set | Analysis | | ICC | Lower 95% CI | Upper 95% CI |
|---|---|---|---|---|---|
| Combined | Full revolution | | 0.902* | 0.794 | 0.953 |
| | Two phases | Power phase | 0.730* | 0.73 | 0.953 |
| | | Recovery phase | 0.602 | 0.602 | 0.911 |
| | Four phases | Top phase | 0.770* | 0.77 | 0.948 |
| | | Drive phase | 0.838* | 0.566 | 0.931 |
| | | Bottom phase | 0.780* | 0.535 | 0.896 |
| | | Recovery phase | 0.711 | 0.388 | 0.863 |
| 60 rev·min$^{-1}$ | Full revolution | | 0.902* | 0.384 | 0.994 |
| | Two phases | Power phase | 0.891* | 0.424 | 0.993 |
| | | Recovery phase | 0.823* | 0.355 | 0.993 |
| | Four phases | Top phase | 0.965* | -1.024 | 0.984 |
| | | Drive phase | 0.847* | 0.876 | 0.998 |
| | | Bottom phase | 0.890* | -0.324 | 0.988 |
| | | Recovery phase | 0.730 | 0.234 | 0.992 |
| 80 rev·min$^{-1}$ | Full revolution | | 0.928* | 0.447 | 0.992 |
| | Two phases | Power phase | 0.813* | -0.442 | 0.980 |
| | | Recovery phase | 0.990* | 0.910 | 0.999 |
| | Four phases | Top phase | 0.641 | -2.494 | 0.963 |
| | | Drive phase | 0.737 | -0.503 | 0.971 |
| | | Bottom phase | 0.908* | 0.082 | 0.990 |
| | | Recovery phase | 0.981* | 0.853 | 0.998 |
| 100 rev·min$^{-1}$ | Full revolution | | 0.899* | 0.121 | 0.989 |
| | Two phases | Power phase | 0.823* | -0.251 | 0.981 |
| | | Recovery phase | 0.892* | -0.332 | 0.989 |
| | Four phases | Top phase | 0.754* | -0.500 | 0.973 |
| | | Drive phase | 0.682 | -1.026 | 0.965 |
| | | Bottom phase | 0.851* | 0.003 | 0.984 |
| | | Recovery phase | 0.764* | -2.853 | 0.976 |
| 120 rev·min$^{-1}$ | Full revolution | | 0.856* | -6.96 | 0.961 |
| | Two phases | Power phase | 0.548 | -1.594 | 0.957 |
| | | Recovery phase | 0.460 | -1.491 | 0.937 |
| | Four phases | Top phase | 0.656 | -1.983 | 0.964 |
| | | Drive phase | 0.695 | -4.381 | 0.97 |
| | | Bottom phase | 0.061 | -1.987 | 0.903 |
| | | Recovery phase | 0.565 | -0.446 | 0.944 |

**Table 4.44-6. Levels of agreement between the Camera system and IMUs at the Knee-Ankle coupling.**

| Data set | Analysis | | ICC | Lower 95% CI | Upper 95% CI |
|---|---|---|---|---|---|
| Combined | Full revolution | | 0.765* | 0.364 | 0.902 |
| | Two phases | Power phase | 0.780* | 0.516 | 0.899 |
| | | Recovery phase | 0.523 | 0.018 | 0.772 |
| | Four phases | Top phase | 0.815* | 0.608 | 0.913 |
| | | Drive phase | 0.656 | 0.201 | 0.847 |
| | | Bottom phase | 0.417 | -0.224 | 0.727 |
| | | Recovery phase | 0.455 | -0.108 | 0.742 |
| 60 rev·min$^{-1}$ | Full revolution | | 0.837* | 0.186 | 0.971 |
| | Two phases | Power phase | 0.809* | 0.090 | 0.966 |
| | | Recovery phase | 0.787* | -0.371 | 0.964 |
| | Four phases | Top phase | 0.699 | -0.430 | 0.946 |
| | | Drive phase | 0.719 | -0.273 | 0.950 |
| | | Bottom phase | 0.323 | -1.938 | 0.877 |
| | | Recovery phase | 0.605 | -0.596 | 0.927 |
| 80 rev·min$^{-1}$ | Full revolution | | 0.826* | -0.209 | 0.973 |
| | Two phases | Power phase | 0.693 | -0.273 | 0.943 |
| | | Recovery phase | 0.749 | -0.223 | 0.956 |
| | Four phases | Top phase | 0.901* | 0.492 | 0.983 |
| | | Drive phase | 0.785* | -0.765 | 0.977 |
| | | Bottom phase | 0.667 | -0.535 | 0.940 |
| | | Recovery phase | 0.649 | -0.330 | 0.934 |
| 100 rev·min$^{-1}$ | Full revolution | | 0.712 | -0.467 | 0.958 |
| | Two phases | Power phase | 0.843* | 0.214 | 0.972 |
| | | Recovery phase | 0.682 | -0.407 | 0.951 |
| | Four phases | Top phase | 0.958* | 0.749 | 0.993 |
| | | Drive phase | 0.871* | 0.222 | 0.978 |
| | | Bottom phase | 0.873* | -0.113 | 0.987 |
| | | Recovery phase | 0.528 | -0.561 | 0.921 |
| 120 rev·min$^{-1}$ | Full revolution | | 0.807* | -0.053 | 0.957 |
| | Two phases | Power phase | 0.782* | -0.398 | 0.963 |
| | | Recovery phase | 0.739 | -0.191 | 0.953 |
| | Four phases | Top phase | 0.661 | -0.682 | 0.940 |
| | | Drive phase | 0.700 | -0.966 | 0.950 |
| | | Bottom phase | 0.711 | -0.414 | 0.949 |

| | | | |
|---|---|---|---|
| Recovery phase | 0.643 | -0.346 | 0.930 |

### 4.4.4 Discussion

The aim of this study was to investigate the validity of calculating continuous relative phase via measurements taken by skin mounted IMUs compared with the "gold standard" motion capture camera system. As shown in the tables above, levels of agreement are generally either good or excellent for both the Hip-Knee and Knee-Ankle couplings, with some lesser levels displayed at specific cadences, which will be discussed below.

*Hip-Knee Coupling*

As shown in Table 8-1, the Hip-Knee coupling shows excellent levels of agreement between systems (ICC >0.9) when looking across a full revolution at all cadences except 120 rev·min$^{-1}$. At 120 rev·min$^{-1}$ an ICC value of 0.856 still shows good levels of agreement between systems and suggests that measures from the IMU system may still be trusted at this cadence.

This trend towards lower levels of agreement at the highest cadence is also present when the revolution is further divided for either two-phase or four-phase analysis. During two-phase analysis both the power phase and recovery phase shows good levels of agreement (ICC 0.75-0.90) at 60 rev·min$^{-1}$, excellent agreement (ICC >0.9) at 80 and 100 rev·min$^{-1}$ but only moderate (ICC 0.5-0.75) levels of agreement at 120 rev·min$^{-1}$. During four-phase analysis there are either good or excellent levels of agreement in all phases of the revolution at all cadences with the exception of the recovery phase at 60 rev·min$^{-1}$ and bottom and recovery phases at 120 rev·min$^{-1}$ which showed moderate levels of agreement.

Although this would suggest that results from the IMUs may need to be treated with some caution when the participant is working at higher cadences, it is worth noting that 120 rev·min$^{-1}$ is likely to be above the cadence that cyclist would choose for a time trial event. Abbiss, Peiffer and Lauresen (2009) reported that cadences of between 100 and 120 rev·min$^{-1}$ are best suited to sprint events, as this allows power output to be maximised, but that road time trial events benefit from a slightly reduced cadence (~90-100 rev·min$^{-1}$) since this has been shown to improve cycling economy and lower energy demands. In addition, Lucia, Hoyos and Chicharro (2001) reported that professional riders adopt cadences around 90 rev·min$^{-1}$ on the flat and around 70 rev·min$^{-1}$ when ascending steep gradients, both suggesting that cadences above 100 rev·min$^{-1}$ are unlikely to be seen.

*Knee-Ankle coupling*

At the Knee-Ankle coupling, as shown in table 8-2, there are good levels of agreement between systems (ICC = 0.75–0.9) when looking across a full revolution at all cadences except 100 rev·min$^{-1}$. At 100 rev·min$^{-1}$ an ICC value of 0.712 shows that the levels of agreement between systems fall marginally below the "good" boundary and suggests that measures for this coupling may need to be viewed with a degree of caution.

Interestingly, when further subdividing the data recorded at 100 rev·min$^{-1}$ for two-phase analysis, it becomes evident that there is something occurring at this coupling in the latter stages of a revolution which causes lower levels of agreement between systems. This is evidenced by good (ICC = 0.843) levels of agreement during the power phase and only moderate (ICC = 0.682) in the recovery phase. Further investigation seems to point to an event which occurs between 210$^{o}$ and 330$^{o}$ of the revolution as, during four-phase analysis, there are excellent or good levels of agreement in the top, power and bottom phases (ICCs = 0.958, 0.874 and 0.873 respectively) but only moderate agreement during the recovery phase (ICC = 0.528).

This may be linked to riders employing a process known as "ankling" (Wozniak Timmer, 1991) which aims to maintain positive torque production for the entire cycle (Davis and Hull, 1981) via subtle changes in dorsi/plantarflexion at the ankle and therefore changes of pedal orientation.

Houtz and Fischer (1959) originally suggested that this required maximum dorsiflexion to occur between 337 and 23$^{o}$ of a pedal revolution with maximal plantarflexion occurring just past 180$^{o}$. Their suggestion was the this allowed cyclists to overcome "dead spots" in power production by effectively pushing and pulling the pedal past the top and bottom centre positions respectively.

Cavanagh and Sanderson (1986), however, suggested that in elite riders, pedal orientation went only slightly below the horizontal into a dorsiflexed position and that this occurred nearer to 90$^{o}$ through a revolution. Conversely, they showed that the maximum plantarflexed position occurred at approximately 285$^{o}$, placing it firmly in the recovery phase of the current study's four phase analysis. It may be that the orientation of the IMU on the foot makes the subtle motions involved in this "ankling" technique less easy to identify and would go some way to explaining the slightly lower levels of agreement shown in this phase.

Lower levels of agreement in the Knee-Ankle coupling may also be attributed to slightly variable IMU orientation between participants, especially with the foot sensor. Although efforts were taken to orientate the axis perfectly in the desired direction every time this may not have been completely possible due to the participants' choice of footwear and the difficulties reported by Seel, Raisch and Schauer (2014) when they identified that the human body lacks even surfaces and right angles upon which to base sensor orientations. This is not something which can be easily rectified going forwards, especially as the participants in outdoor studies will be required to wear their chosen cycling footwear, but the levels of agreement shown here are high enough to suggest confidence in using IMUs in place of a motion capture system.

*Overall rating of agreement and limitations*

The overall levels of agreement seen at the Hip-Knee coupling (0.902) and Knee-Ankle Coupling (0.765) during this investigation give confidence that this provides a valid method of calculating CRP during outdoor cycling events. At the time of writing, there appeared to be no published articles which had investigated the validity of Xsens Dots in this way and only one which reported ICC values to rate the agreement between two systems.

Bailey, Uchida, Nantel and Graham (2021) reported levels of agreement between systems of 0.24, 0.26 and 0.10 for flexion/extension ROM of the hip, knee and ankle respectively when investigating variability in during gait. They also reported agreements of 0.70, 0.48 and 0.24 at the same joints when investigating the variability of these measures across multiple gait cycles. It should be acknowledged that Bailey et al.'s study reported agreements for joint ROM in isolation rather than as coupled pairs so this is not a like for like comparison, but the levels of agreement reported in the current study are far greater than those reported in the only published article that had tested data in the same way which was available and still concluded that ICCs were mostly good to excellent in the primary plane of motion for ROM and in all planes for variability of movements.

The lack of similar published papers makes it difficult to compare the current findings and it should be acknowledged that some may question the findings reported here as they are based on data from relatively few participants. Although it is true that there were only 8 participants in this study, the analysis of 10 revolutions per participant per cadence results in a total of 320 comparisons between systems when combining all cadences. If the confidence that the reader has in this investigation is based on the number of comparisons between systems, rather than the number or participants these comparisons have come from, then this should provide adequate evidence of rigor.

**4.5.5 Conclusion**

Despite the limitations outlined above, the levels of agreement between systems reported here are generally either good or excellent for both the Hip-Knee and Knee-Ankle couplings during indoor cycling. This is especially true in the cadence range that it is expected athletes would adopt for a cycling time trial performance. It is also worth noting that the levels of agreement displayed here suggest far greater validity than either of the methods investigated in Studies 3 or 4. It can, therefore, be suggested that the use of Xsens Dots is a valid method of measuring continuous relative phase and is recommended to be used in field-based testing.

Having shown evidence of a relationship between greater levels of movement variability and better overall performance in a cycling time trial (Study 1), established a valid method of measuring power output (Study 2) and a valid method for recording kinematic measures of joint coupling behaviours (Study 5), Study 6 was designed to make use of the validated methods to investigate whether cyclists alter their technique across a number of measurement windows within a single time trial performance. In essence, the aim was to investigate whether cyclists display movement variability in order to adapt to changing task constraints?

# 5. STUDY SIX: Intra-individual variability in sagittal plane kinematics during field-based time trial events.

## 5.1 Introduction

Cycling is a worldwide pastime with more than 5 million people over the age of 16 cycling at least once a month in England alone (Cycling UK, 2019). As such, cycling has received significant scientific attention with the most common method of motion analysis being to focus on the movement of the lower limbs (Enoka, 2000). This analysis has typically been limited to the sagittal plane (Ferrer-Roca, Roig, Galilea and Garcia-Lopez, 2012; Carpes et al., 2006) due to the large ranges of motion seen at the hip (42-44°), knee (73-78°) and ankle joints (21-25°) in this plane (Bini, Senger, Laferdini and Lopes, 2012) compared to the frontal and transverse planes (Umberger and Martin, 2001).

The values above were produced in laboratory-based investigations as this allows researchers to overcome a number of methodological challenges when studying cycling. The way in which this is typically achieved is to recreate the cyclist's equipment set up using an ergometer in a controlled environment (Fonda and Sarabon, 2010). Although this is undoubtedly the easiest approach for researchers, there is a readily available body of literature which focusses on the ecological validity of such an approach.

For example, studies by Jobson et al. (2007) and Jobson, Nevill, George, Jeukendrup and Passfield (2008) have consistently shown that there is a significant difference in cycling speed and power output between laboratory and road conditions during time trial events. In addition, Bertucci, Grappe and Groslambert (2007) have shown more broadly that crank torque profiles are significantly different when comparing laboratory-based and outdoor cycling conditions.

In addition, there is growing support for the notion that intra-individual movement variability may perform a functional role in task performance (Van Emmerik, Hamill, and McDermott, 2005), especially when the task requires adaptability of complex motor patterns within dynamic performance environments (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006). By using a cycle ergometer in a laboratory setting it is possible that the dynamic elements of the performance environment are controlled to such a degree that there isn't enough demand placed on the system in order to require a variable response. That is to say, removing task perturbations such as variations of road surface, weather conditions, and incline may unintentionally limit the amount of intra-individual movement variability a cyclist exhibits in order to complete the task. As a result, laboratory-based testing may not give a true representation of the movement strategies employed by cyclists; outdoor assessment may provide further information during training and/or racing in a more ecological scenario (Carpes, Bini and Quesada, 2014).

In field-based assessments of cycling performance there is evidence that cyclists displayed differing levels of maximal aerobic power and produce altered crank torque profiles depending on the gradient of the course (Bertucci, Grappe and Groslambert, 2007) and will also adopt altered joint kinematics during hill climbing (Arkesteijn, Jobson, Hopker and Passfield, 2013) or when the cyclist pedals while out of the saddle (Wozniak-Timmer, 1991). In addition, elite endurance cyclists changed their pedalling technique when faced with an increasing workload at constant cadence (Kautz, Feltner, Coyle and Baylor, 1991), all of which suggests they display a level of intra-individual movement variability.

Despite the evidence above, there are very few studies which have investigated the role of intra-individual variability within a single cycling performance. The closest approximation of this would be studies which have investigated the effects of differing pacing strategies during time trial performances. For example, Swain (1997) investigated the effect that varying power output would have on cycling performance in hilly or windy conditions. This simulation exercise concluded that significant time savings could be produced by slightly increasing power on uphill or headwind segments while compensating with reduced power on downhill or tailwind segments.

Seeking to go beyond a theoretical model, Cangley, Passfield, Carter and Bailey (2011) investigated this by instructing 20 experienced cyclists to ride 4 trials over a 4 km course. For 2 trials, riders were asked to maintain a constant power output while in the other 2 trials power output was varied in response to gradient. In this instance the variable power output strategy reduced completion time by 12 ± 8 s (2.9 %), which was statistically significant ($p < 0.001$). It was concluded that applying a variable power strategy can improve cycling performance in a field time trial where the gradient is not constant.

Although this would appear to evidence the functional role of movement variability within cycling, it should be noted that Cangley, Passfield, Carter and Bailey (2011) used a relatively homogenous sample group (Age 34 ± 8 yrs, mass 76 ± 8 kg, competitive experience 8 ± 4 yrs) who were similar in terms of their competitive level (current times of 21–25 min for a 10-mile time trial), required them to complete a relatively short course (4 km/2.49 miles) and only reported power output and completion time. As such, Cangley, Passfield, Carter and Bailey (2011) offer no comment on the movement patterns employed by the cyclists and whether they may have differed across the duration of the event.

The aim of this study, therefore, was to investigate if cyclists of differing skill levels employ differing levels of intra-individual movement variability across a number of successive measurement points during a ten-mile cycling time trial event. The suggestion being that the more experienced riders would have more experience solving the “degrees of freedom problem” (Bernstein, 1967) and therefore adapting their movement patterns to address the specific combination of task perturbations seen at various stages of a time trial performance.

The hypothesis was that more experienced cyclists would display greater levels of intra-individual movement variability, as measured via continuous relative phase analysis, than their less experienced counterparts.

**5.2 Methods**

*Participant information*

11 participants volunteered to take part in this study (8 Male, 3 Female, age 37.1 ± 8.47yrs, height 1.75 ± 0.08m, mass 79.66 ± 8.31kg). There was a range of experience levels across the sample with mean cycling activity self-reported as 5.31 ± 3.96 hours or 68.10 ± 75.20 miles per week. All participants were injury free at the time of testing, maintained their normal diet and daily activity patterns throughout the testing period and provided written informed consent before taking part in the study. Local ethical approval was provided by the University of Winchester.

*Testing procedure and instrumentation*

Participants were required to complete three time trial events on a standardised 10mile (16km) course which was selected due to the variable nature of the terrain and, more specifically, the presence of two significant climbs. A course profile is displayed in Figure 9-1.

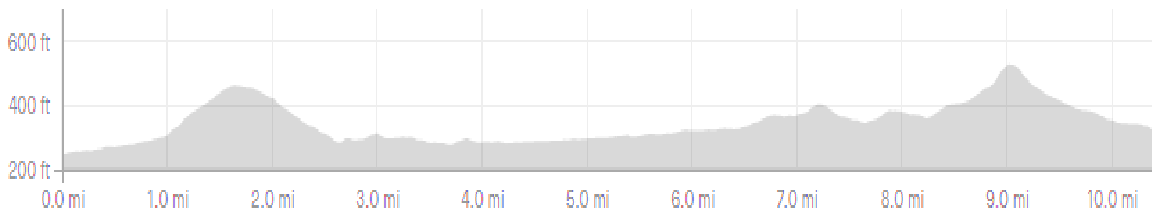



**Figure 5-1. Course Profile.**

Throughout all testing sessions, participants used their own bike and choice of clothing. The use of a helmet was mandatory and all participants had safety lights attached to their bike due to testing events taking place on public roads. All testing events took place in, as close as possible, similar weather conditions (Mean Temperature = 17.7 ± 4.8 °C, Wind speed = 12.2 ± 3.3 km·hr$^{-1}$) and in the event of poor weather, tests were postponed. Testing events were separated by a minimum of 48hrs to allow complete recovery between time trial events.

For the first event participants were instructed to ride at a relaxed pace so that they could note any features of the course and familiarise themselves with the turn-by-turn navigational cues given by the Garmin Head Unit (Garmin Edge 1000, Garmin Ltd., Schaffhausen, Switzerland).

During the second and third time trial events, participants were instructed to complete the course as fast as possible and were given access to the data they would typically use to monitor rides (e.g. heart rate, power output, speed) via a Garmin head unit (Garmin Edge 1000, Garmin Ltd., Schaffhausen, Switzerland) mounted on their handlebars. Participants were given no instructions concerning body position, gearing, cadence or pacing strategy.

Inertial measurement units (Xsens Dot, Xsens technologies, Netherlands) were attached at the midpoint of the thigh and shank segments and on the superior aspect of the foot. The thigh sensor was placed on the lateral aspect, mid-way along the line between the greater trochanter and lateral femoral condyle markers oriented so that the x axis of the sensor's local co-ordinate system ran along the longitudinal axis of the limb segment. Similarly, the shank sensor was also placed on the lateral aspect, mid-way along the line between the lateral femoral condyle marker and lateral malleolus markers, again oriented so that the x axis of the sensor ran along the longitudinal axis of the limb segment. The foot sensor was attached to the superior aspect of the participant's shoe, as close to the border between intermediate and lateral cuneiforms as was possible to determine via palpation. The sensor was oriented such that the x axis of the sensor ran along the longitudinal axis of the foot and was as horizontal as possible given the underlying structure and footwear.

Participants used their own cycling shoes and those who normally rode with cleats incompatible with the PowerTap P1 pedals (CycleOps, Madison, WI, USA) had their cleat position replicated with 3 bolt Kéo cleats (Look cycle international, Nevers, France) to allow for power output to be measured throughout the ride. It should be noted, however, that two participants typically rode with flat pedals and another three were unwilling to have their pedals changed. In these cases, the PowerTap pedals were not used and, as such, power output will not be discussed here due to the incomplete nature of the dataset.

*Data analysis*

Data was only recorded during the third time trial where all devices were set to record for the full duration of the ride. IMUs (Xsens Dot, Xsens technologies, Netherlands) measured at a frequency of 800Hz and applied a strap down integration method to compute orientation and velocity values from gyroscope and acceleration data. 3D orientation of the sensor was calculated by the manufacturer's built in Kalman filter core algorithm which, they claim, is optimized for human motions and reduces drift during longer duration measurements. Data was reduced to reported values at 120Hz by the onboard processing native to the manufacturer's app to allow Bluetooth transfer of data to a logging device (Samsung S9, Samsung Electronics, South Korea) without presenting an excessive computational load.

Once data was extracted from the IMUs, seven measurement windows were identified across the duration of the ride using GPS and time data from the Garmin Head Unit. The measurement windows were chosen to allow comparison of limb movement across similar gradients early and late in the ride and the addition of a window at the point of maximum gradient allowed a comparison of the extremes of gradient experienced on course. Details of measurement locations can be seen in Table 9-1.

**Table 5-1. Details of measurement windows across the 10mile (16.09km) time trial course.**

| Point | Nickname | Elapsed distance from start | Gradient |
|---|---|---|---|
| 1 | Flat 1 | 0.4 miles (0.64 km) | 0.0% |
| 2 | Climb 1 | 1.5 miles (2.41 km) | 4.0% |
| 3 | Descent 1 | 2.1 miles (3.38 km) | -4.5% |
| 4 | Flat 2 | 5.1 miles (8.21 km) | 0.0% |
| 5 | Climb 2 | 8.7 miles (14.00 km) | 4.0% |
| 6 | Steepest climb | 8.9 miles (14.32 km) | 12.9% |
| 7 | Descent 2 | 9.3 miles (14.97 km) | -4.5% |

At each measurement window, 10 seconds of IMU orientation data was selected and converted to sagittal plane joint angles at the hip, knee and ankle using a custom-built Excel spreadsheet (Microsoft Excel, Microsoft corporation, Washington, USA). Joint angles were then used to calculate joint angular velocity values. Using the point of maximum knee flexion as the start of each revolution, data was extracted for 10 complete pedal revolutions per participant per measurement point and then interpolated to 100 time points. This was then used to calculate mean continuous relative phase (CRP) across the 10 pedal revolutions at two intra-limb couplings: (i) knee flexion/extension–ankle plantarflexion/dorsiflexion (KA) and (ii) hip flexion/extension–knee flexion/extension (HK).

CRP was used in acknowledgement of the fact that the motion of one segment subsequently influences the motion of an adgecent segment, and therefore the study of isolated joints does not effectively capture the complexity of the coordinated motion (Bartlet et al. 2007). This is especially true when one end of the kinetic chain is attached to a pedal and Chapman et al. (2009) sugested that the consideration of the coupling relationship between segments may therefore be espiecially crucial in the analysis of motion within the field of cycling.

Additionally, CRP analysis has been deemed to be more sensitive to changes in coordination (Davids, Bennett and Newell, 2006) and could offer greater insight into the changing techniques employed in response to learning, environmental changes such as wind speed or road surface or other independent variables (Burgess-Limerik, Abernathy and Neal, 1993).

Having calculated CRP at the HK and KA couplings, the coefficient of variation (CV%) for these values was calculated using the formula below:

$$\text{Co-efficient of variation} = (\text{standard deviation}/\text{mean})*100$$

This produced a percentage value (CV%) which represents the amount of variance each participant displayed between the seven measurement windows. This was designed to ascertain whether a relationship existed between the amount of variation a cyclist showed between measurement points and the time taken for them to complete the time trial. As such, a Pearson's product moment correlation coefficient was calculated to test for the relationship between CV% and the time taken to complete the 10-mile time trial ($Time_{TT}$).

This process was repeated with each pedal revolution being split into "power" and "recovery" phases (0-180$^o$ and 180-360$^o$ respectively) in a similar manner to Sides and Wilson (2012) and this was further extended to subsequently divide each revolution into four phases as described by Dorel, Couturier and Hug (2009) to produce separate top, drive, bottom and recovery phases (see Figure 9-2).

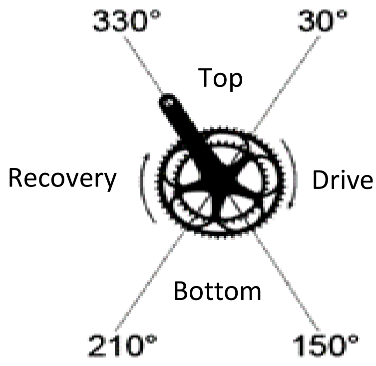



**Figure 5-2. The four phases per pedal revolution.**

**Adapted from Dorel, Couturier and Hug (2009)**

In addition to calculations of CV% of CRP, maximum and minimum flexion/extension values were taken at the hip, knee and ankle for each of the 70 extracted revolutions per participant (10 per measurement window). These values were then tested via a one-way repeated measures ANOVA to check for significant differences between measurement windows. Any significant ANOVA results were followed up by Bonferroni adjusted T-tests to establish where the differences occurred. Follow up testing consisted of pairwise comparisons of all measurement windows across the time trial course. The 21 comparisons between measurement windows (e.g. Flat 1 – Climb 1, Flat 1 – Descent 1, Flat 1 – Flat 2…, etc.) were completed for all six variables (Minimum hip ankle, Maximum hip angle, Minimum Knee angle, Maximum Knee angle, Minimum ankle angle and Maximum ankle angle), providing a total of 126 comparisons per participant. Significant differences between matched pairs of time points (e.g. flat 1 vs flat 2, climb 1 v climb 2) would represent an alteration of technique due to fatigue.

All statistical testing was performed using IBM SPSS statistics version 24 (IMB Corporation, New York, NY, USA), with a significance level set at $p < 0.05$.

### 5.3 Results

*Full revolution analysis*

Using data from the full, undivided pedal revolutions, the correlation coefficient between CV% of CRP and $Time_{TT}$ at the Hip-Knee joint coupling was considered to be a statistically significant, strong negative relationship ($r = -0.719$, $p = 0.013$). This relationship can be seen in figure 9-3.

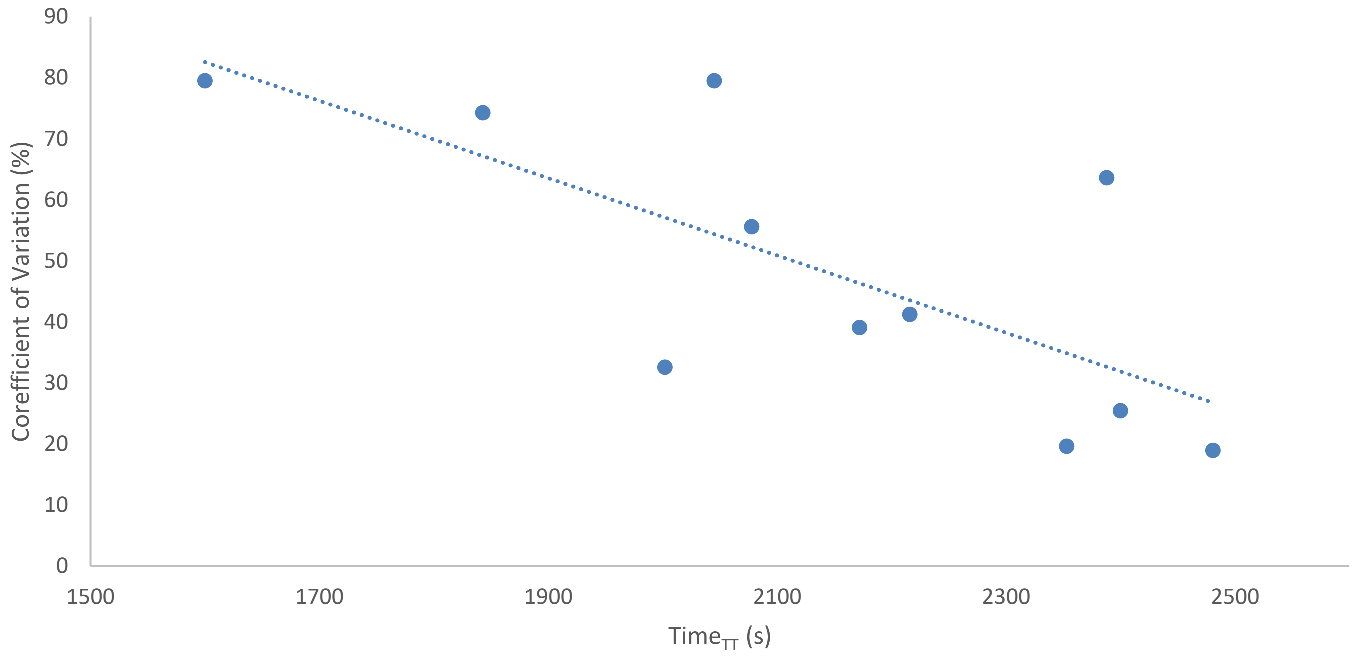



**Figure 5-3. Relationship between Coefficient of Varitaion (CV%) and finishing time (Time$_{TT}$) for full pedal revolution data at the Hip-Knee coupling.**

Similarly, the correlation coefficient for the relationship between CV% of CRP and Time$_{TT}$ at the Knee-Ankle coupling also suggested a statistically significant strong negative correlation ($r = -0.812$, $p = 0.002$). This relationship is displayed in figure 9-4.

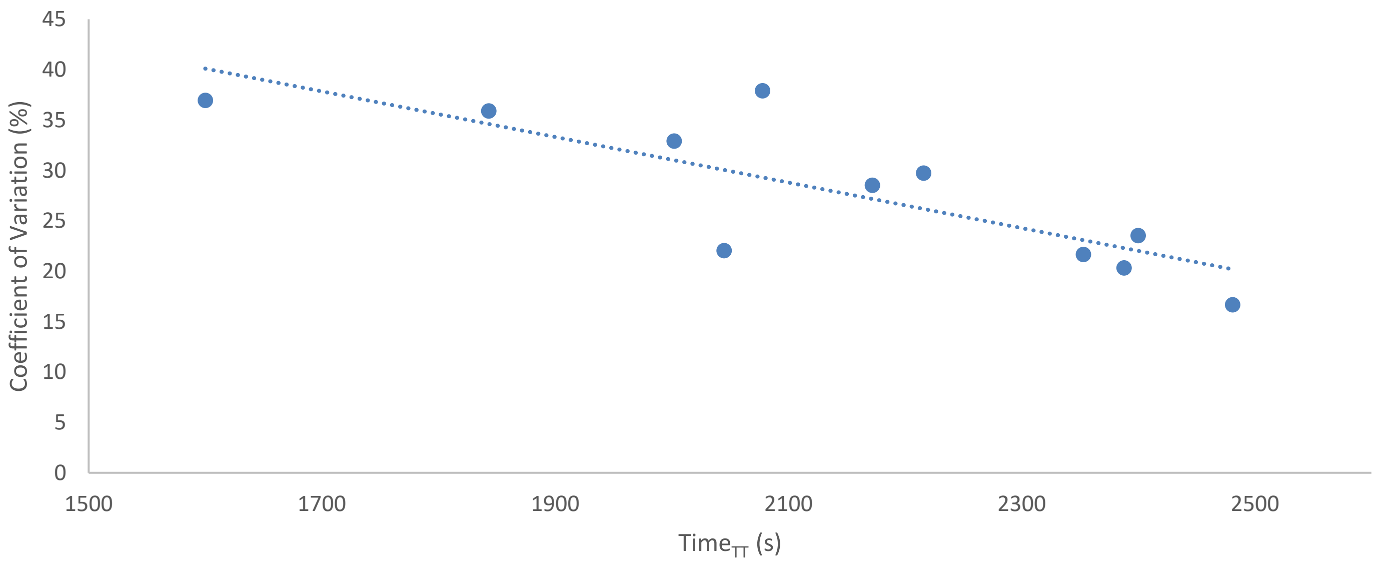



**Figure 5-4. Relationship between Coefficient of Variation and finishing time for full pedal revolution at the Knee-Ankle coupling.**

*Two phase analysis*

Once pedal revolutions were divided for two phase analysis the CV% of CRP as in the power (0-180°) and recovery (180-360°) phases was correlated against $Time_{TT}$.

When considering the power phase, the correlation coefficient between CV% of CRP and $Time_{TT}$ for the Hip-Knee coupling resulted in a non-statistically significant moderate negative correlation at the Hip-Knee coupling (r = -0.543, p = 0.084) but a statistically significant moderate negative correlation at the Knee-Ankle coupling (r = -0.660, p = 0.027). Both relationships for the power phase are displayed in Figure 9-5.

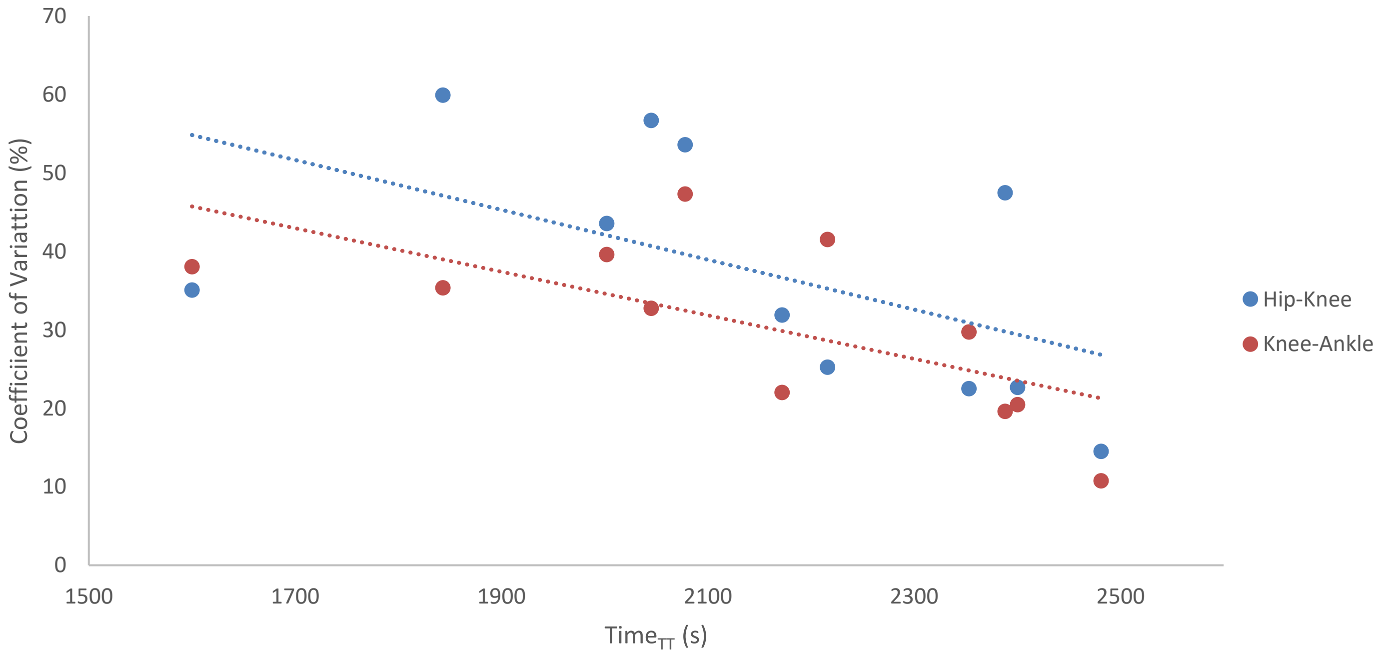



**Figure 5-5. Relationship between CV% of CRP and $Time_{TT}$ during the power phase.**

During the recovery phase, the correlation coefficient between CV% of CRP and $Time_{TT}$ for the Hip-Knee coupling (r = -0.566, p = 0.069) and the Knee-Ankle coupling (r = -0.544, p = 0.084) both suggest a moderate negative relationship but neither of these represent a statistically significant correlation. The relationships displayed during the recovery phase have been plotted in Figure 9-6.

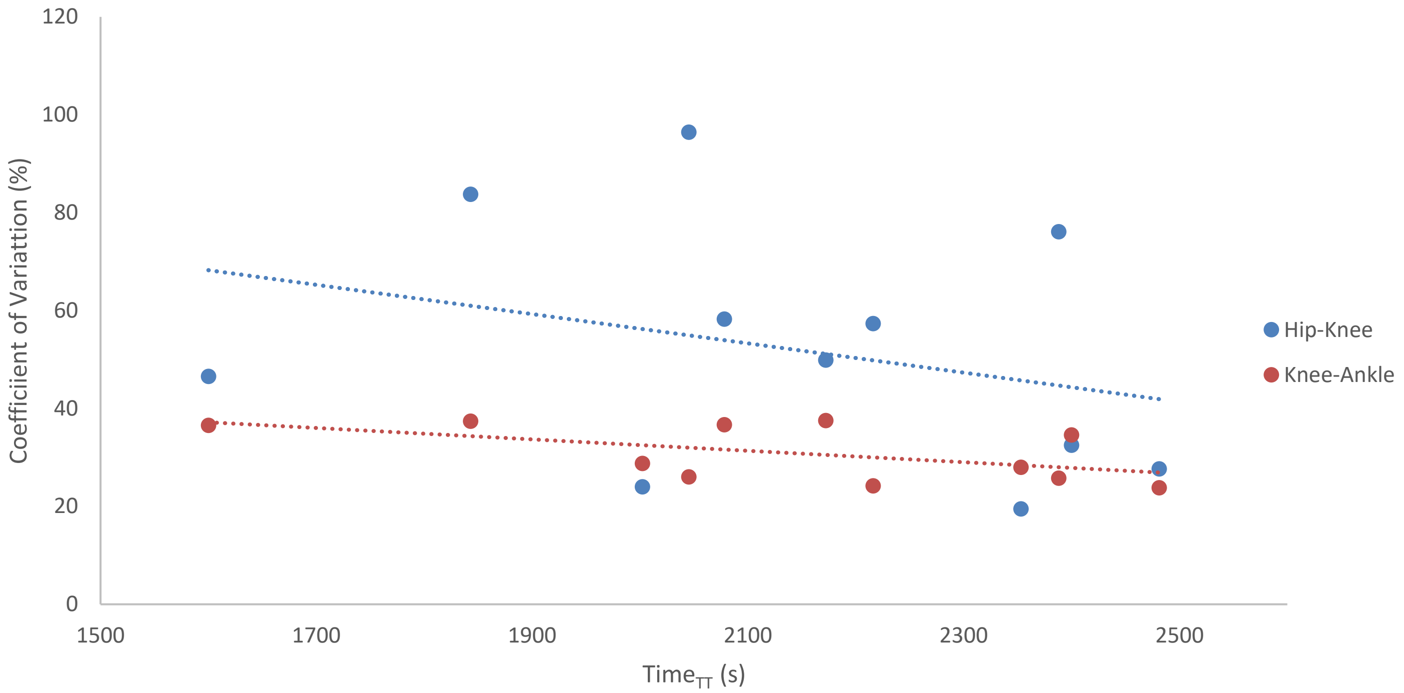



**Figure 5-6. Relationship between CV% of CRP and TimeTT during the recovery phase.**

*Four phase analysis*

Having further divided pedal revolutions into top (330-30$^o$), drive (30-150$^o$), bottom (150-210$^o$) and recovery (210-330$^o$) phases. CV% of CRP was once more correlated against Time$_{TT}$.

Correlation coefficients and significance values for both joint couplings at each phase of the pedal stroke are displayed in Table 9-2. For this mode of analysis, statistically significant correlations between CV% of CRP and Time$_{TT}$ were seen for both couplings during the top phase. All other correlations were not statistically significant.

**Table 5-2. Correlation between CV% of CRP and Time$_{TT}$ during four phase analysis. Statistically significant results are denoted by an asterisk (*).**

| Coupling | Phase | r | p |
|---|---|---|---|
| Hip-Knee | Top | -0.629 | 0.038* |
| | Drive | -0.566 | 0.069 |
| | Bottom | -0.324 | 0.331 |
| | Recovery | -0.228 | 0.499 |
| Knee-Ankle | Top | -0.682 | 0.021* |
| | Drive | -0.596 | 0.053 |
| | Bottom | 0.262 | 0.437 |
| | Recovery | -0.218 | 0.520 |

For ease of interpretation, the relationships described in Table 9-2 have been displayed in Figures 9-7 to 9-10.

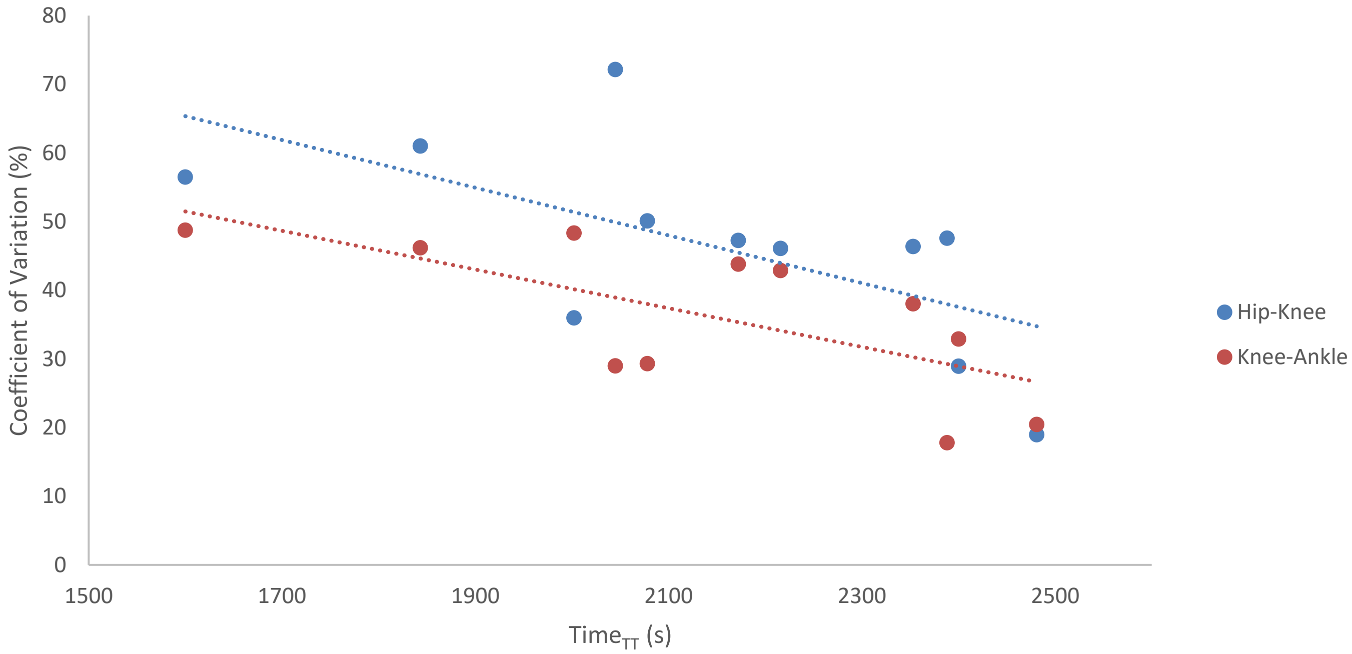



**Figure 5-7. Relationship between CV% of CRP and Time$_{TT}$ in the top phase.**

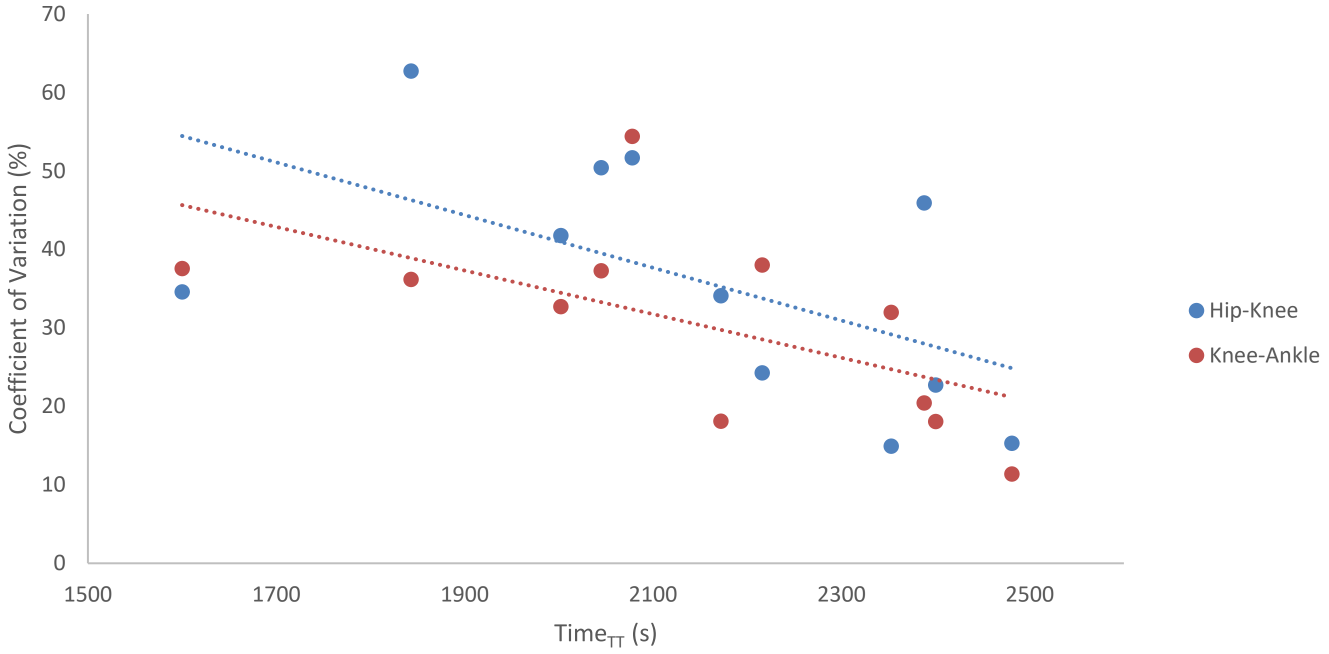



**Figure 5-8. Relationship between CV% of CRP and Time$_{TT}$ during the drive phase.**

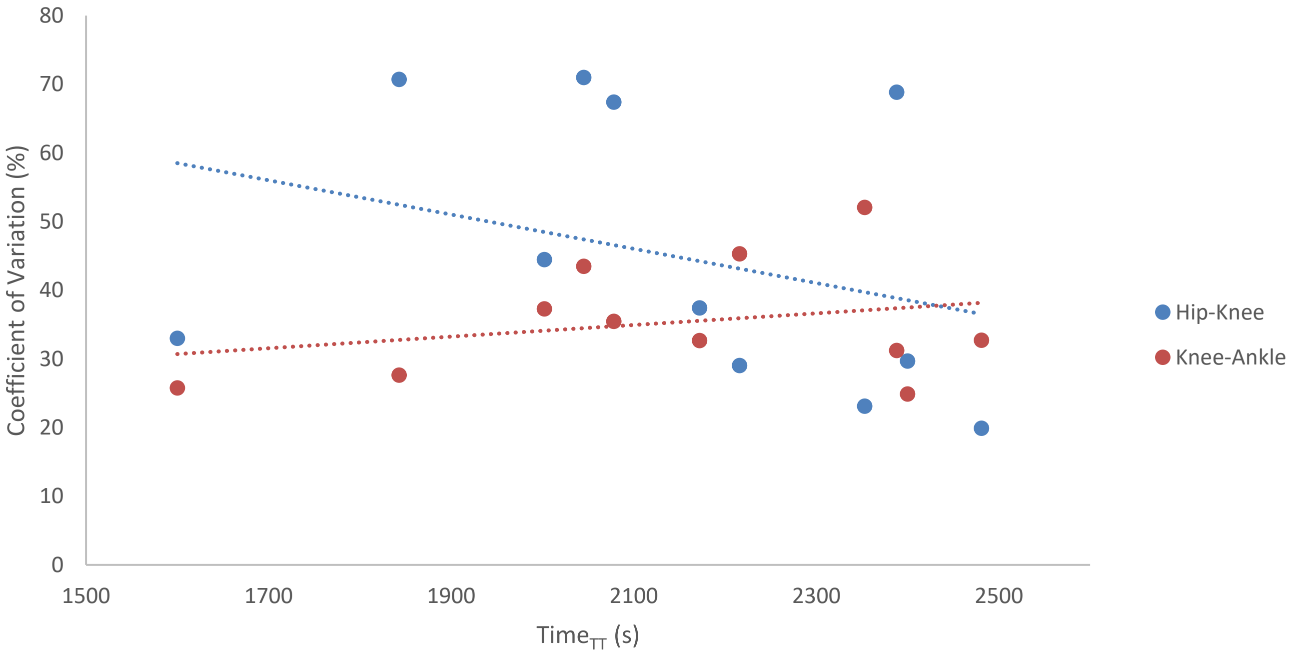



**Figure 5-9. Relationship between CV% of CRP and TimeTT during the bottom phase.**

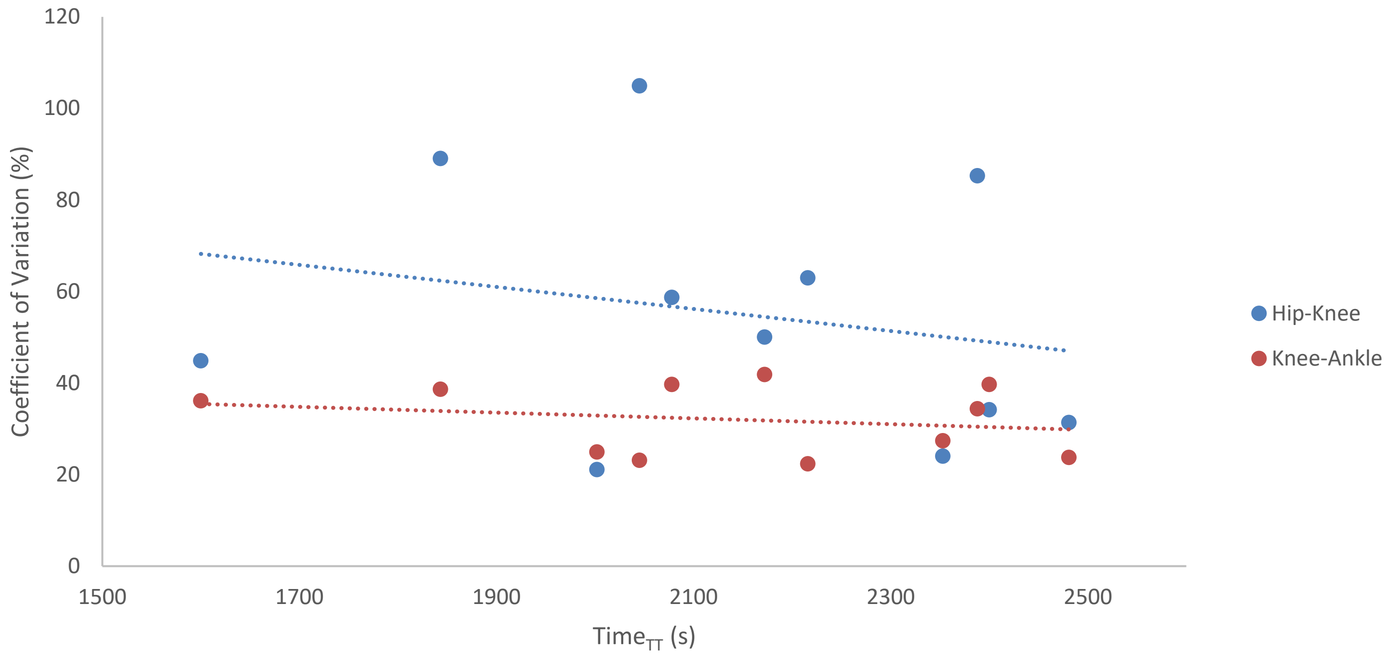



**Figure 5-10. Relationship between CV% of CRP and TimeTT during the recovery phase.**

*Maximum/minimum joint angle testing*

Overall ANOVA results suggested that there was a statistically significant difference ($P < 0.05$) between measurement windows for all participants in all variables (Minimum hip ankle, Maximum hip angle, Minimum Knee angle, Maximum Knee angle, Minimum ankle angle and Maximum ankle angle).

Follow up pairwise comparison testing revealed statistically significant differences ($p < 0.05$) were present for all participants but there was no obvious relationship between the number of differences recorded and the time taken to complete the time trial. P values for the pairwise comparisons of gradient matched pairs of measurement windows are presented in table 9-3 with statistically significant differences denoted by an asterisk.

It should be noted at this stage that the table below only features 10 participants as the recording capacity of the IMUs was such that the final two measurement windows were not recorded for the slowest rider. Therefore, matched comparisons for the “climb” and “descent” pairings are not available for the 11th ranked rider.

**Table 5-3. Comparisons between matched pairs of measurement windows for all participants.**

| Variable | Comparison | Participant rank | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1st | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | 10th |
| Minimum Hip Angle (°) | Flat 1 – Flat 2 | 0.001* | 1.000 | <0.001* | 1.000 | 1.000 | 1.000 | <0.001* | <0.001* | 1.000 | 0.042* |
| | Climb 1 – Climb 2 | 0.542 | 1.000 | 0.093 | <0.001* | 0.039* | 1.000 | 0.448 | 0.048* | <0.001* | 1.000 |
| | Descent 1- Descent 2 | 1.000 | 0.212 | 1.000 | <0.001* | 1.000 | 1.000 | 1.000 | 0.115 | 1.000 | <0.001* |
| Minimum Knee Angle (°) | Flat 1 – Flat 2 | 0.049* | 1.000 | <0.001* | 1.000 | 1.000 | <0.001* | 0.047* | <0.001* | 1.000 | <0.001* |
| | Climb 1 – Climb 2 | <0.001* | 0.004* | 1.000 | <0.001* | <0.001* | 1.000 | 0.481 | 0.007* | <0.001* | 0.336 |
| | Descent 1- Descent 2 | 0.885 | 1.000 | 0.644 | 0.253 | <0.001* | <0.001* | <0.001* | <0.001* | 0.885 | 0.525 |
| Minimum Ankle Angle (°) | Flat 1 – Flat 2 | 1.000 | 1.000 | 1.000 | 1.000 | 0.003* | 1.000 | <0.001* | 1.00 | 0.066 | 0.744 |
| | Climb 1 – Climb 2 | <0.001* | <0.001* | 1.000 | 0.537 | 1.000 | 1.000 | 1.000 | 0.009* | <0.001* | <0.001* |
| | Descent 1- Descent 2 | <0.001* | <0.001* | 0.012* | <0.001* | 1.000 | 1.000 | 0.004* | <0.001* | 1.000 | <0.001* |
| Maximum Hip Angle (°) | Flat 1 – Flat 2 | 0.875 | 1.000 | <0.001* | 1.000 | 1.000 | 1.000 | 0.016* | 0.351 | 1.000 | 0.453 |
| | Climb 1 – Climb 2 | 0.502 | 0.002* | 1.000 | <0.001* | 1.000 | 1.000 | 1.000 | 0.040* | <0.001* | <0.001* |
| | Descent 1- Descent 2 | 0.223 | 1.000 | <0.001* | 1.000 | 0.564 | 1.000 | 1.000 | 1.000 | 1.000 | <0.001* |
| Maximum Knee Angle (°) | Flat 1 – Flat 2 | 0.016* | 0.546 | 1.000 | 1.000 | 1.000 | 1.000 | 0.025* | <0.001* | 0.663 | <0.001* |
| | Climb 1 – Climb 2 | 1.000 | <0.001* | <0.001* | <0.001* | <0.001* | 1.000 | 1.000 | 0.009* | <0.001* | <0.001* |
| | Descent 1- Descent 2 | <0.001* | 1.000 | 1.000 | 1.000 | 0.002* | 1.000 | 0.027* | <0.001* | 1.000 | 0.099 |
| Maximum Ankle Angle (°) | Flat 1 – Flat 2 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | <0.001* | 0.570 | 1.000 | 1.000 |
| | Climb 1 – Climb 2 | <0.001* | 1.000 | 1.000 | 0.004* | 0.004* | 1.000 | 1.000 | 0.556 | 0.106 | <0.001* |
| | Descent 1- Descent 2 | <0.001* | 0.015* | 0.078 | 1.000 | 1.000 | 0.005* | <0.001* | <0.001* | 1.000 | 1.000 |

* Denotes a significant difference between measurement points (p<0.05).

## 5.4 Discussion

The results of this study suggest that skilled cyclists exhibit greater levels of intra-individual movement variability compared to their less experienced counterparts when completing a ten-mile cycling time trial. Far from being detrimental to normal function as historically thought (Bartlett, Wheat and Robins, 2007; Davids, Glazier, Araújo and Bartlett, 2003; Van Emmerick and Van Wegen, 2000), the greater movement variability exhibited by faster riders suggests that it is indeed "essential noise" (Davids et al., 2004) and that it can play a functional role in cycling performance.

*Full revolution analysis*

As displayed in Figure 9-3, when analysing data from a full pedal revolution, there is a negative linear relationship between the coefficient of variation of CRP values (CV%) shown across the course of the time trial event and the amount of time taken to complete the event ($Time_{TT}$). For both the Hip-Knee and Knee-Ankle joint couplings, this relationship results in statistically significant ($p<0.05$) correlations which are both above the ±0.70 threshold required to be considered as evidence of a strong correlation (Hip-Knee = -0.719, Knee-Ankle = -0.812) according to the guidelines reported by Schober, Boer and Schwarte (2018).

Button, Davids and Schöellhorn (2006) and Bradshaw and Aisbett (2006) stated that a more variable movement pattern during the execution of a sporting skill enables greater adjustment for intrinsic factors, such as confidence and fatigue, and extrinsic factors, such as wind, temperature and gradient. Therefore, it was expected that there would be a negative correlation between the CV% values and finishing time in the present investigations as the cyclists who completed the course in the shortest time would therefore be displaying the greatest amounts of variation.

These findings are at odds with those of previous studies which, instead of a linear relationship, reported a U-shaped relationship when working with handball players (Schorer, Baker, Fath and Jaitner, 2007) and triple jumpers (Wilson, Simpson, Van Emmerik and Hamill, 2008). In these studies, the level of intra-individual movement variability displayed by the least skilled athletes was increased, advanced athletes demonstrated a period of stability and the highest performers again showed increased variability. The shape of relationship reported by Schorer, Baker, Fath and Jaitner (2007) and Wilson, Simpson, Van Emmerik and Hamill (2008) could be linked to traditional models of motor learning which typically indicate two (Adams, 1971; Gentile, 1972) or three (Anderson, 1982; Fitts & Posner, 1967) relatively distinct stages of learning with performance stability in the final stage. Whether this applies to the acquisition of expert-level skill or whether skill learning happens due to continuous adaptation to performance constraints (Newell, Lui, & Mayer-Kress, 2001, Ericsson, 2007) and learning to solve the “degrees of freedom problem” in multiple ways (Bernstein, 1967) is debateable but it seems that, for the sample of participants recruited for this study at least, there is a more linear relationship within cycling.

*Two phase analysis*

Following the example of Sides and Wilson (2012), it was deemed important to go beyond full revolution analysis to investigate the nuances of pedalling technique in greater detail. Accordingly, the pedal revolution was divided into power and recovery phases (0-180$^{o}$ and 180-360$^{o}$ respectively). This was designed to allow inferences to be made as to whether the greater variation demonstrated by faster riders was displayed in the phase where they were applying power to the pedal or during the phase where the leg was more passive and not actively contributing to the forward propulsion of the bike (Wozniak-Timmer, 1991).

As shown in Figure 9-5, the significant correlation which was seen during the full revolution analysis was still present in the power phase for the Knee-Ankle joint coupling ($r = -0.660$, $p = 0.027$). Despite showing consistently negative relationships, no other correlations reached a level of statistical significance.

The lack of significant correlations could potentially be attributed to variations in terms of participant's footwear and pedal choices. The participants for this investigation represented a range of experience levels (average weekly training load self-reported as 5.31 ± 3.96 hours or 68.10 ± 75.20 miles per week) which included two relatively inexperienced participants who were uncomfortable using clipless pedals. This means that these participants were unable to pull up on the pedal during the recovery phase where those using clipless pedals could. Although it has long been questioned as to whether this actually happens (e.g. Kautz, Feltner, Coyle and Baylor, 1991), it may be that this is a method of adjusting crank torque profiles which was not available to the least experienced participants but that could have been employed by the more experienced participants to overcome greater workloads (Bini and Diefenthaeler, 2010), alterations in cadence (Bini, Tamborindeguy and Mota, 2010) or the effect of fatigue (Amoroso, Sanderson and Henning, 1993). Given the relatively small sample size recruited for this study, having two participants who were unable to adjust their technique in this way may have artificially masked an existing relationship.

It could also be that dividing the pedal revolution into two phases masks the variability that is present by artificially partitioning the pedal revolution into phases which do not truly align with events that are inherent within the technique. For example, this simple division does not acknowledge the presence of "dead centres" at the top and bottom of the crank revolution (So, Ng and Ng, 2005). These events during the crank rotation occur at approximately 0 and 180° and denote points where applying a vertical force to the pedal will not result in a rotation of the crank and, instead, a tangential force is required to continue crank progression. It is possible that, by dividing the revolution into two simple phases, these dead centre events span across the boundary of the phases and therefore the evidence of variable motion is lost.

To overcome this, a quarter split which is rotated by some 30° was adopted, similar to that of Dorel, Couturier and Hug (2009), Dorel et al., (2009) and Lanferdini, Jacques, Bini and Vaz, (2014). This ensures that the influence of top and bottom dead centres are contained within phases at the top and bottom of the rotation and the remaining phases more closely align with the pattern of pedal force application identified in previous studies (e.g. Soden Adeyefa, 1979; Peiffer and Abbiss, 2010; García-López, Díez-Leal, Ogueta-Alday, Larrazabal and Rodríguez-Marroyo, 2016).

*Four phase analysis*

One surprising result from the four phase analysis is that there appears to be a weak positive correlation (r = 0.262) during the bottom phase of the revolution for the Knee-Ankle joint coupling. This is at odds with all other relationships displayed in this analysis as, regardless of the phase or joint coupling in question, all other results suggest a negative relationship.

This result could potentially be attributed to slightly variable IMU orientation between participants with regards the foot sensor. Although efforts were taken to orientate the axis in the desired direction this may not have been completely possible due to the participants' choice of footwear and the difficulties reported by Seel, Raisch and Schauer (2014) when they identified that the human body lacks even surfaces and right angles upon which to base sensor orientations. This is obviously not something which can be easily overcome and it is unclear why it should only affect the results in this particular phase of the pedal revolution.

In contrast, there were statistically significant negative linear correlations in the top phase of the revolution for both the Hip-Knee joint coupling (r = -0.629) and Knee-Ankle joint coupling (r = -0.682). According to the guidelines published by Schober, Boer and Schwarte (2018) these correlation co-efficient are both at the high end of what should be considered to represent a moderate correlation (±0.400–0.690) with the Knee-Ankle joint coupling very close to being considered as strong. This suggests that there is a greater level of adjustment being made at the top of the pedal stroke (330-30$^{o}$) by the riders who finished the time trial in less time. This is similar to the findings of Christiansen, Bradshaw and Wilson (2008) who observed increased movement variability at the top and bottom dead centres of the pedal revolution and suggested that this would allow for greater adaptation to changing conditions (extrinsic, e.g. terrain; intrinsic, e.g. fitness, fatigue) and that it would reduce the repetitive stress on the individual joints. It is also interesting to note that this phase is very closely aligned to the period where Houtz and Fischer (1959) originally suggested that cyclists should undertake "ankling".

Ankling requires maximum dorsiflexion to occur between 337 and 23$^{o}$ of a revolution and was suggested to allow cyclists to overcome "dead spots" in power production by effectively pushing the pedal past the top dead centre position. Theoretically, this would mitigate the effects of the top dead centre position, maintain positive torque production for the entire cycle and, therefore, maintain a higher average speed (Davis and Hull, 1981).

There is some debate as to whether cyclists are even able to adopt this strategy. Cavanagh and Sanderson (1986) concluded that the ankling pattern is "anatomically and mechanically impossible if the rider remains in the seat" and a number of dated studies claim that many elite cyclists do not adopt this technique (Cavanagh and Nordeen, 1976; Faria and Cavanagh, 1978; Lafortune and McLean, 1989).

In contrast, Kautz, Feltner, Coyle and Baylor (1991) saw an ankling adaptation in response to increased workload in half of their participants and Zommers (2000) concluded in his doctoral dissertation that it was indeed physically possible. Regardless of whether it is widely adopted or not, it is interesting that a recognised strategy of technique adaption exists in the exact phase where this investigation has seen a significant relationship between the level of variability a participant displays and the time it takes them to complete a time trial event. In order to further investigate the potential alterations made to joint movements, the focus of this investigation shifted from the variability of CRP values to the variability of finite joint positions themselves.

*Maximum/Minimum joint angles*

Having seen evidence of greater variability in faster riders between measurement windows, the next step was to investigate the finite values for extremes of joint angle displayed within each measurement window. It was hypothesised that there would be a greater number of significant differences between measurement windows for the faster riders as this would represent them being more capable of adapting their motor patterns within a dynamic performance environment (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006).

Overall ANOVA results suggested that there was a statistically significant difference ($p < 0.05$) between time points for all participants in all variables. Thus, all participants demonstrated a statistically significant alteration of their minimum and maximum joint angles at the hip, knee and ankle across the course of the time trial. This could potentially be to cope with the ongoing perturbations of gradient (Bertucci et al, 2005) or the onset of fatigue (Amoroso, Sanderson, and Henning, 1993) but, regardless of reason, it suggests that all participants employed a degree of movement variability across the ride.

In order to establish the location, and potentially the reason for differences, follow up testing consisted of pairwise comparisons of all measurement windows across the time trial course. The 21 comparisons between measurement windows (e.g. Flat 1 – Climb 1, Flat 1 – Descent 1, Flat 1 – Flat 2…, etc.) were completed for all six variables (Minimum hip ankle, Maximum hip angle, Minimum Knee angle, Maximum Knee angle, Minimum ankle angle and Maximum ankle angle), providing a total of 126 comparisons per participant.

Again, statistically significant differences ($p < 0.05$) were present for all participants but there was no obvious relationship between the number of differences recorded and the time taken to complete the time trial. For example, the 5th, 8th and 10th ranked participants all displayed a similar number of differences (85.67 ± 3.05) but finished the time trial with over 5 minutes difference (322 seconds) in their finishing times. Conversely, the two participants who finished in the most similar times (a difference of 33 seconds) showed 54 and 83 significant differences respectively and were ranked near the middle of the group (4th and 5th) in terms of finishing time.

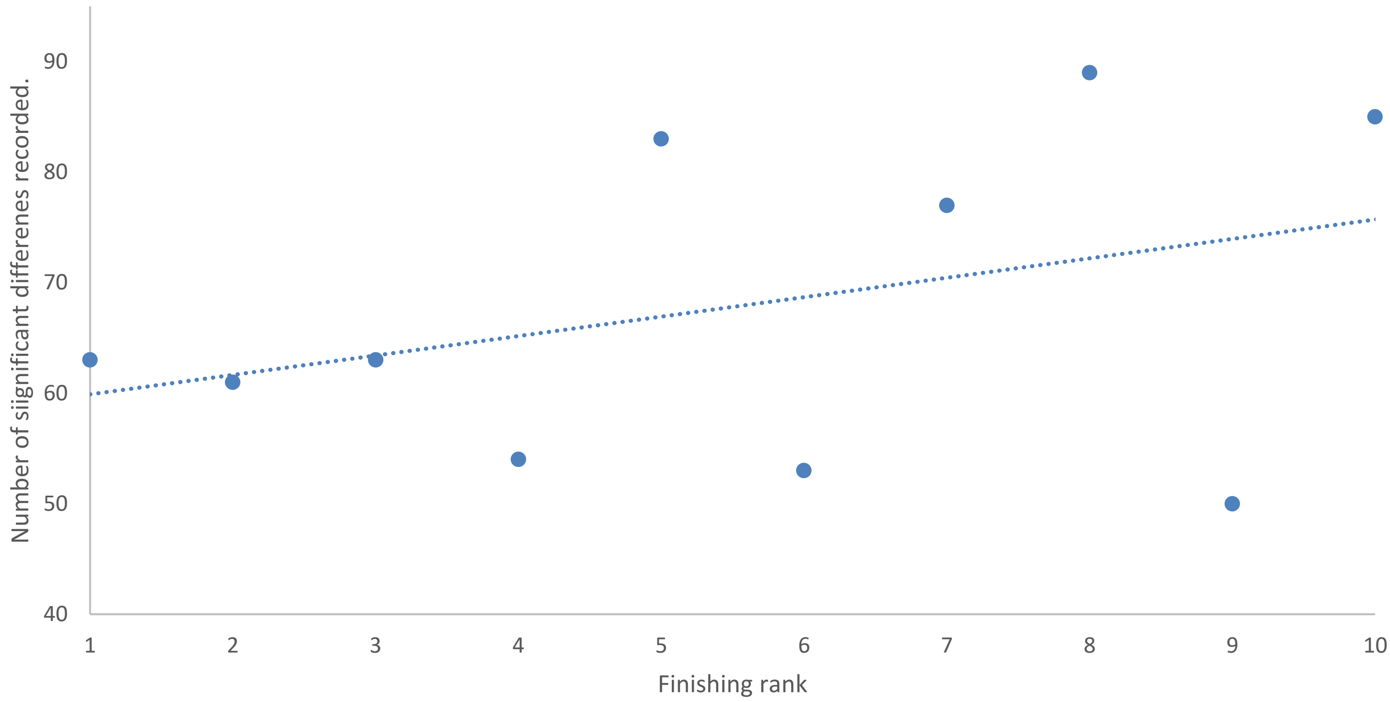



**Figure 5-11. Relationship between the number of significant differences recorded and finishing rank.**

This lack of a clear pattern was further supported by a correlation co-efficient of 0.315 between the number of differences seen and the finishing time trial (see Figure 9-11). It should be noted at this stage that the figure above only features 10 participants as the recording capacity of the IMUs was such that the final two measurement windows were not recorded for the slowest rider.

That there isn't an established relationship here ($r = 0.315$) is perhaps unsurprising when compared with the findings of previous studies that have considered the effect of skill level or gradient. When comparing novice and elite cyclists, Chapman et al (2009) reported that, despite using different patterns of leg muscle recruitment when cycling, the two groups did not display significantly different joint angles or joint velocities. They did concede that there were some minor differences between novice and elite cyclists in terms of the absolute range of motion at the ankle but concluded that this was not of consequence. Likewise, Fonda and Sarabon (2012) reviewed a wealth of literature concerned with uphill cycling and concluded that, although changes in muscular activity are present, joint dynamics are not substantially altered during seated cycling compared to cycling on level terrain.

In order to assess whether participants adjusted their technique to mitigate fatigue, the comparisons between gradient matched pairs of measurement windows (e.g. flat 1 vs flat 2) were of the most interest (see Table 9-3). In theory this allowed for comparison of technique throughout the time trial where the participant was faced with the same combination of task constraints but was performing at a heightened state of fatigue in the later window of each comparison. Fatigue is unavoidable in a cycling time trial due to the intensity of performance (Kenefick et al., 2002) and yet there did not seem to be any pattern as to which participants demonstrated significant differences between measurement windows. This is, perhaps, indicative that the gradient a participant is cycling over is a greater driver of movement variability than their fatigue state in much the same way as Padulo et al.  (2023) concluded that variability during running is more effected by gradient than speed.

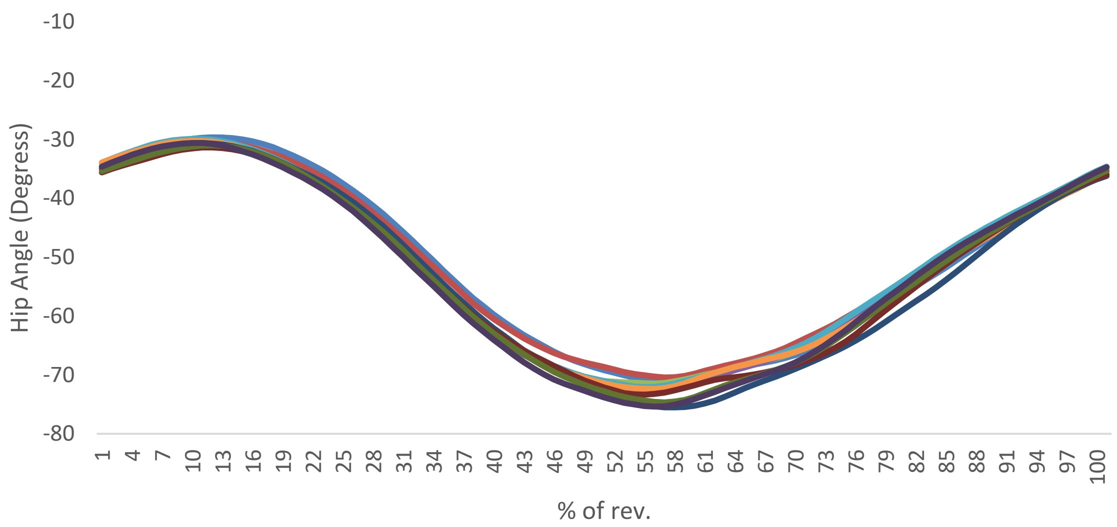
*Two participant comparisons*

Despite the results discussed above, the statistically significant strong negative relationship shown in CV% of CRP suggest that slower riders displayed less variability. This also became apparent while extracting the joint angle data as there was a persistent qualitative impression that the data from slower riders appeared to be more consistent. In order to investigate this further, the decision was taken to compare joint angle kinematic data from the fastest and slowest riders.

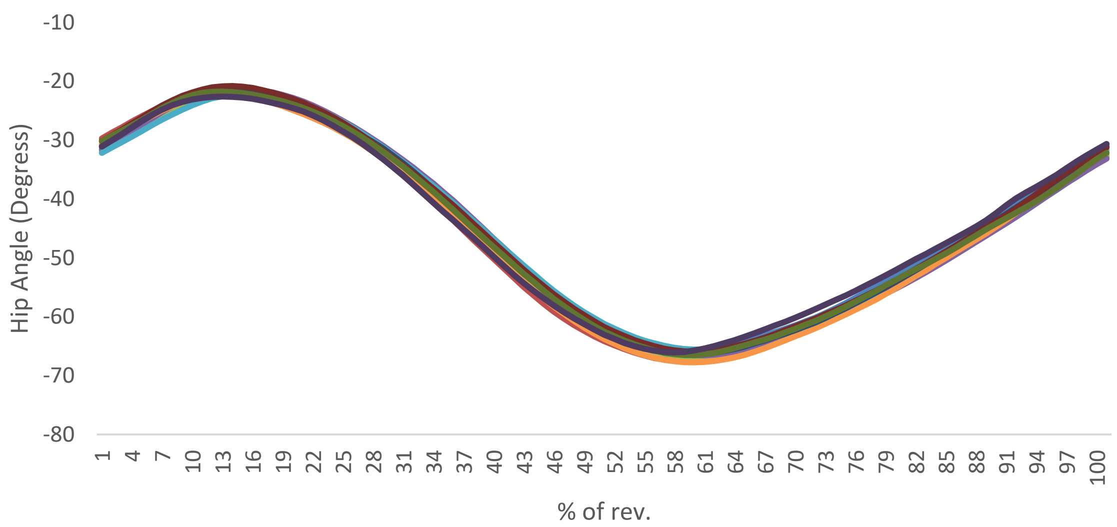
For context, the fastest rider (Male, 43yrs, 1.85m, 85kg) self-reported their average weekly training load at approximately 14 hrs or 214 miles. At the time of the study, they held a Category 3 British Cycling race license and had been in this category for the previous 8 seasons. They reported their personal best 10-mile (16km) time trial result at 19 minutes and 12s (1152 seconds) and completed the course for this study in 26 minutes and 40s (1600 seconds).

The slowest rider (Male, 36yrs, 1.80m, 90kg), by contrast, self-reported their average weekly training load at approximately 2 hours or 20 miles, most of which was completed off road. They had never held a British Cycling race licence and had never previously completed a 10-mile (16km) time trial. They completed the course for this study in 41 minutes and 21 seconds (2481 seconds).

In order to compare the two riders, the normalised joint angle data from all 10 pedal revolutions recorded during the "Flat 1" measurement window were graphed for the hip (Figure 9-12), Knee (Figure 9-13) and Ankle (Figure 9-14).

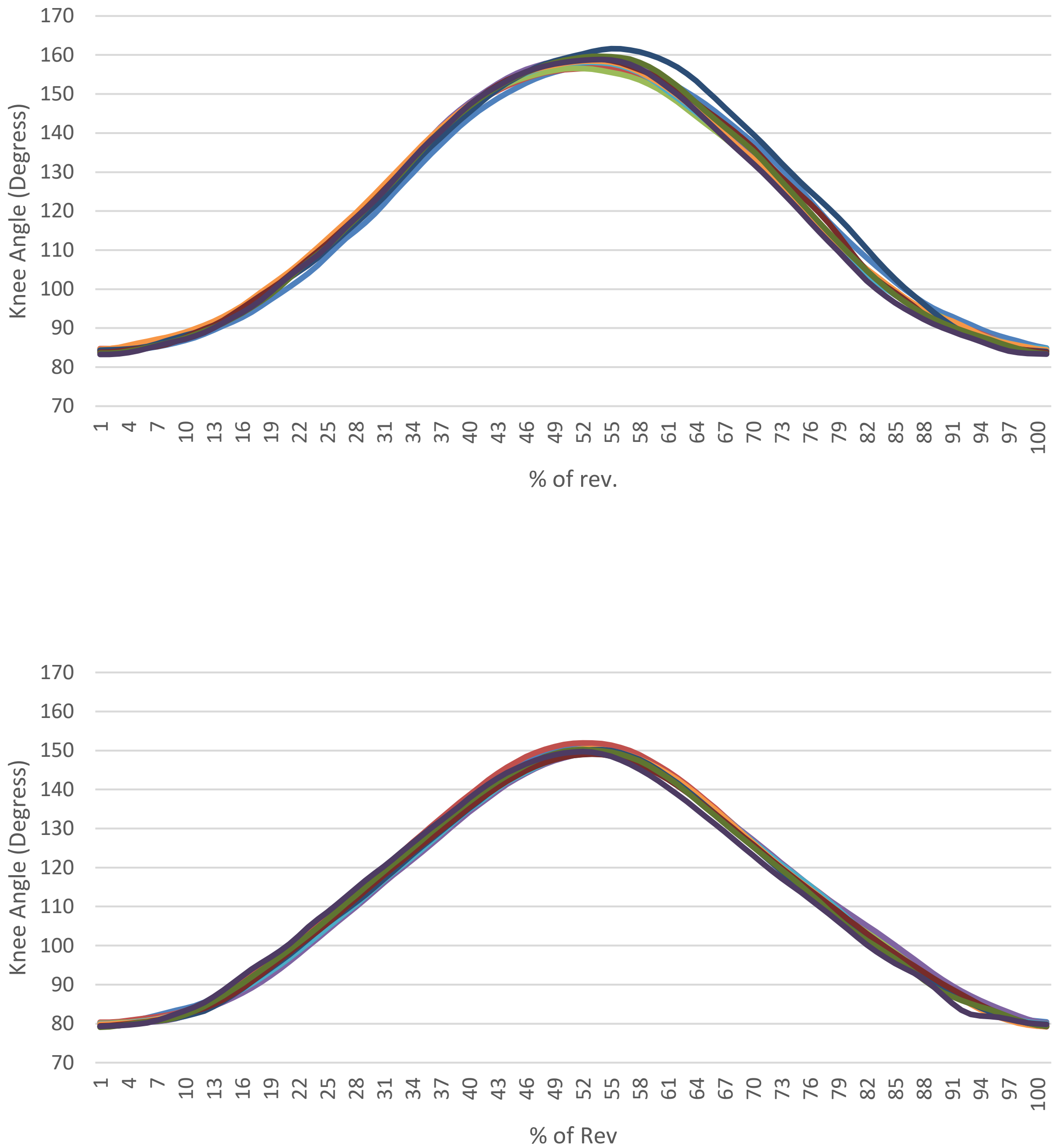



a)




b)

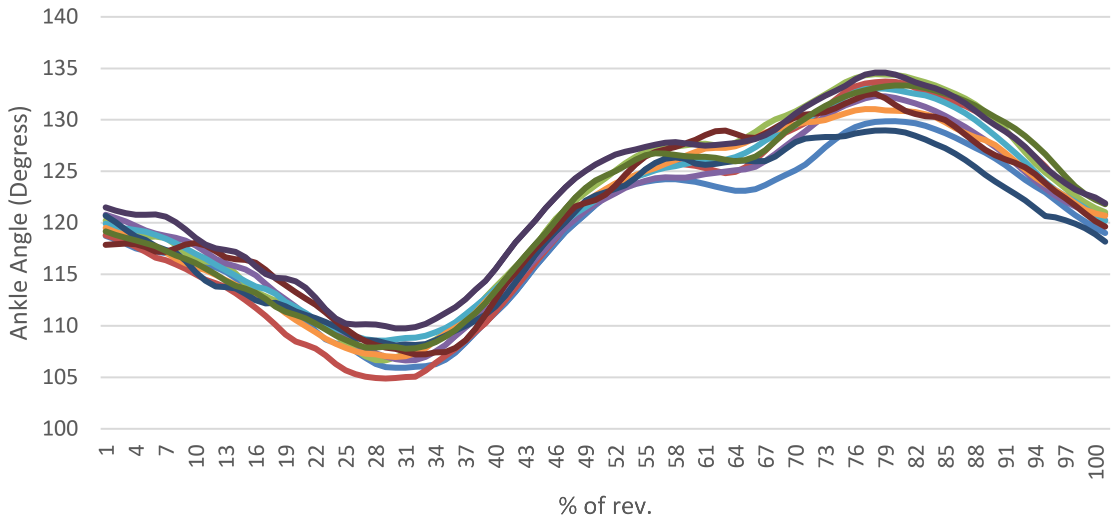
**Figure 5-12. Hip angle displayed through all 10 pedal revolutions during "Flat 1" for the fastest rider (a) and the slowest rider (b).**



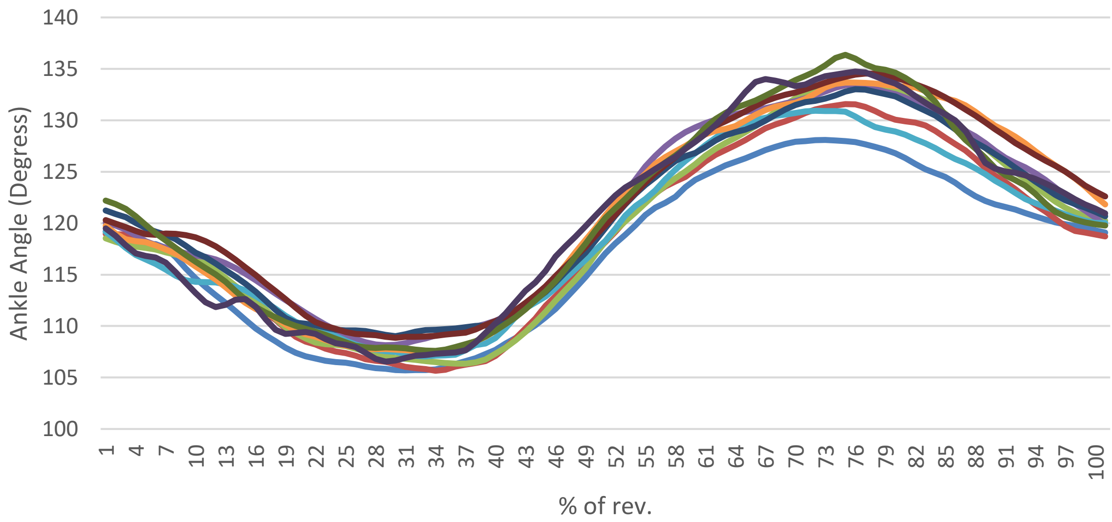

a)

b)

**Figure 5-13. Knee angle displayed through all 10 pedal revolutions during "Flat 1" for the fastest rider (a) and the slowest rider (b).**




a)

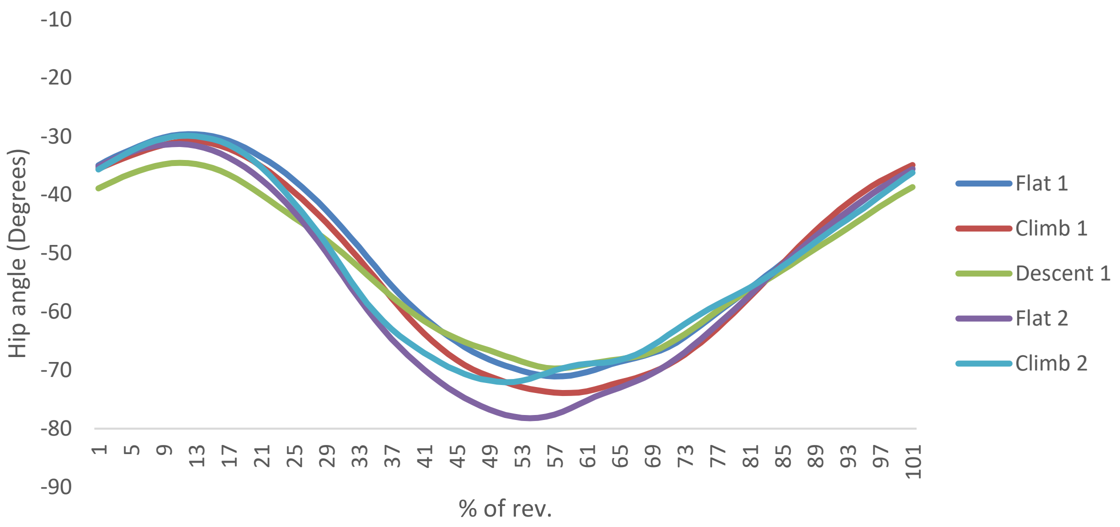



b)

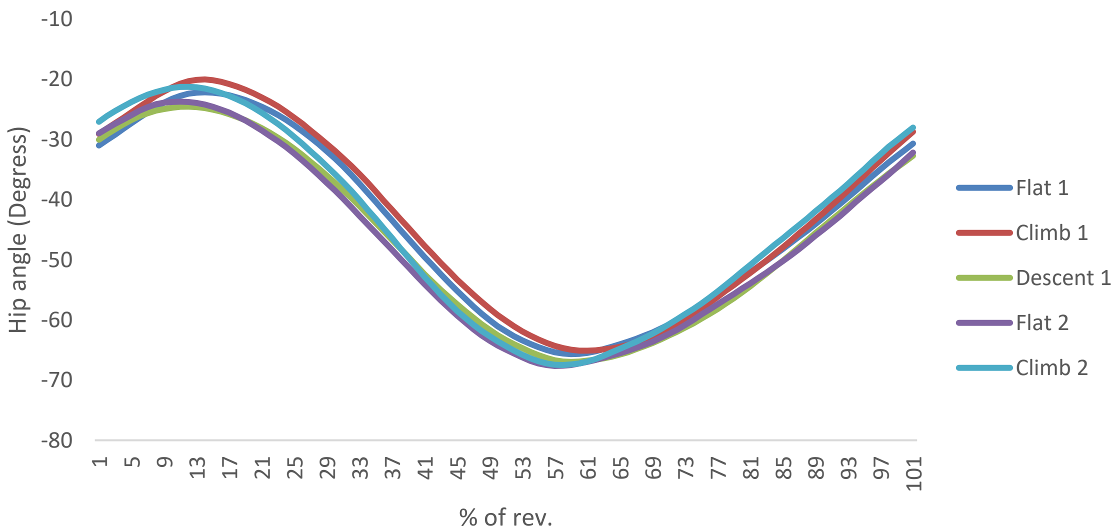
**Figure 5-14. Ankle angle displayed through all 10 pedal revolutions during "Flat 1" for the fastest rider (a) and the slowest rider (b).**

Figures 9-12, 9-13 and 9-14 suggest that the faster rider (graph a in all figures) appears to show more variation across the sample of the 10 revolutions than the slower rider. This is especially apparent when looking at the hip and knee data (Figures 9-12 and 9-13). It may be less evident in the ankle data but, as shown in Study 5 of this thesis, the IMU data at the ankle joint is potentially less reliable and therefore should be interpreted with caution.

Having somewhat confirmed the qualitative impression that the faster riders were more variable across the 10 revolutions recorded in the first measurement window (Flat 1), it was then important to explore whether this trend continued in all other measurement windows. In order to achieve this, an initial graphing exercise was undertaken which plotted the normalised joint angle data for the 1st revolution from each measurement window (Figures 9-15 to 9-17). It should be noted at this stage that the figures below only feature the first 5 measurement windows because, as mentioned earlier, the recording capacity of the IMUs was such that the final two measurement windows were not recorded for the slowest rider. As such, data from the "Steepest climb" and "Descent 2" windows have been omitted from the fastest rider graphs to allow for clearer comparisons to be drawn.

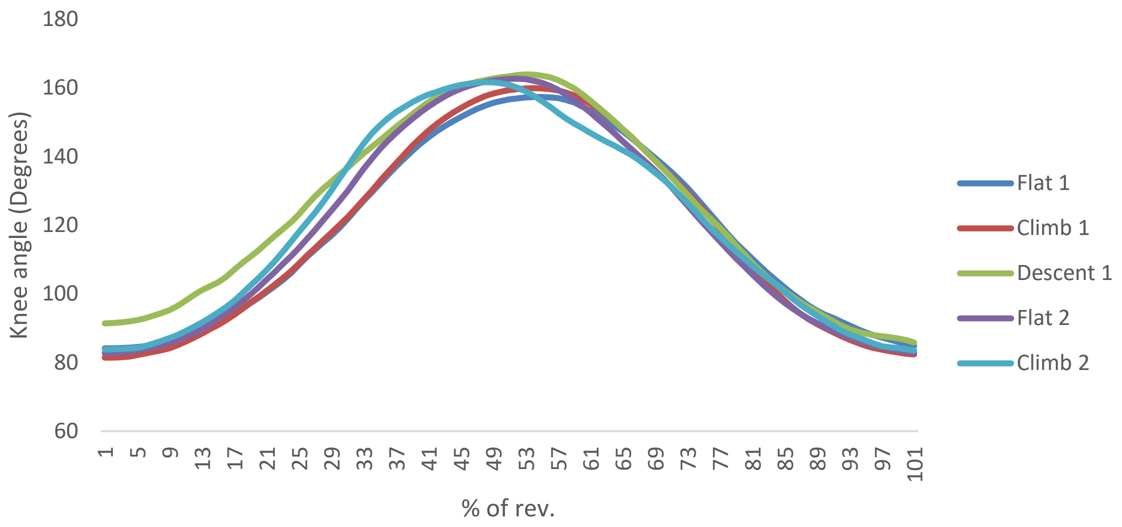



a)

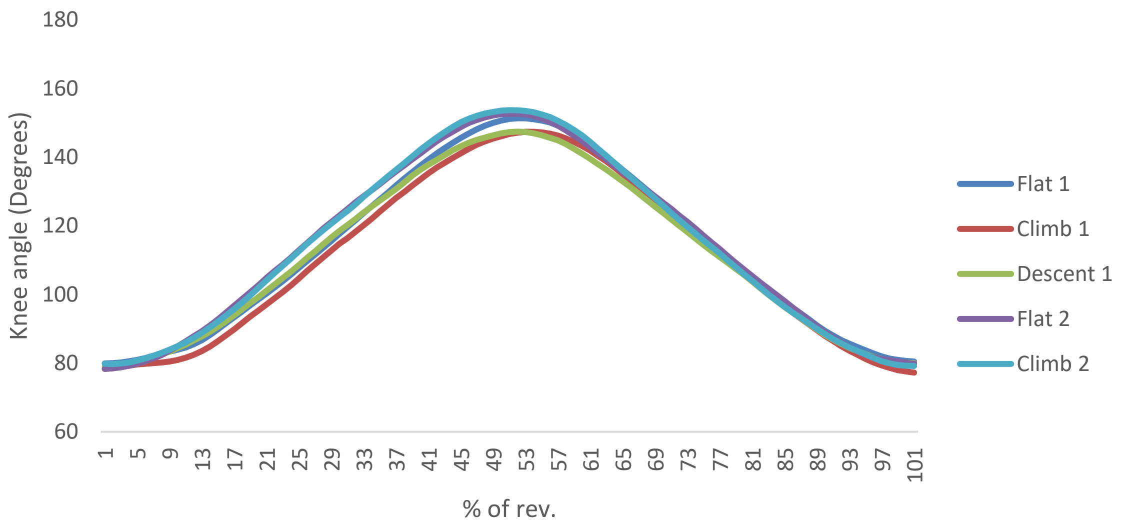



b)

**Figure 5-15. Normalised Hip joint angle taken from the 1st revolution at each measurement window for the fastest rider (a) and the slowest rider (b).**

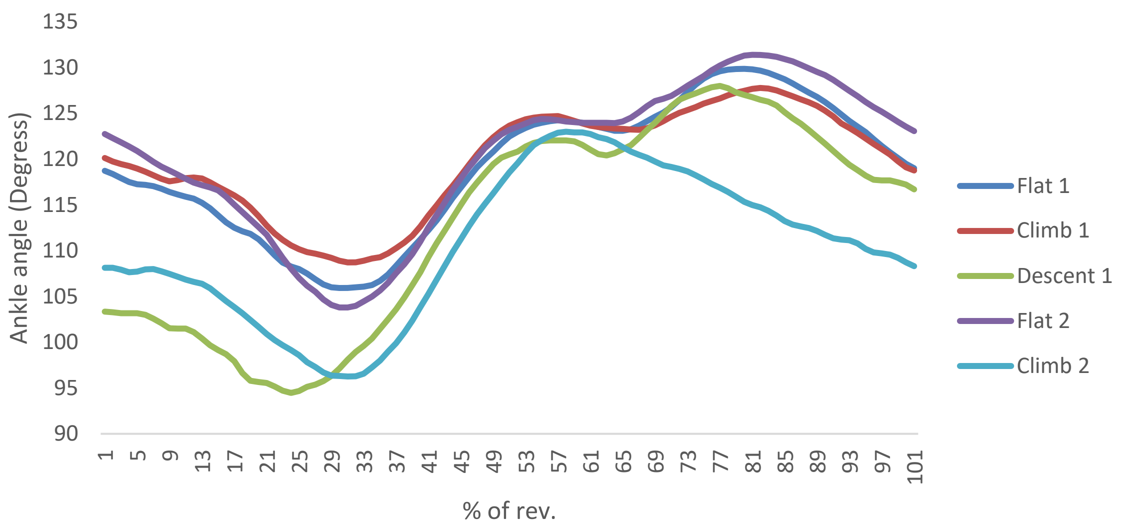



a)

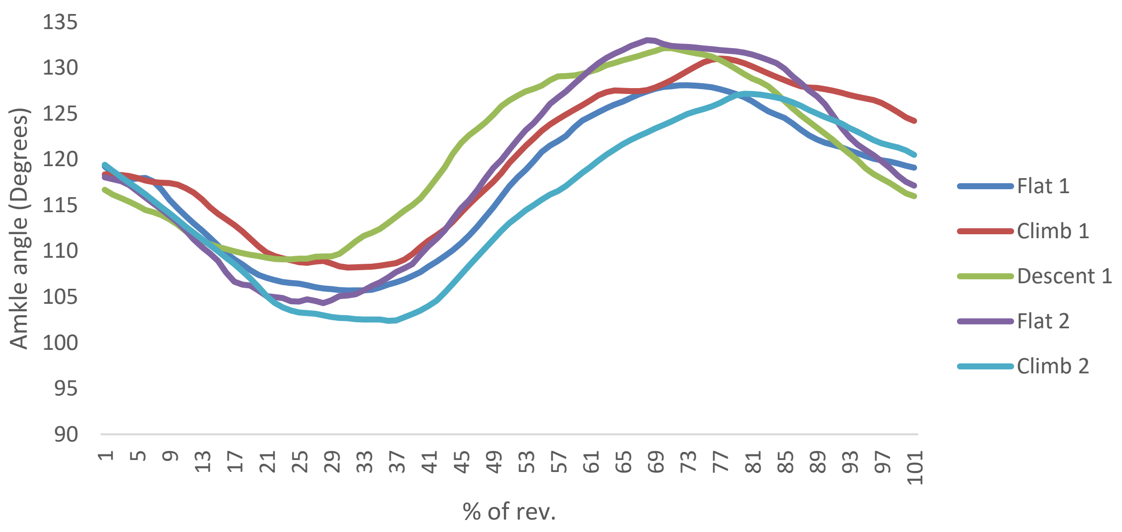



b)

**Figure 5-16. Normalised Knee joint angle taken from the 1st revolution at each measurement window for the fastest rider (a) and the slowest rider (b).**




a)




b)

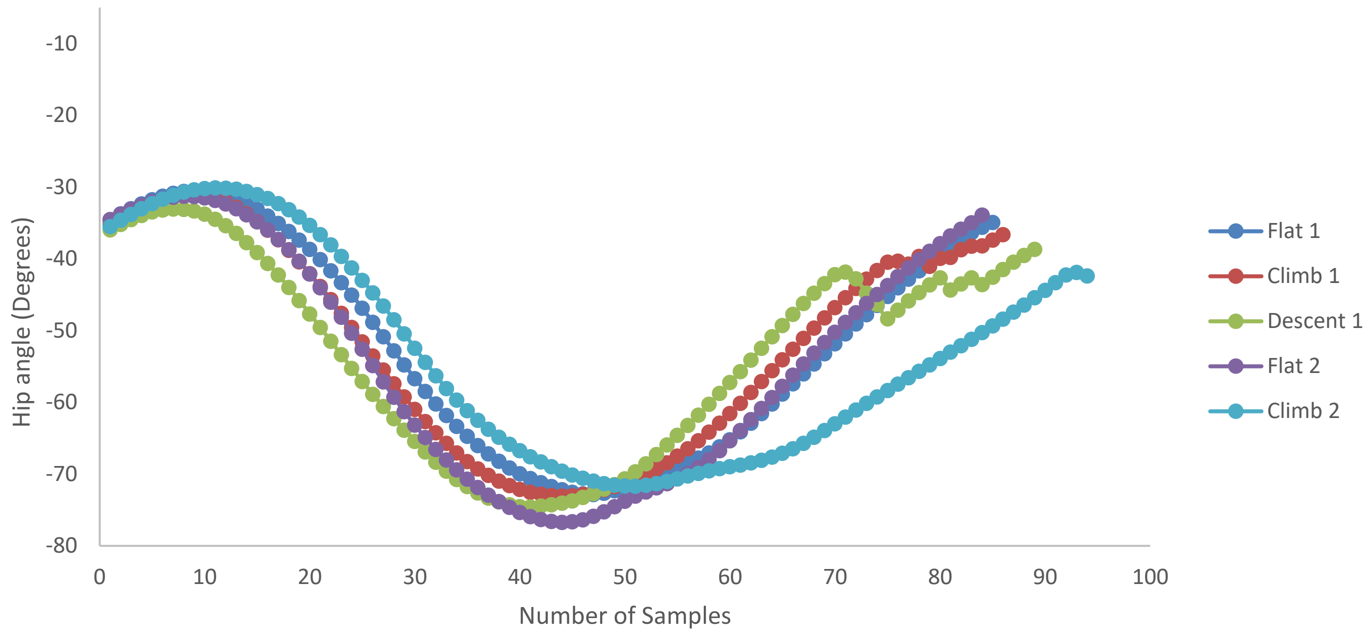
**Figure 5-17. Normalised Ankle joint angle taken from the 1st revolution at each measurement window for the fastest rider (a) and the slowest rider (b).**

Again, qualitative judgements from the figures above seem to confirm that there is more variation between measurement windows for the faster rider. This appears especially apparent at the knee (Figure 9-16) where the slowest rider is visually more consistent between measurement windows.

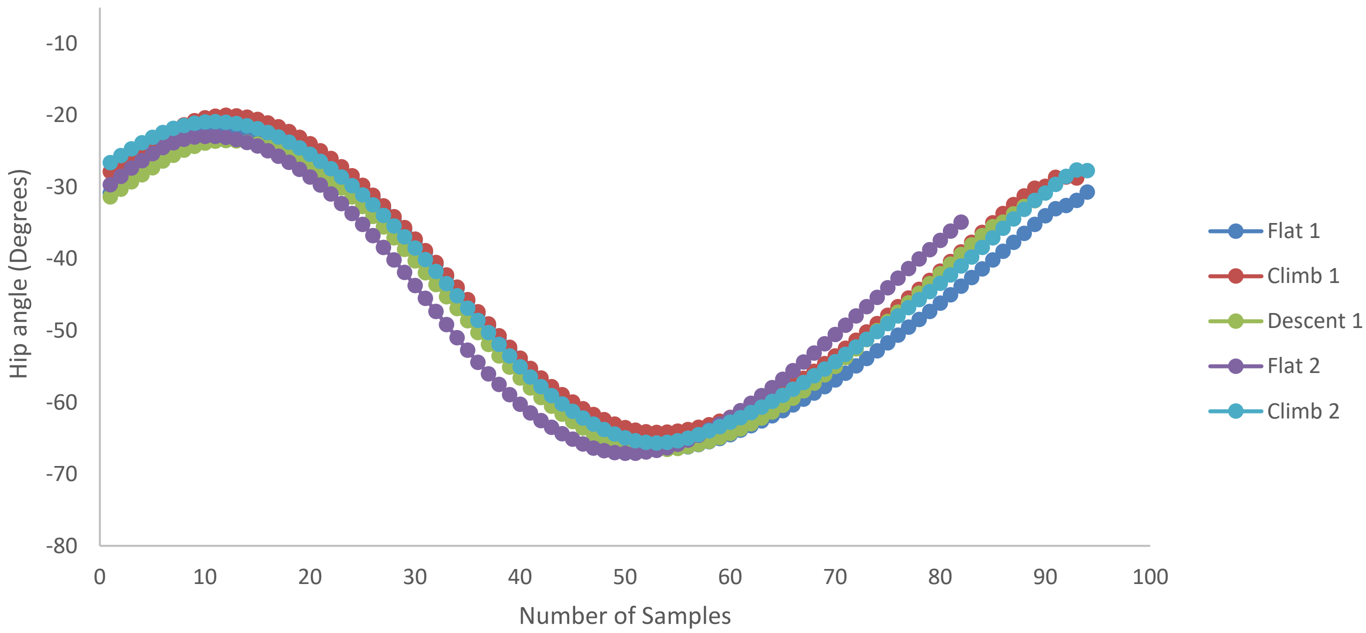
It is important to acknowledge that the figures above only include the first analysed revolution from each measurement window and therefore are open to misinterpretation due to the incomplete dataset. Additionally, the practice of normalising the data to a standardised number of time points, although helpful to allow for comparison, may be masking elements of variability which are present. If, for example, the participants adjusted their cadence in order to meet the changing demands of the task, this would affect the number of samples that are recorded during each pedal revolution. Such variation would not be present in data which has been interpolated to 101 time points and so potential sources of variability may be missed.

In order to address these concerns, the next exploratory step was to use non-normalised joint angle data to amalgamate the 10 recorded revolutions at each measurement window. This enabled the visualisation of a representative curve for each measurement window using mean values from all 10 revolutions (Figures 9-18 to 9-20). Once again, data from the final two measurement windows has been omitted from the fastest rider graphs so as not to create unfair comparisons.

Here it is clear to see that, as suggested by the correlations reported earlier, the fastest rider displays far greater variability in terms of ankle position than the slowest rider. This somewhat confirms the suggestion that better riders were able to adapt their technique to a changing set of task perturbations. This is especially evident in the ankle data (Figure 9-20) where it appears that the faster rider employed a similar technique for both climbs, which was notably different from that used during the flat and downhill sections.

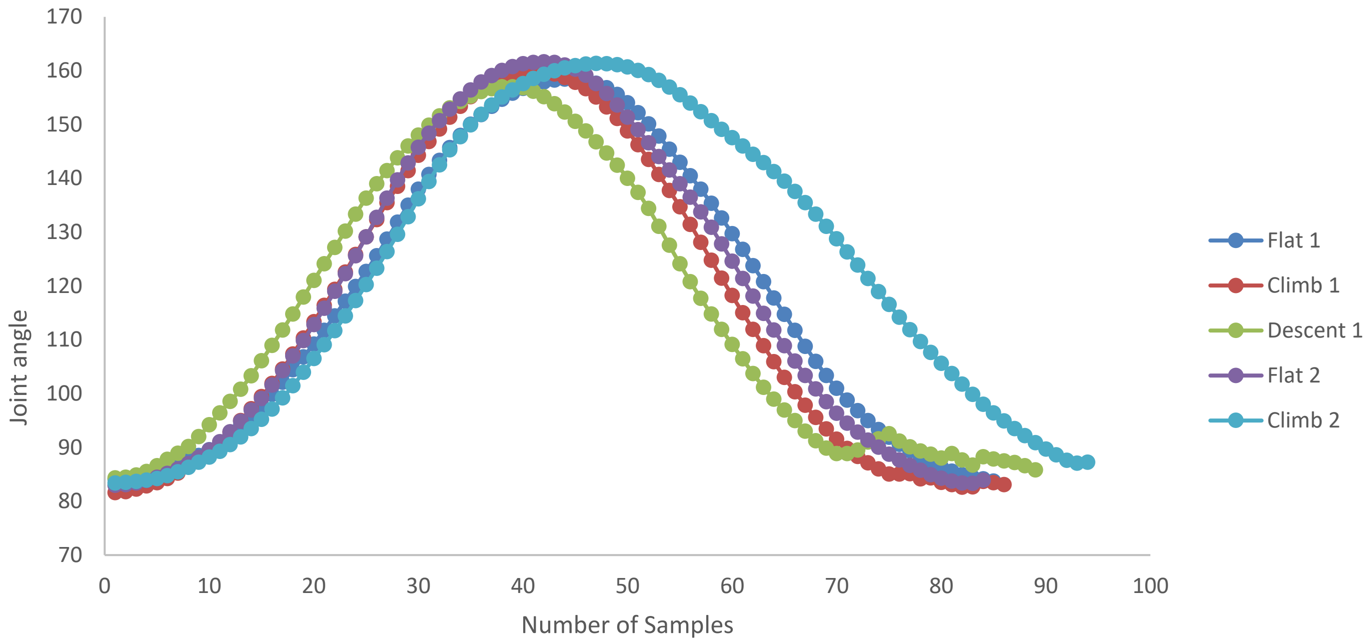



a)

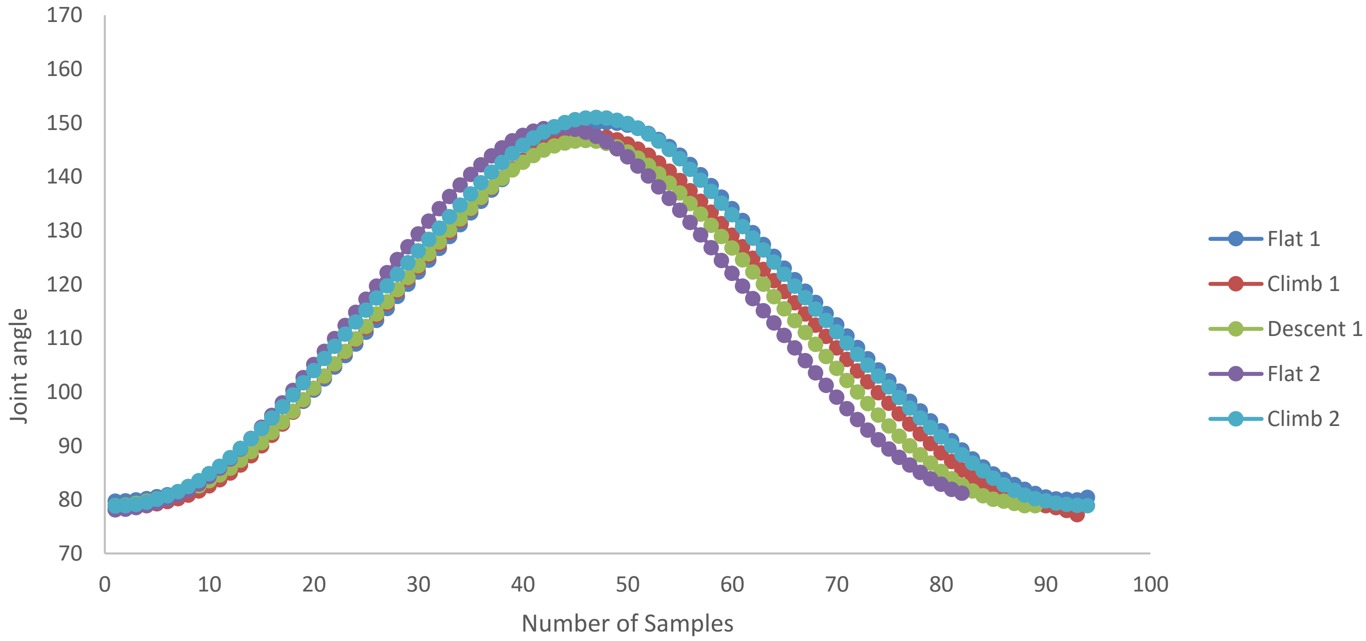



b)

**Figure 518. Representative amalgamated Hip angle traces for the fastest (a) and slowest (b) participants.**

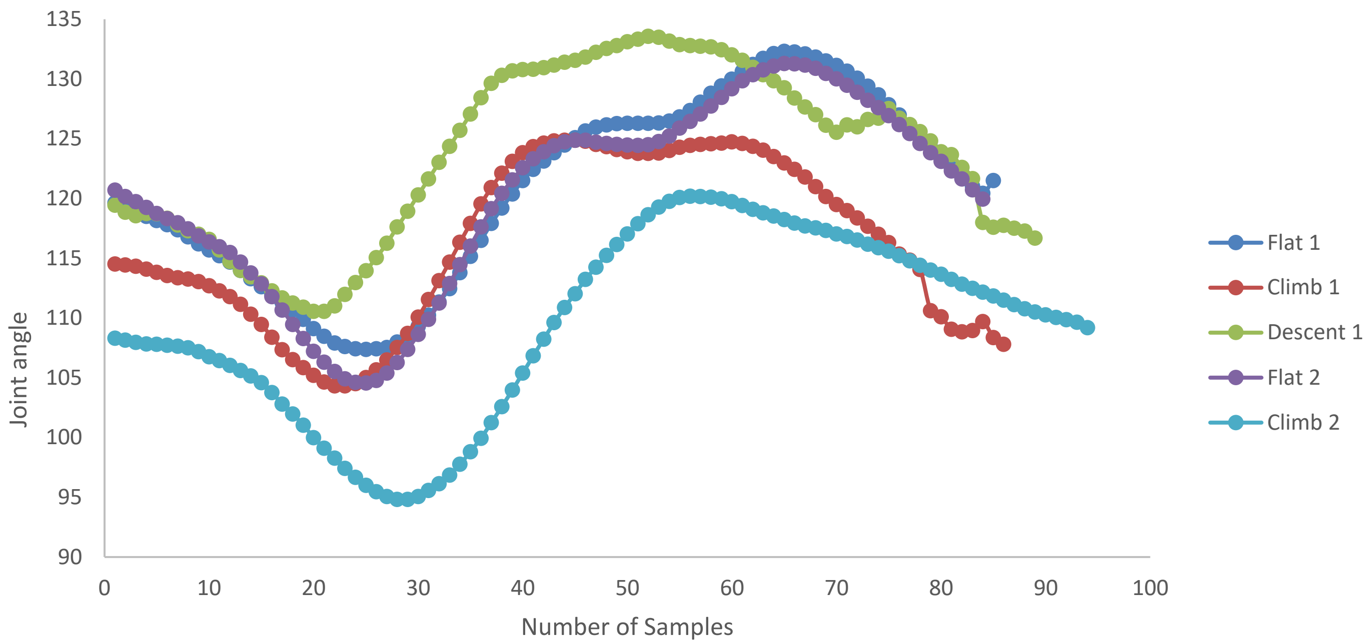



a)

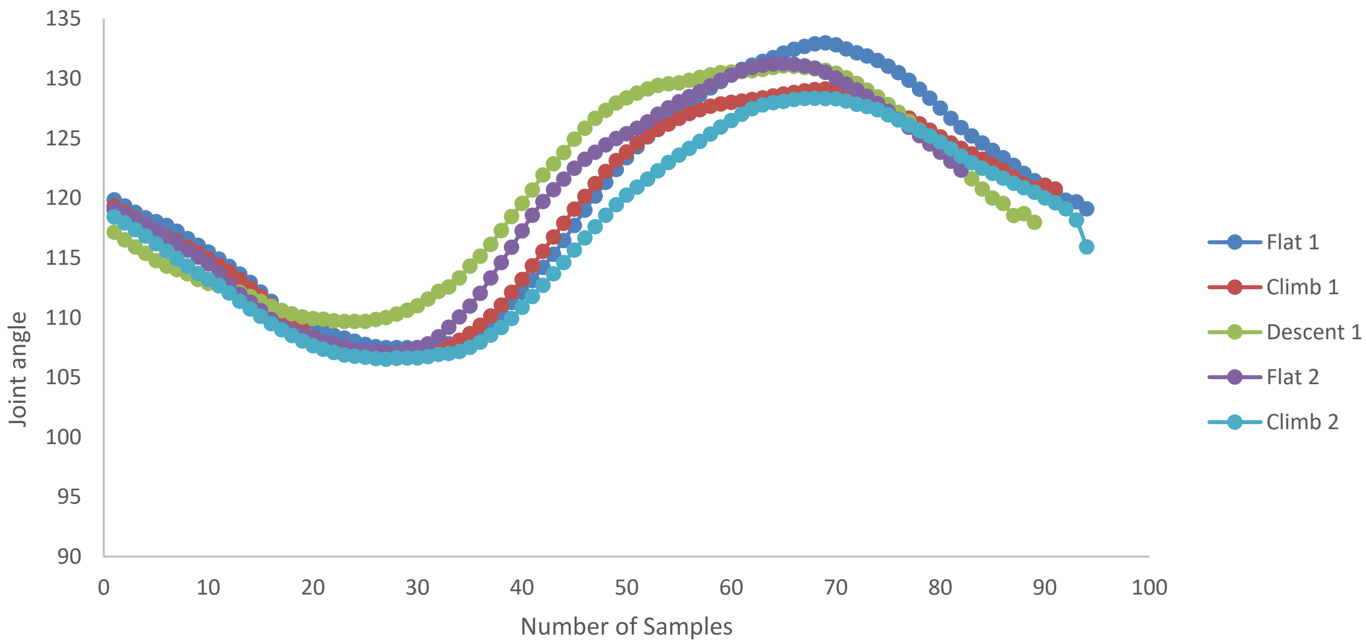



b)

**Figure 5-19. Representative amalgamated Knee angle traces for the fastest (a) and slowest (b) participants.**




a)




b)

**Figure 5-20. Representative amalgamated Ankle angle traces for the fastest (a) and slowest (b) participants.**

*Comparison with laboratory-based data (from Study 1)*

Although it sits outside the scope of the current study, the overall research question of the thesis means that it is worth establishing whether the outdoor testing environment did actually require a more variable response due to changing task constraints. As such the correlation coefficients for both testing environments (indoor data from Study 1 and outdoor data from the current study ) are displayed in the table below.

***Table 5-4*. Comparison of correlation coefficients between CV% of CRP and $Time_{TT}$ for different testing environments.**

| Analysis Method | Coupling | Phase | Indoor | Outdoor |
|---|---|---|---|---|
| Full Revolution | Hip-Knee | | -0.375 | -0.719* |
| | Knee-Ankle | | -0.126 | -0.812* |
| Two-Phase | Hip-Knee | Power | -0.218 | -0.543 |
| | | Recovery | -0.096 | -0.566 |
| | Knee-Ankle | Power | -0.144 | -0.66 |
| | | Recovery | -0.489 | -0.544 |
| Four-Phase | Hip-Knee | Top | -0.017 | -0.629* |
| | | Drive | 0.019 | -0.566 |
| | | Bottom | 0.59 | -0.324 |
| | | Recovery | -0.072 | -0.228 |
| | Knee-Ankle | Top | -0.378 | -0.682* |
| | | Drive | 0.082 | -0.596 |
| | | Bottom | -0.04 | 0.262 |
| | | Recovery | -0.505 | -0.218 |

**Denotes a statistically significant result (p<0.05).*

As shown in table 5.4, there is a stronger negative relationship between the amount of movement variability a rider displayed and the time in which they completed the time trial shown during outdoor time trials than those reported for the equivalent indoor event. This is the case regardless of how many phases the pedal revolution is divided into, or which phase is being investigated. The suggestion of a stronger relationship in the outdoor setting is further supported by the presence of significant relationships for the outdoor data where none were recorded indoor.

Although it must be noted that the data being compared here is not from the same group of participants performing in both conditions, and therefore does not provide a true comparison, that there are stronger relationships displayed in the outdoor data suggests that the variability displayed here has a greater overall impact than when the time trial was completed indoors. That is to say that the intra-individual movement variability performs a greater functional role when cycling outdoors. This serves to support the suggestion that gradient is a greater driver of movement variability than fatigue state but would also seem to suggest that, in an environment which includes more task variation due to changing conditions throughout an event, the amount of movement variability that a cyclist is able to display will more strongly be linked to their finishing time for the event.

This finding also somewhat validates the conclusions drawn at the end of the indoor investigation (Study 1) that there was not enough requirement for a variable movement response due to a lack of changes in the task constraints during indoor cycling on a static ergometer. The lack of task perturbations indoors may have masked the true nature of the relationship between movement variability and performance which is now evident having transferred to a field-based setting.

*Limitations and recommendations*

Throughout this investigation, finishing time for the ten-mile time trial was used as a measure of cyclist skill level as it was assumed that cyclists of higher skill levels would finish the event in a shorter time. Although there are a number of issues with this approach which have been highlighted elsewhere in this thesis (see Section 3.2.4), this was deemed the most appropriate outcome measure for this investigation as it is the one which would be of most interest in a competitive setting.

The IMUs used in this investigation (Xsens Dot, Xsens technologies, Netherlands) have previously been validated for use in functional movement activities (Cudejko, Button and Al-Amri, 2022) and rehabilitation applications (Schlage, Kitzig, Stockmanss and Naroska, 2021). Although this initially seems positive, it should be noted that, with the exception of the validation conducted as part of this thesis (see Study 5), the majority of these applications involve relatively slow movements which do not require a particularly high sampling rate to ensure all the relevant information is collected.

Despite the IMUs sampling orientation data at 800Hz, the manufacturers then implement an unavoidable strap down integration method which reduced the reported values to 120Hz so as not to present an excessive computational load on the receiving device and allow data transfer via Bluetooth. Although the manufacturer insists that the accuracy and sensitivity of the data is preserved, this unavoidable down-sampling of data may have affected the ability to capture the nuance of the pedalling action. For example, if a participant adopted a cadence of 100 rev·min$^{-1}$, which is at the lower end of the typical range adopted for maximal power output (Baron, 2001; Baron et al., 1999; Sargeant et al., 1981), reporting at 120 Hz means approximately 72 samples per pedal revolution. This then had to be increased back up to 101 timepoints to allow normalised comparisons meaning, once more, that the finite details of the data may have been compromised.

An additional limitation relating to the IMUs was their recording capacity. As mentioned before, the capacity of the devices meant that data was not collected for the final two measurement windows for the slowest rider. The Xsens Dots do have the option to adjust the reporting frequency of the system to only 60 Hz which would have increased the capacity but, as a consequence, would have further exacerbated the issues described above.

Aside from limitations of the equipment, it is also worth acknowledging that this investigation has only explored simple flexion/extension couplings in the sagittal plane. Although this is typical of most kinematic analysis of cycling (Ferrer-Roca, Roig, Galilea and Garcia-Lopez, 2012; Carpes et al., 2006), it is possible that participants may be making small adjustments in other planes in order to alter their technique from one pedal revolution to the next. The range of motion involved in these adjustments is unlikely to be in the order of magnitude seen in the sagittal plane at the hip (42-44$^{o}$), Knee (73-78$^{o}$) and ankle joints (21-25$^{o}$) (Bini, Senger, Laferdini and Lopes, 2012), but nevertheless it is an area which would be recommended for investigation in future.

Likewise, the environmental perturbations explored here are limited only to the effects of gradient. Given that Glazier, Araújo and Bartlett (2003) suggested that movement variability may perform a functional role in helping individuals to adapt to the potentially changeable constraints of a given task and that Button, Davids and Schöellhorn (2006) and Bradshaw and Aisbett (2006) both suggested that it is particularly important in skills which are performed in dynamic performance environments, this is an aspect of this investigation which could be expanded in the future.

Task perturbations relating to environmental weather condition changes and aerodynamic effects from passing vehicles were not measured within this investigation. It is unlikely that these factors contributed substantially to the overall finishing time achieved by each participant but, nevertheless, it is a factor which may have provided an additional stimulus to promote variability of movement and ideally would have been controlled. All testing events took place in, as close as possible, similar weather conditions (Mean Temperature = 17.7 ± 4.8 °C, Wind speed = 12.2 ± 3.3 km·hr$^{-1}$) and in the event of poor weather, tests were postponed. Additionally, traffic volume did not change noticeably over the duration of any participants' trials, but a closed course would have been preferrable.

Finally, due to the impact of the COVID-19 pandemic (see Section i), this study featured a smaller participant sample than planned. The original intention was to recruit three groups of cyclists, each featuring a minimum of 8 participants, in order to garner suitable levels of statistical power. These three groups would have ideally been: 1) recreational cyclists who had never entered a competitive event or had limited cycling experience but were still able to complete the required 10 mile event; 2) experienced cyclists, typically cycling club members, who either spent significant time training each week or had entered a number of competitive events; and 3) elite competitive cyclists who had entered numerous competitive events, had a structured training regimen and/or made their living through cycling. It was felt that this might address some of the issues encountered during the indoor study (Study 1 of this thesis) where participants were, perhaps, not spread far enough along the performance spectrum to enable a true comparison of "novice" versus "experienced" cyclists (see Section 3.2.4 for more details about issues with participant groupings).

Arguably both ends of the desired spectrum were represented in this sample and there was a range of expertise across participants (self-reported training load of 5.31 ± 3.96 hours or 68.10 ± 75.20 miles per week). Although this resulted in a range of 14 min and 41 seconds (881 seconds) across the participants' time trial finishing times (mean 2145 ± 266s for the time trial), there were certainly not enough participants to group them in the way described above and provide any level of appropriate statistical power. Not only did the small sample limit what was possible in terms of statistical testing, it also means that the impact of any single participant on the overall relationship is far greater.

In addition, it should be noted that the fastest rider recruited for this study only held a Category 3 British Cycling race license. Despite reporting a personal best 10-mile (16km) time trial result of 19 minutes and 12s (1152 seconds) they completed the course for this study in 26 minutes and 40s (1600 seconds). Not only is this far slower than their personal best, presumably due to the presence of two significant climbs, it could be argued that this is not far enough towards the elite end of the performance spectrum to allow evidence of the 'U' shaped relationship displayed in previous studies of movement variability relating to handball players (Schorer, Baker, Fath and Jaitner, 2007) and triple jumpers (Wilson, Simpson, Van Emmerik and Hamill, 2008).

**5.5 Conclusion**

The aim of this study was to investigate whether skilled cyclists exhibit differing levels of intra-individual movement variability compared to their less experienced counterparts when completing a ten-mile cycling time trial. Having shown statistically significant strong negative correlations between the coefficient of variation of continuous relative phase values at two joint couplings and the time taken to complete the time trial, it can be concluded that this is indeed the case. Intra-individual movement variability does appear to play a functional role in cycling performance and, as such, should perhaps be encouraged rather than dismissed as has historically been the case.

In order to gain greater insight into how this variability is being produced, it is recommended that future studies investigate muscular recruitment patterns and power output as well as the kinematic variables discussed here.

# 6. STUDY SEVEN: Intra-individual variability of surface EMG during indoor time trials

Following the results of kinematic investigations throughout this thesis, it became apparent that an investigation into areas other than kinematic data may be useful in terms of understanding the mechanisms at play which may be responsible for producing the movement variability seen during a time trial event. This, therefore, led to the consideration of electromyographic data in an effort to understand the underlying recruitment patterns being employed by cyclists of varying skill levels and the role of muscular activation in driving movement variability.

## 6.1 Introduction

As noted in Sections 2.2.4 and 2.3.1, there is a significant body of historical literature reporting muscular recruitment patterns during cycling (e.g. Houtz and Fischer, 1959; Ericson, 1986; Jorge and Hull, 1986; Ryan and Gregor, 1992). This literature is invaluable in understanding relative contribution of each muscle to overall force production and would, ideally, have been conducted via direct measures involving surgically implanted measurement devices (e.g. buckle transducers) which record directly from the tendon (Nigg, 2007). Understandably, this approach is rarely used within sporting literature with only very few examples available which have used either non-human participants (Prilutsky, Herzog and Leonard, 1996) or severely injured populations (Fleming et al., 1998). Instead, the majority of studies have adopted an indirect measure of force production by monitoring muscular recruitment as a force measure proxy (Bini and Carpes, 2014) via the use of surface electromyography.

This approach is not without its limitations (see Section 3.4) but it has been widely adopted as a method of studying the activation and co-ordination of various lower limb muscles with the aim of understanding how the cycling movement is produced across a range of participant populations. As a result, authors have been able to establish profiles of the relative levels and timing of muscular activation which can be expected during cycling activities (e.g., Hug and Dorel, 2009. See Figure 10-1). This "normative data" of sorts is undoubtedly useful for comparison between, for example, an injured athlete and a healthy population or for technique optimisation in terms of adjusting an individual's co-ordination but, being constructed from group data as it is, it tells us very little about the existence of individual variations away from this "normal" profile.

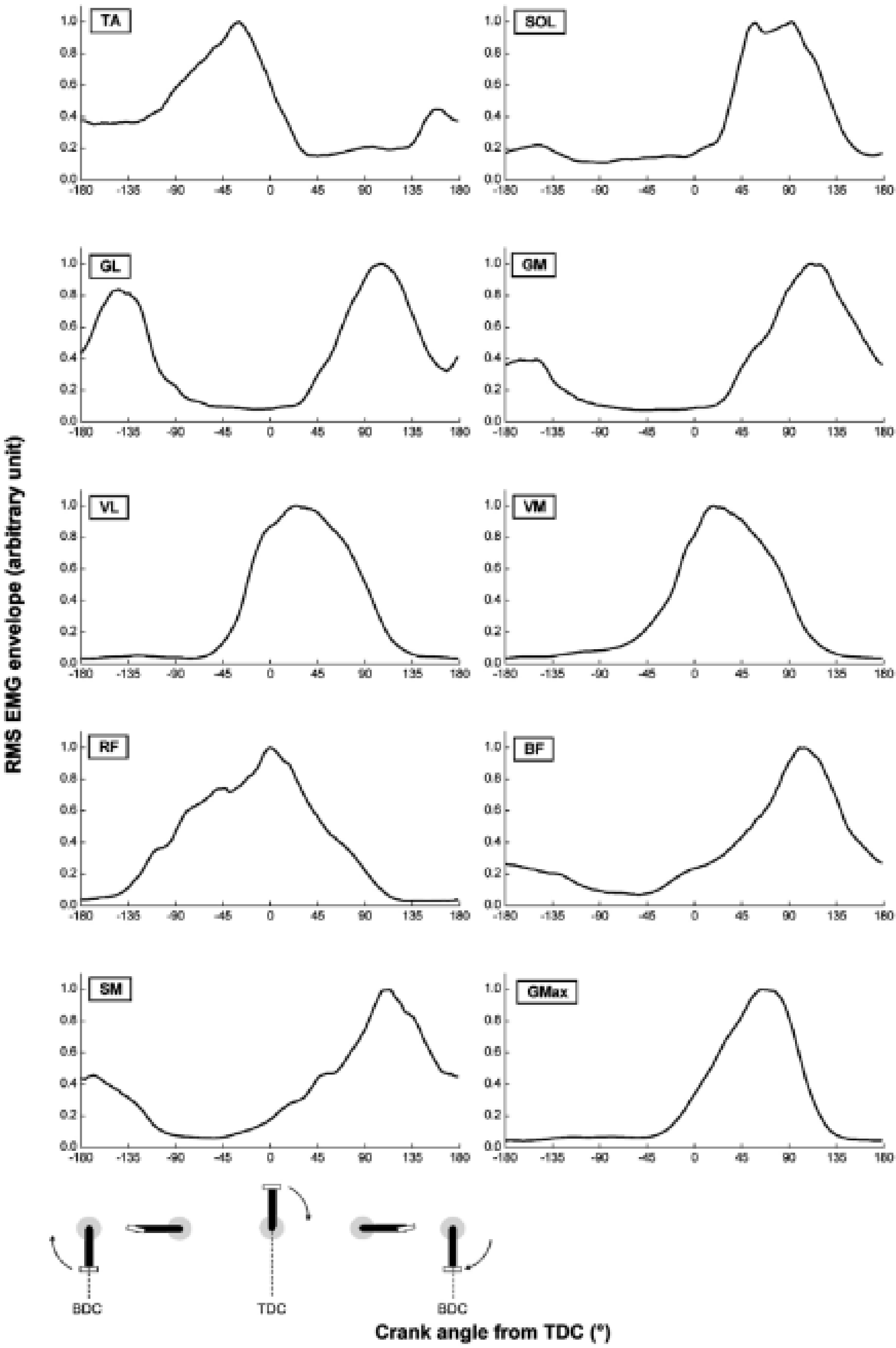



**Figure 6-1. Ensemble curves of muscular activation for 10 different lower limb muscles.**

Once again, this is indicative of the traditional assumptions that movement patterns for skilled performers are invariant (Bartlett, Wheat and Robins, 2007) and is a position which is increasingly being challenged. There is a body of literature which suggests that movement variability may play a functional role in producing a more consistent sporting outcome despite the altering demands placed on the performer (Van Emmerik, Hamill and McDermott, 2005) and therefore should be viewed as a form of “essential noise” (Davis, Shuttleworth, Button, Renshaw and Glazier, 2004).

Despite this body of evidence, there is little research that has focussed on intra-individual movement variability within cycling. This is even more surprising when considering the fact that the human motor system is viewed as “highly redundant” and, as a consequence, it is believed that a single motor task can be performed in many ways with a similar end result (Hug, Turpin, Guével and Dorel, 2010).

Hug, Bendahan Le Fur, Cozzone and Grelot (2004), Hug, Drouet, Champoux, Couturier and Dorel (2008) and Hug, Turpin, Guevel and Dorel (2010) have all shown that, within a population of trained cyclists, there are multiple different muscle activity patterns adopted in order to produce a pedalling movement. Ryan and Gregor (1992) suggested that the single-joint hip and knee extensors (Gluteus maximus, Vastus medialis, and Vastus lateralis) had the lowest Coefficient of Variation (CV) values (less than 30%) and attributed this to the role of these muscles as power generators. In contrast, variability was generally higher in the hamstring muscles. This suggested that inter-individual differences of the EMG patterns were especially apparent for biarticular muscles compared to monoarticular ones but, interestingly, higher levels of variability were recorded in the first 20% of the pedalling cycle, as measured from top dead centre, for all muscles studied.

These comparisons, however, are only conducted between participants rather than investigating whether a single participant was capable of altering their muscular recruitment patterns within the continuous performance of a single skill to better suit the demands of the task. That is to say, there was no investigation into the prevalence and potentially functional role of intra-individual variability.

There are a range of authors who would suggest that as an individual gains expertise in a given skill, they are able to develop flexibility within movement patterns to incorporate adjustments due to the environmental factors which are imposed upon them (Davids, Bartlett and Wheat, 2008). This is said to be especially true when the task requires adaptability of complex motor patterns within dynamic performance environments (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006) and is theorised to enable greater adjustment for both intrinsic and extrinsic factors, which may influence an athlete’s performance.

Another potential benefit of intra-individual variability of muscular recruitment is the potential for this to mediate the effects of fatigue. Fatigue is unavoidable in a cycling time trial due to the intensity of performance (Kenefick et al., 2002) and, should invariant movement patterns be employed, this would result in the utilisation of the same muscle tissues repeatedly (Heiderscheit, Hamill and van Emmerik, 2002). This would place a great amount of cumulative stress on the tissues involved and thus high levels of fatigue become almost inevitable. It has, therefore, been suggested that micro adjustments in muscular recruitment patters, and therefore a level of intra-individual movement variability, may be a preventative method used to distribute the workload across a wider range of tissues (Bartlett, Wheat and Robins, 2007; James, Dufek and Bates, 2000).

Although it has been suggested that fatigue reduces the adaptability of the neuromuscular system (Dingwell et al., 2008; Cignetti, Schena and Rouard, 2009), the ability of higher-skilled athletes to utilise multiple muscular recruitment strategies (Hug et al., 2010 and Chapman et al., 2008) and employ these to produce a similar movement pattern (Ting, & McKay, 2007; Latash, Scholz & Schöner, 2007), combined with evidence that muscle activation variation is not accompanied by high inter-individual variability in pedal force application patterns (Hug et al. 2008) may mean that they are more able to mitigate the effects of fatigue.

Employing a level of variability in muscular recruitment may, therefore, be beneficial not only because it allows a cyclist to adapt their movement patters to the constraints of the task at the time, but also because it could reduce the effects of fatigue. This maintains the overall power output of the cyclist but also preserves their ability to react to changing conditions and constraints within a prolonged event. This would mean that the cyclist is always able to employ the most appropriate technique for the particular combination of perturbations they are faced with and, ultimately, improve their performance.

The aim of this study, therefore, was to investigate levels of intraindividual variability of muscular activation during an indoor time trial event to ascertain whether these vary in cyclists of differing experience levels and if this plays a functional role in the completion of a simulated indoor time trial event.

It was hypothesised that more experienced cyclists would display greater levels of intra-individual movement variability between successive measurement windows throughout the time trial and that this would lead to faster overall times in the completion of the simulated event.

## 6.2 Methods

*Participant information*

Ten trained cyclists volunteered to take part in the study (see Table 10-1). Participants all held a current British Cycling Race License (Category 1 *n* = 1, Category 2 *n* = 2, Category 3 *n* = 2, Category 4

$n$ = 5) and mean training load was self-reported as 10.85 ± 4.21 hours or 156.00 ± 48.35 miles per week. Participants maintained their normal diet and daily activity patterns throughout the testing period and provided written informed consent before taking part in the study. Local ethical approval was provided by the University of Winchester.

**Table 6-1. Participants' descriptive characteristics**

| | **Age (years)** | **Height (metres)** | **Mass (kg)** | **Maximum one minute Power Output (W)** | **Maximum one minute Power Output ($W \cdot kg^{-1}$)** | **$\dot{V}O_2$ max ($ml \cdot kg \cdot min^{-1}$)** |
|---|---|---|---|---|---|---|
| **Mean** | 31.90 | 1.80 | 72.10 | 365.50 | 5.13 | 73.21 |
| **Standard Deviation** | ±10.31 | ±0.09 | ±9.40 | ±69.21 | ±0.53 | ±12.24 |

*Testing procedure and instrumentation*

*Graded exercise testing*

Initial testing consisted of a graded exercise test (GXT) to establish $\dot{V}O_2$max values for each participant to ensure physiological similarities across the sample (See Table 10-1). An electromagnetically braked cycle ergometer (SRM, Germany) was used to conduct a continuous incremental cycling GXT where workload was increased by 5 W per 15 seconds. Initial workload was adjusted according to participant's self-reported estimate of maximal power output so that the total duration of the GXT was between 8 and 10 minutes. Criteria for termination of the maximal GXT was primarily based on volitional exhaustion.

Throughout the GXT, online respiratory gas analysis was performed using a breath-by-breath automatic gas exchange system (MetaLyzer 3B, Cortex, Germany) following volume and gas calibration. HR was monitored using a wireless chest strap telemetry system (Polar Electro T31, Kempele, Finland) as well as ratings of perceived exertion every minute using the Borg 6-20 RPE scale.

*Time trial events*

Participants then visited the laboratory on 3 occasions, separated by a minimum of 48 h to allow full recovery from the previous trial. During these testing sessions, wireless active surface EMG sensors (Delsys Tigno Avanti, Delsys, USA) were attached to the Vastus Medialis, Vastus Lateralis, and both heads of the Gastrocnemius on both sides of the body. All sensors were placed in accordance with guidance from The SENIAM project (Surface Electromyography for the Non-Invasive Assessment of Muscles, http://www.seniam.org/) and were set to record at 1259 Hz. Participants subsequently undertook a self-directed warm up followed by a simulated 10mile (16km) time trial and self-directed cool down. Time trials were conducted from a standing start and participants were given free choice of gearing and cadence throughout.

All trials were conducted in an air-conditioned laboratory using a Wattbike Pro cycle ergometer (Wattbike Ltd., Nottingham, UK), with PowerTap P1 pedals (CycleOps, Madison, WI, USA). Participants used their own cycling shoes and those who normally rode with cleats incompatible with the PowerTap pedals had their cleat position replicated with 3 bolt Kéo cleats (Look cycle international, Nevers, France). The ergometer was set to, as closely as possible, replicate the dimensions of each participant's own bicycle and participants were given access to any data they would normally ride with to monitor their cycling effort (cadence, power output etc.).

Perceived exertion was recorded throughout each time trial using Borg's RPE scale. This was conducted at 2 minutes intervals after an initial 5 minutes of riding had been completed. Time trial completion time was retrieved from the Wattbike using Wattbike Expert software version 2.60.20 (Wattbike Ltd., Nottingham, UK).

*Data analysis*

One time trial was selected per participant for analysis. This was typically the last performance to allow the first two to act as familiarisation sessions unless, due to technical errors with sensor adhesion, there was insufficient data to make this feasible. In this case, the most complete trial was selected for analysis.

Before any data analysis, the raw EMG signal from all muscles was run through a Butterworth bandpass filter (40/450 Hz) using the onboard capability of the Avanti sensors (Delsys, USA). This output was then used to identify 10 individual pedal revolutions at four time points throughout the time trial (5min, 10min, 15min, and 20min). Pedal revolutions were identified using the ensemble curves shown in Figure 10-1 as it could be expected that each muscle would have a single peak activation point per revolution, with the exception of the lateral head of the Gastrocnemius which should display two distinct peaks per revolution.

To investigate muscular activation, data underwent a Route Mean Square Envelope Calculation with 100ms duration windows in order to obtain peak amplitude of muscular activation values (V) per pedal revolution.

To investigate fatigue, data underwent a Fast Fourier Transformation in order to display the power spectral density for each individual revolution at the same four time points. This allowed for the recording of the median frequency (Hz) of muscular activation per pedal revolution.

All signal processing and value identification was conducted in EMGWorks v4.5.4 (Delsys, USA).

Having ascertained mean and standard deviation values for the above variables, these could then be converted into co-efficient of variation (CV%) using the calculation below.

$$\text{Co-efficient of variation} = (\text{standard deviation}/\text{mean})*100$$

CV% was reported rather than a normalised reading of muscular activation as the emphasis is on the *variability* of muscular recruitment and not the finite levels. Calculating CV% in itself provides a degree of normalisation (Bedeian and Mossholder, 2000) as it was specifically invented to eliminate the influence of the finite magnitude of a value on variability (Pearson, 1897). It does so by relating the spread of a data set relative to its own mean and this produces a value which is unitless and divorced from any scale of measurement (Simpson, Roe, & Lewontin, 1960). This, therefore, negates the need for normalising EMG values at the recording stage as the variation in muscular recruitment can be expressed as a percentage and effectively normalised at the reporting stage.

*Statistical testing*

Initial testing was conducted to investigate whether peak amplitude of muscular activation and median frequency of muscular activation significantly changed across the time points via two, Bonferroni adjusted, one-way repeated measures ANOVAs. This was conducted to ascertain whether participants were significantly altering their muscular recruitment patterns between successive measurement points due to the influence of changing task constraints (i.e. fatigue). This process was then repeated for the variability of these values.

Following this, testing was conducted to correlate each participant's CV% for the measured variables with the time taken to successfully complete the time trial ($Time_{TT}$). This was conducted using

Pearson's Product moment correlation co-efficient and was repeated at each time point (5 min, 10 min, 15 min and 20 min) throughout the time trial.

All statistical testing was performed using IBM SPSS statistics version 24 (IMB Corporation, New York, NY, USA), with a significance level set at $p < 0.05$.

**6.3 Results**

*Peak amplitude of muscular activation*

Mean and standard deviation of the peak amplitude of muscular activation across each time point are displayed in Figure 10-2.

There were no statistically significant differences ($p>0.05$) between timepoints during the time trial for any of the studied muscles.

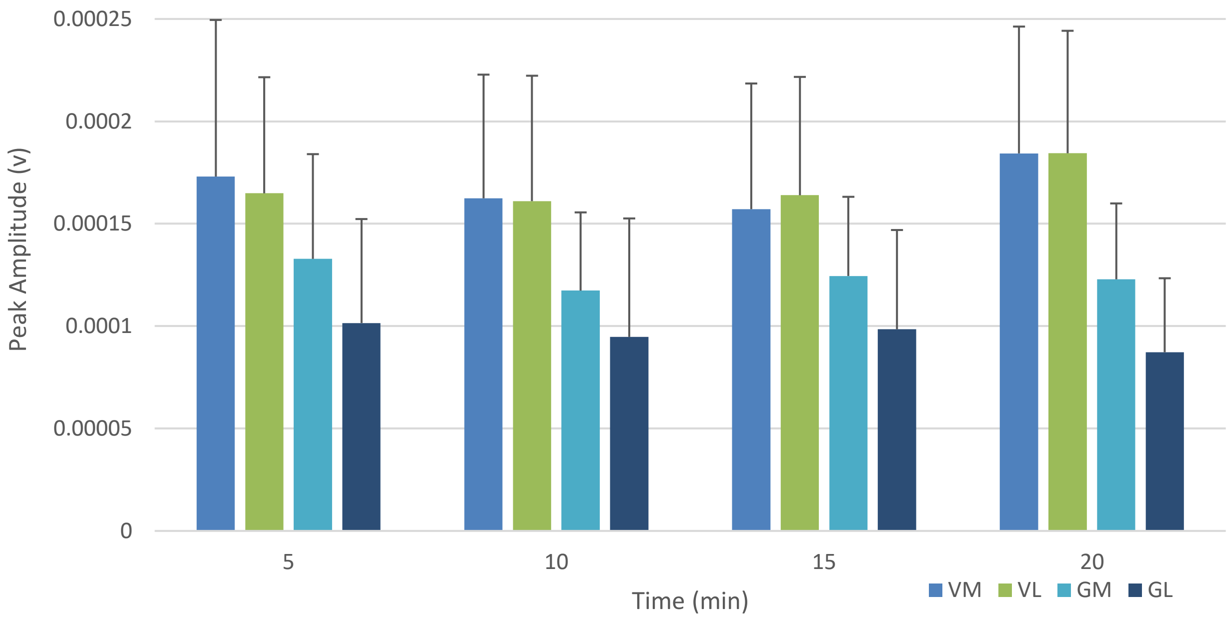



**Figure 6-2 - Showing Peak Muscular Activation across time trial performance.**

*Median Frequency of muscular activation*

Mean and standard deviation of the median frequency of muscular activation across each time point are displayed in Figure 10-3. In this figure, an asterisk denotes a significant difference in median frequency of muscular activation compared to the previous time point.

Within the Vastus Medialis, a statistically significant difference was found between 10 and 15 minutes (P = 0.02) and 15 and 20 minutes (P <0.001).

Within the medial head of the Gastrocnemius a statistically significant difference was found between 10 and 15 minutes (P = 0.032) and 15 and 20 minutes (P < 0.001).

Within the lateral head of the Gastrocnemius a statistically significant difference was found between 10 and 15 minutes (P = 0.017).

All other comparisons were not statistically significant (p>0.05).

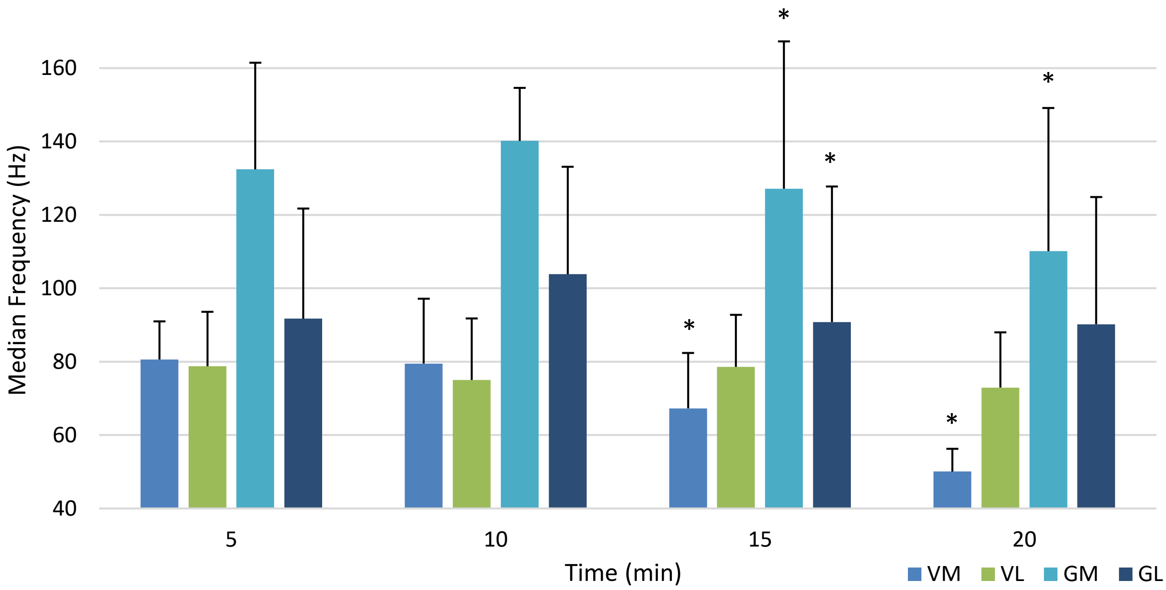



**Figure 66-3. Median frequency of muscular activation across the duration of the time trial performance.**

*Variability of peak amplitude of muscular activation*

When considering the mean variability of peak amplitude across all muscles there was an increase from 5 - 10 minutes (CV% = 12.10 ± 1.92 – 14.30 ± 4.54), another increase from 10 – 15 minutes (14.30 ± 4.54 – 16.40 ± 5.86) and then a decrease from 15 – 20 minutes (16.40 ± 5.86 – 14.58 ± 2.59). None of these differences, however, were found to be statistically significant (p>0.05).

Data was then separated to investigate each muscle individually. Comparisons can be seen in Table 10-2. No statistically significant differences were seen across these comparisons, suggesting no significant difference in the variability of peak amplitude of muscular activation in any muscle across the duration of the time trials ($p>0.05$).

**Table 6-2. Variability of Peak Muscular Activation throughout a time trial effort.**

| | CV% at 5 mins (mean ± SD) | CV% at 10 mins (mean ± SD) | CV% at 15 mins (mean ± SD) | CV% at 20 mins (mean ± SD) |
|---|---|---|---|---|
| **Vastus Medialis** | 12.62 ± 4.28 | 13.82 ± 5.24 | 15.04 ± 6.56 | 16.95 ± 5.13 |
| **Vastus Lateralis** | 14.03 ± 3.82 | 13.78 ± 4.32 | 13.22 ± 4.47 | 15.38 ± 4.87 |
| **Gastrocnemius Medialis** | 9.67 ± 2.31 | 10.76 ± 3.91 | 12.02 ± 4.41 | 11.34 ± 4.99 |
| **Gastrocnemius Lateralis** | 13.46 ± 6.12 | 18.69 ± 26.21 | 25.24 ± 37.90 | 14.72 ± 4.45 |

To investigate the influence of expertise, levels of variability of peak muscular activation were then correlated against the time taken to successfully complete the time trial ($Time_{TT}$). Results can be seen in Table 10-3 with statistically significant correlations ($p<0.05$) denoted by an asterisk (*).

**Table 6-3. Correlation values for CV% against finishing time.**

| | Time point | Correlation co-efficient | Sig. |
|---|---|---|---|
| **Vastus Medialis** | 5 min | -0.089 | 0.772 |
| | 10 min | 0.422 | 0.151 |
| | 15 min | 0.606 | 0.028* |
| | 20 min | 0.060 | 0.860 |
| **Vastus Lateralis** | 5 min | 0.182 | 0.441 |
| | 10 min | -0.074 | 0.758 |
| | 15 min | 0.239 | 0.310 |
| | 20 min | 0.304 | 0.205 |
| **Gastrocnemius Medialis** | 5 min | -0.277 | 0.250 |
| | 10 min | 0.503 | 0.028* |
| | 15 min | 0.519 | 0.027* |
| | 20 min | -0.445 | 0.064 |
| | 5 min | -0.3 | 0.904 |

| | | | |
|---|---|---|---|
| **Gastrocnemius Lateralis** | 10 min | -0.159 | 0.502 |
| | 15 min | 0.127 | 0.615 |
| | 20 min | -0.491 | 0.045* |

Statistically significant correlations between CV% of peak amplitude and $Time_{TT}$ were seen at 15 minutes for the Vastus Medialis, 10 and 15 minutes for the Gastrocnemius Lateralis and 20 minutes for the Gastrocnemius Medialis. All other correlations were found to be not statistically significant.

*Variability of median frequency of muscular activation*

When considering the mean variability of median frequency across all muscles there was an increase from 5 - 10 minutes (CV% = 30.14 ± 14.58 – 31.40 ± 11.88), another increase from 10 – 15 minutes (31.40 ± 11.88 – 32.13 ± 15.01) and then a decrease from 15 – 20 minutes (32.13 ± 15.01 – 29.86 ± 10.28). None of these differences were statistically significant (p>0.05).

Data was then separated to investigate each muscle individually. Comparisons can be seen in table 10-4.

**Table 6-4. CV% of median frequency of muscular activation.**

| | **CV% at 5 mins (mean ± SD)** | **CV% at 10 mins (mean ± SD)** | **CV% at 15 mins (mean ± SD)** | **CV% at 20 mins (mean ± SD)** |
|---|---|---|---|---|
| **Vastus Medialis** | 28.40 ± 13.65 | 29.76 ± 13.15 | 29.69 ± 12.80 | 27.92 ± 10.78 |
| **Vastus Lateralis** | 27.79 ± 12.24 | 30.17 ± 10.82 | 30.95 ± 11.97 | 27.31 ± 8.52 |
| **Gastrocnemius Medialis** | 29.11 ± 11.20 | 30.95 ± 9.92 | 34.75 ± 19.18 | 34.14 ± 12.74 |
| **Gastrocnemius Lateralis** | 35.00 ± 19.88 | 34.55 ± 14.60 | 32.33 ± 15.67 | 29.85 ± 8.61 |

No statistically significant differences were seen across these comparisons, suggesting no significant difference in the variability of median frequency of muscular activation was shown in any muscle across the duration of the time trial efforts ($p>0.05$).

To investigate the influence of expertise, levels of variability of median frequency were then correlated against the time taken to successfully complete the time trial ($Time_{TT}$). Results can be seen in Table 10-5 with statistically significant ($p<0.05$) correlations denoted by an asterisk (*).

**Table 6-5. Variability of median frequency correlated against the time taken to successfully complete the time trial ($Time_{TT}$).**

| | Time point | Correlation co-efficient | Sig. |
|---|---|---|---|
| **Vastus Medialis** | 5 min | 0.256 | 0.422 |
| | 10 min | 0.064 | 0.851 |
| | 15 min | 0.083 | 0.821 |
| | 20 min | 0.059 | 0.88 |
| **Vastus Lateralis** | 5 min | 0.021 | 0.93 |
| | 10 min | -0.345 | 0.137 |
| | 15 min | 0.457 | 0.043* |
| | 20 min | 0.136 | 0.568 |
| **Gastrocnemius Medialis** | 5 min | 0.254 | 0.295 |
| | 10 min | 0.634 | 0.005* |
| | 15 min | 0.039 | 0.882 |
| | 20 min | 0.217 | 0.419 |
| **Gastrocnemius Lateralis** | 5 min | 0.669 | 0.002* |
| | 10 min | 0.312 | 0.239 |
| | 15 min | -0.207 | 0.442 |
| | 20 min | -0.06 | 0.831 |

Statistically significant correlations between CV% of median frequency and $Time_{TT}$ were seen at 15 minutes for the Vastus Lateralis, 10 minutes for the Gastrocnemius Medialis and 5 minutes for the Gastrocnemius Lateralis. All other correlations were found to be not statistically significant ($p>0.05$).

## 6.4 Discussion

The results presented above show little evidence for an established relationship between the level of intra-individual movement variability employed by participants and the time taken to complete an indoor simulated time trial performed on a cycle ergometer. This is at odds with the stated hypothesis which suggested that, if intra-individual variability plays a functional role in the completion of a simulated indoor time trial event, those who completed the time trial quickest should also be adopting the most variable patterns of muscular recruitment.

*Peak Amplitude of Muscular Activation*

As demonstrated in Figure 10-2, with all participants grouped together, there were no statistically significant differences ($p>0.05$) in the peak amplitude of muscular activation across the four measured time points. There is some debate within the published literature as to the expected results for this variable with some authors (eg. Petrofsky, 1979; Housh et al., 2000 and Saunders et al., 2000) reporting significant increases in muscular activation while working at relatively high intensities (80 - 95% of peak power output or 60 - 100% of $\dot{V}O_{2\ max}$) and others (eg. Lucia, Hoyos and Chicharro, 2000 and Duc, Betik and Grappe, 2005) showing no statistically significant differences over time.

This difference in findings may potentially be attributed to the difference in sample populations utilised for the studies mentioned above. Those authors who reported significant differences in muscular activation have done so after testing untrained cyclists while Lucia, Hoyos and Chicharro (2000) recruited nine professional road cyclists and Duc, Betik and Grappe (2005) studied participants with a between 2 and 11 years of competitive experience. The participant group of the current study were similarly experienced, all holding a current British Cycling Race License and self-reporting their training load as 10.85 ± 4.21 hours or 156.00 ± 48.35 miles per week. The tested of $\dot{V}O_{2\ max}$ capacities of the current sample (73.2 ± 12.2 ml/ml/kg) also compare very favourably with the studies of Lucia, Hoyos and Chicarro (2000) and Duc, Betik and Grappe (2005) who reported mean values of 72.6 ± 2.2 ml/kg/min and 73.8 ± 5.3 ml/kg/min respectively.

In addition, it is worth considering that the reported values from this study were recorded over a ten-mile simulated time trial effort which was completed in an average of 23 min 30s (± 2 min 21s). This makes it far more logical to compare results against those produced during a 20 minute test performed at 80% of $\dot{V}O_{2\ max}$ (Lucia, Hoyos and Chicarro, 2000) or an “all out” 30 minute time trial exercise on a cycle ergometer (Duc, Betik and Grappe, 2005) than those produced during two 15-minute bouts (Saunders et al., 2000), four 15-minute bouts (Housh et al., 2000) or measures taken at very low intensities (20 and 40% of $\dot{V}O_{2\ max}$) over a duration of 80 minutes (Petrofsky, 1979).

As such, it can be said that the lack of statistically significant differences in muscular activation across time points was expected for a participant group of this nature. This is not to say that changes in muscular activation did not occur, as Dorel at al. (2009) showed significant increases in the activation of the Biceps Femoris and Gluteus maximus in the final stages of a test to exhaustion. These muscles, however, were not part of the current investigation.

*Median Frequency of muscular activation*

Throughout the time trial effort, due to the well-established belief that that muscle fibre conduction velocity decreases during a fatiguing exercise (De Luca, 1984) and that muscles will display negative trends of spectral variables (Merletti, Knaflitz and De Luca, 1990), it was expected that a reduction in median frequency of muscular activation would be seen. This holds true, to some degree as there was a statistically significant ($p<0.05$) reduction in median frequency of activation for the Vastus Medialis and Medial head of the Gastrocnemius between ten and fifteen minutes and again between fifteen and twenty minutes. There was also a significant reduction in median frequency of activation for the Lateral head of the Gastrocnemius between ten and fifteen minutes. These findings conflict with those of Duc, Betik and Grappe (2005) who reported a significant increase in MPF (Mean power frequency) in the Vastus Medialis from five to ten minutes and another in the final stages of their test.

It is interesting that no such corresponding reduction in median frequency was seen in the Vastus Lateralis, especially considering that Ryan and Gregor (1992) identified it as one of the primary power producers in the cycling movement. It is possible, however, that reporting median frequency for a whole revolution is not sensitive enough to show the changes that may be present as Von Tscharner (2002) showed that the reduction of the frequency of activation is specific to only certain periods during the crank revolution. The findings of this investigation do, however, concur with Lucia, Hoyos and Chicarro (2000) who reported that, during their investigation, MPF remained almost constant throughout the tests. They suggested that, as they had not seen a decline in frequency and a corresponding increase in amplitude of muscular activation, there was no evidence of neuromuscular fatigue in their participants.

Citing their previous research which had established that EMG variables from the Vastus Lateralis of professional cyclists and are valid indicators of neuromuscular fatigue in these subjects, Lucia, Hoyos and Chicarro (2000) concluded that cyclists of this level must have “a considerable resistance to fatigue of recruited motor units” and that “such adaptation is probably attained after years of highly demanding training”.

Although it is possible that the Vastus Lateralis of highly trained cyclists is resistant to fatigue, it is also possible that, as suggested by Tucker, Rauch, Harley and Noakes (2004) and Bini and Carpes

(2014), cyclists subconsciously manage muscle activation in order to postpone exhaustion during time trial events. This may be achieved by employing a level of variability as invariant movement patterns would result in the employment of the same muscle fibres repeatedly (Heiderscheit, Hamill and van Emmerik, 2002). Consequently, a great amount of cumulative stress would be placed on the tissues involved and thus heightened fatigue would be a logical outcome. Movement variability may be a preventative method used to distribute this load upon a wider range of tissues (Bartlett, Wheat and Robins, 2007; James, Dufek and Bates, 2000) and is therefore the focus of the rest of this discussion.

*Variability of peak amplitude of muscular activation*

If all muscles and all participants are taken into account, there appears to be a trend for increased variability of peak amplitude from five to ten minutes (CV% = 12.10 ± 1.92 – 14.30 ± 4.54), another increase from ten to fifteen minutes (14.30 ± 4.54 – 16.40 ± 5.86) and then a decrease in variability at the 20 minute measurement (16.40 ± 5.86 – 14.58 ± 2.59). Although none of these differences were found to be statistically significant ($p>0.05$) it does suggest that there is a pattern of increasing variability of muscular activation throughout the mid stages of the time trial, potentially in an effort to reduce the influence of fatigue. This would be in line with the findings of Gates and Dingwell (2011) and Yang et al. (2018) who both found that variability increased with fatigue during repeated task performance, but movement timing errors and endpoint spatial variability were mostly preserved. It should be acknowledged that both these papers produced their findings while studying repeated upper body tasks and therefore lack some relevance here but, nonetheless it does appear to show previous evidence of increased variability in response to fatigue.

To further investigate the variability of peak muscular activation, the data was reduced to study each muscle individually. There were no statistically significant differences found between time points ($p>0.05$) for any of the muscles studied but, again, the trends would suggest a gradual increase in both quadriceps muscles (VM and VL) over time with both heads of the gastrocnemius showing an increase in variability up until the 15 minute measure followed by a reduction at the final measurement.

The lack of significant differences across time points was, perhaps, expected, given that Ryan and Gregor (1992) reported “very consistent” patterns of activity within a single cycling trial. Specifically, they reported that the Vastus medialis and Vastus lateralis showed CV% values of less than 30% and that this supported their role as power generators. As seen in table 10-2. the highest CV% for these muscles falls well within the previous findings with a peak value of 16.95 ± 5.13 being recorded for the Vastus Medialis at 20 minutes.

In order to answer the main question of this study, however, testing in this way is not ideal as it is possible that using mean values obtained from all participant's data combined may be masking the influence of rider expertise. Interestingly, as seen in Figure 10-4, if the participants are grouped according to overall finishing time for the time trial, the fastest five riders display peak variability at 10 minutes (15.43 CV%) and then only show a slight reduction across the remaining time points. In contrast, the slower five riders do not peak until the 15-minute measure, show a higher level of peak variability (17.96 CV%) and a greater reduction after this point which resulted in lower variability than the fastest 5 riders by the time the final measure was taken.

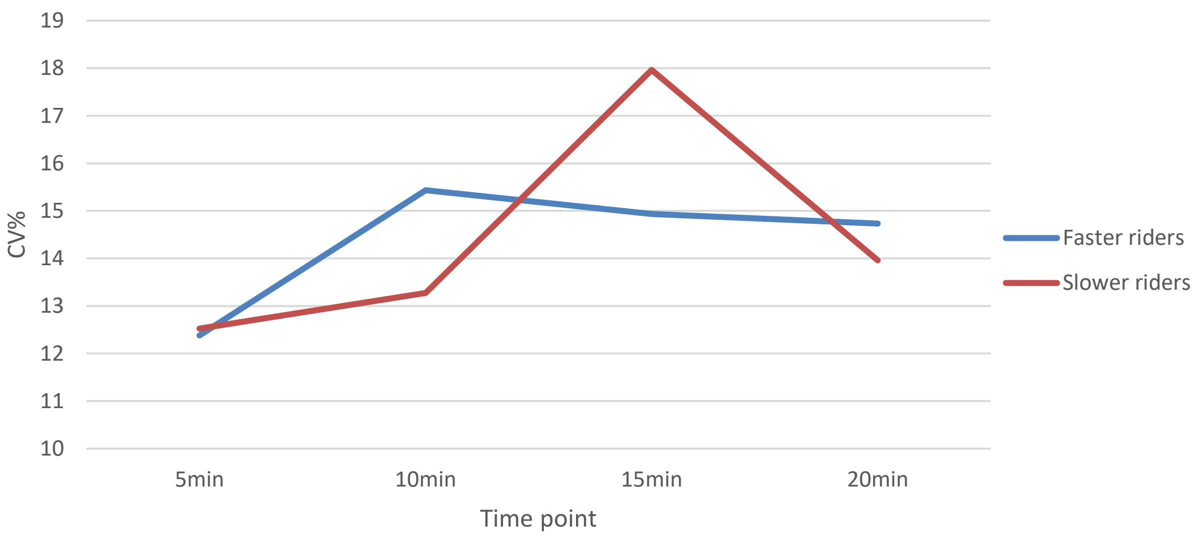



**Figure 6-4. Trends of changing Continuous Relative Phase values across the course of a simulated time trial effort.**

In order to quantify the effect of expertise, the decision was taken to test for a relationship between the level of variation and the overall time taken to complete the time trial ($Time_{TT}$). This showed there was a statistically significant correlation between CV% of muscular activation and $Time_{TT}$ at 15 minutes for the Vastus Medialis, 10 and 15 minutes for the Gastrocnemius Lateralis and 20 minutes for the Gastrocnemius Medialis. Using the guidelines from Koo and Li (2016), for the VM and GM these correlations were interpreted as moderately positive (r = 0.606, 0.503 and 0.519 respectively) with the GL, in contrast, showing a negative correlation (r = -0.491) which very nearly meets the criteria for a moderate correlation in the opposite direction.

Such contrasting results are very difficult to explain, especially concerning the presence of two opposing correlations within the same muscle complex. Viewed in isolation, the opposing correlations shown within the gastrocnemius could suggest that differing levels of athlete employ different movement strategies in order to produce the pedalling action. This, however, would contrast with findings from Hug, Bendahan, Le Fur, Cozzone and Grelot (2004) who suggested that there was no consistent pattern of activation within experienced cyclists and Hug, Turpun, Guevel and Dorel (2010) who identified at least three differing patterns of muscular activation within trained cyclists and concluded that this "does not represent differences in the overall locomotor strategy for pedalling".

It is worth noting that the studies mentioned here, in addition to Hug et al. (2008) are all focussed on *inter*-individual variability and therefore do not offer a true comparison for this investigation. They also offer no grounding to explain why there appears to be significant correlations between variability of muscular activation and overall time taken to complete the time trial at some time points and not at others, even within the same muscle.

*Variability of median frequency of muscular activation*

As with the recorded levels of variation within the peak amplitude of muscular activation, the mean variability of median frequency of muscular activation generally follows a trend of increasing from five to 10 minutes (CV% = 30.14 ± 14.58 – 31.40 ± 11.88), increasing again from ten to fifteen minutes (31.40 ± 11.88 – 32.13 ± 15.01) and then decreasing from fifteen to twenty minutes (32.13 ± 15.01 – 29.86 ± 10.28).

Again, none of these differences were considered statistically significant ($p>0.05$) but the presence of a similar pattern across both amplitude and frequency variables suggests that there is some level of compensation or control at play here which is common to both. As previously mentioned, this could be similar to the findings of Gates and Dingwell (2011) and Yang et al. (2018) and the decrease between the fifteen and twenty minute measurements points could be indicative of fatigue overcoming theses compensatory mechanisms. It is worth noting that there was a relatively linear increase in mean RPE values recorded across the time trial efforts with no obvious point at which participants perceived their workload to dramatically increase. This would suggest that the reduction in variability seen towards the later stages of the effort are entirely subconscious as suggested by Tucker, Rauch, Harley and Noakes (2004) and Bini and Carpes (2014).

Once more, the correlation of CV% against $Time_{TT}$ showed little in the way of statistically significant relationships. The only statistically significant correlations ($p<0.05$) were seen at 5 minutes for the lateral head of the Gastrocnemius (r = 0.669), 10 minutes for the Medial head of the Gastrocnemius (r =0.634), and 15 minutes for the Vastus Lateralis (r = 0.457). That there should only be statistically significant correlations at one time point for each muscle (3 significant results out of 16 correlations), and that this is a different time point for each muscle is unexpected. Combining this with the fact that all observed correlations here were positive in contrast to the amplitude variable which had a mix of positive and negative makes the results shown here all the harder to explain.

*Summary and limitations*

The general lack of statistically significant correlations between recorded variability of muscular activation and $Time_{TT}$ shows little evidence for an established relationship between the level of intra-individual movement variability employed by participants and the performance outcome during indoor simulated time trials performed on a cycle ergometer.

There are, however, some limitations present within the current investigation which may go some way to explaining why elevated levels of variability were not seen in "better" riders as expected.

Firstly, it is worth noting that there were some data points which could potentially seem erroneous. For example, levels of peak amplitude variability within the Gastrocnemius Lateralis generally range between 8 and 20%, depending on participant and timepoint. Participant 2, however was recorded as having 124.42% variability at the 15-minute measure for this muscle. Although large inter-individual differences have been shown previously (Hug et al 2004; 2008; Chapman et al., 2007), this magnitude of difference does seem to suggest an error in the measurement which may have artificially masked the true correlation as this is a very high CV% value and the participant's finishing time ranked 9$^{th}$ out of 10.

This also highlights a potential weakness in the approach taken to correlate variability against finishing time. As with Study 1, expertise was originally to be inferred by grouping participants according to the different categories they were competing at within the established competitive structure set out by British Cycling. It quickly became evident that this was not appropriate (see Study 1 and Section 3.2.4) as, for example, grouping the 4$^{th}$ category riders together would have created a group which included the 2nd, 4th, 7th, 8th and 10th ranked riders in terms of finishing time.

When considering the processes of data analysis, it is also possible that the ten-revolution window used for this investigation does not accurately reflect the true variability being displayed by the participants. Given the exploratory work displayed in section 3.3.4 and the previous studies who have also employed this method (e.g. Dorel et al., 2010; Chapman et al., 2008, Carpes et al., 2011;

Sides and Wilson, 2012) we are reasonably convinced this is not the case, but it is nonetheless worth acknowledging.

In addition, a small number of previous studies (eg. Von Tscharner, 2002 and Farina et al. 2004) have reported variability in terms of muscle coordination changes at specific points throughout the pedal revolution and found that there are significant reductions in the frequency of activation at some points but not others. Testing only the peak amplitude and median frequency values for each full revolution may, therefore, have reduced the level of detail present in the data to a point where changes that were present have been missed. Unfortunately, with the equipment available at the time that data collection was performed, it was not possible to synchronise multiple systems to accurately attribute muscular actions to specific phases of the pedal revolution.

Finally, and perhaps most importantly, the decision to design a study which was very controlled in nature may go some way to explaining the results displayed here. As mentioned previously, there is growing support for the notion that intra-individual movement variability may perform a functional role in task performance (Van Emmerik, Hamill, and McDermott, 2005), especially when the task requires adaptability of complex motor patterns within dynamic performance environments (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006). By choosing to use a cycle ergometer in a laboratory setting it is possible that the dynamic element of the performance environment has been controlled to such a degree that there isn't enough demand placed on the system in order to require a variable response. That is to say, removing the task perturbations such as variations of road surface, weather conditions, incline etc. may have unintentionally limited the amount of intra-individual movement variability the cyclists need to exhibit in order to complete the task. As a result, this study may not give a true representation of the functional role intra-individual movement variability can play and a more ecologically valid setting should be sought for future investigations.

### 6.5 Conclusion

The results presented here show little evidence for an established relationship between the level of intra-individual movement variability employed by participants and the performance outcome during indoor simulated time trials performed on a cycle ergometer.

The presence of some statistically significant relationships and concerns about the ecological validity of the testing environment does, however, suggest there is merit to continuing this investigation further. It is recommended that future research should aim to investigate the intra-individual movement variability employed by cyclists of differing levels during outdoor cycling in order to represent the actions of riders more accurately in a “real world” scenario which may, in turn, elicit a more variable response.

# 7. OVERALL DISCUSSION

The aim of this chapter is to summarise the work contained within this thesis in order to highlight the major findings and consistent themes running throughout. There will be a discussion of the implications and impact that this work may have and, following an acknowledgment of the limitations of this work, directions for future investigations will also be suggested.

## 7.1 Summary

This thesis has presented a number of investigations into the potentially functional role that intra-individual movement variability may play within cycling.

Movement variability is a feature of human movement which has historically been dismissed as merely "noise" (Bartlett, Wheat and Robins, 2007) or viewed as detrimental to normal function (Araújo and Bartlett, 2003; Sides and Wilson, 2012; Padulo et al., 2022) due to the implicit assumption that movement patterns for skilled performers are invariant. This thesis, however, hypothesised that variability in movement systems should be considered to be an essential element of normal, healthy function and is aligned with those authors who suggest that it may help individuals to adapt to the changing constraints encountered during a given task (e.g. Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006; Bradshaw et al., 2007).

In order to investigate this hypothesis, a quantitative, empirical approach was taken, initially focussing on kinematic measures of movement variability. The series of experimental investigations presented here generally progress from highly controlled, laboratory-based experiments, through a number of validation exercises, to measurements of cycling performance in more ecologically valid, field-testing settings.

A lack of significant findings in early investigations (Study 1) was generally attributed to a lack of task perturbations in the laboratory setting. That is to say, replicating a time trial effort in a laboratory setting meant that the dynamic elements of the performance environment were controlled to such a degree that there wasn't enough demand placed on the system in order to require a variable response. This led to the requirement for validation of various mobile measurement devices (Studies 2 to 5) in order that confidence could be placed in these devices when investigations moved to a more ecologically valid setting.

Having established a valid method of collecting kinematic data without using the traditional motion capture systems (Study 5), investigations moved to a field-based mode of data collection (Study 6). Here it became apparent that there was a statistically significant relationship between the amount of variability displayed by a cyclist and the time taken to complete a ten-mile time trial on a standardised course. This relationship was apparent at both the Hip-Knee joint and Knee-Ankle joint angle couplings and suggests that more highly skilled cyclists were employing greater levels of intra-individual movement variability than their less skilled counterparts.

In order to better understand the underlying mechanisms that led to this increased level of movement variability, investigations then returned to the controlled setting of the laboratory to investigate muscular recruitment patterns during time trial performance (Study 7). This study showed limited evidence for an established relationship between the level of intra-individual movement variability employed by participants and the time taken to complete an indoor simulated time trial on a cycle ergometer. As with the indoor kinematics investigation (Study 1), this was largely attributed to a lack of task perturbations in the laboratory setting and, despite some methodological imitations, Study 7 provides a good grounding for post-doctoral work in a field-based setting which might better replicate the “real world”.

## 7.2 Implications and applications

In contrast to the traditional view that movement variability is detrimental to performance (Padulo et al., 2022; Davids, Glazier, Araújo and Bartlett, 2003; Van Emmerick and Van Wegen, 2000), this thesis has presented evidence that cyclists can benefit from employing a level of intra-individual movement variability which leads to a number of possible applications.

Firstly, these findings can be used to influence coaching practice and training programme composition. Rather than emphasising the development of a single “correct” pedalling technique, these findings suggest that it may be more appropriate to construct training programmes and coaching drills which expose cyclists to a variety of conditions, settings and environmental factors. This would allow cyclists to gain experience practicing the process of dynamically producing a suitable movement pattern to match each novel combination of task constraints and therefore solve the degrees of freedom problem more efficiently (Bernstein, 1967). Such an approach has already been proposed in other sports where Knight (2004) suggested that golfers may be able to develop a more reliable swing by exploring different movement patterns, rather than attempting to perform each swing with absolute invarience and Bradshaw, Maulder and Keogh (2007) stated that it could be more beneficial to place athletes in a multitude of scenarios which offer a multitude of different task demands. A longitudinal applied study with an intervention along these lines would be an interesting avenue of investigation for future work.

The second potential application of the findings within this thesis is in the area of injury reduction/avoidance. If cyclists adopt invariant movement patterns, this would result in the utilisation of the same muscle fibres repeatedly (Heiderscheit, Hamill and van Emmerik, 2002). This would place a great amount of cumulative stress on the tissues involved and, given that fatigue is unavoidable in a cycling time trial due to the intensity of performance (Kenefick et al., 2002), could lead to injuries from overuse. If, instead, cyclists are trained to exhibit a higher degree of movement variability, Kurz, Sterigou, Buzzi and Georgoulis (2005) and Christiansen, Bradshaw and Wilson (2008) both suggested that this may play a functional role in reducing injury as it reduces the repetitive stress on the individual joints by facilitating variable loading of the musculoskeletal features of the joint. Thus, developing a level of intra-individual movement variability may serve as a preventative method used to distribute the workload across a wider range of tissues (Bartlett, Wheat and Robins, 2007; James, Dufek and Bates, 2000).

It is fair to say that the investigations contained within this thesis have shown limited evidence that movement variability can help to mitigate the effects of fatigue but, should further investigations prove this to be the case it would be of interest to cyclists across the participation spectrum. For those cycling at the competitive end of the sport, a reduction in the occurrence of fatigue should result in greater competitive performance and a more predictable adherence to training structures. For those engaging in cycling as a low impact mode of physical activity, and any associated exercise professionals, this would also suggest a level of confidence when trying to increase levels of activity as this can be done without concerns about variable movement patterns causing injuries.

**7.3 Limitations**

There are, as with all research, some persistent limitations which run throughout the work presented in this thesis. Given the impact of the global COVID-19 pandemic (see Section i) some of these were unavoidable but, nevertheless, will be discussed here.

Throughout the thesis, the kinematic investigations (Studies 1 to 6) have only explored flexion/extension couplings in the sagittal plane. Although this is typical of most kinematic analysis of cycling (Ferrer-Roca, Roig, Galilea and Garcia-Lopez, 2012; Carpes et al., 2006), it is possible that participants may exhibit movement variability in other planes in order to alter their technique from one pedal revolution to the next. The range of motion involved in these adjustments is unlikely to be in the order of magnitude seen in the sagittal plane at the hip (42–44°), Knee (73-78°) and ankle joints (21-25°) (Bini, Senger, Laferdini and Lopes, 2012), but nevertheless it is an area which would be recommended for investigation in future.

Likewise, the environmental perturbations explored in the outdoor investigation (Study 6) are limited to variations of gradient. Given the range of potential perturbations which could play a role in eliciting a variable response, especially when the task is being performed in a dynamic performance environment (Button, Davids and Schöellhorn, 2006; Bradshaw and Aisbett, 2006), this is an aspect of the investigation which could be expanded in the future.

One consistent challenge throughout the thesis has been deciding how to suitably quantify the level of accomplishment shown by participants and effectively group them according to "skill level". These challenges were outlined in section 3.2.4 and have been addressed by using a global outcome measure (i.e. the time taken to complete the time trial) as an analogue for skill level. Although this approach appears logical as it is this outcome measure which would ultimately decide finishing positions in a competitive event, it could be argued that there are a range of factors other than skill level which may lead to a faster time. Additionally, it is somewhat of a gross measurement given the level of detail involved in the analyses presented here.

Had it been feasible to recruit greater numbers of participants, it may have been possible to investigate other grouping methods and more tightly control the physiological variation between participants. Unfortunately, as explained in Section i, this was not the case and, should these investigations be extended in the future, this is certainly an area where improved rigor could be seen.

**7.4 Future investigations**

Aside from the limitations outlined above, there are some additional recommendations to be made for future investigations.

The kinematic data which comprises the majority of this thesis can be viewed as somewhat of a middle stage in terms of the motor control process. That is to say, the kinematic variability displayed here must, logically, be a result of underlying variance in the recruitment patterns and/or co-ordination of the musculature which is involved in creating the motion. In turn, the kinematic movement variability may manifest in greater variation of kinetic outcome measures, such as power output at the pedals, and other factors which may contribute to the overall time taken to complete a cycling event.

It is fair to say that this thesis has made initial inroads into investigations in these areas, but that they warrant further attention in the future. For example, by returning to the controlled setting of the laboratory to investigate muscular recruitment patterns during time trial performance (Study 7), this thesis offers an insight into some of the muscular mechanisms at play but these investigations, like the kinematic investigations before, now needs transporting into a more ecologically valid testing environment to reflect “real world” performance.

Likewise, having validated PowerTap’s P1 pedals for use during this thesis (Study 2), it is somewhat frustrating to not be able to present kinetic pedal data in consort with the kinematic data for the outdoor study. A number of the participants recruited for the final kinematic study (Study 6) were either reluctant to have their pedals changed, preferring to use their established clipless configuration, or were not comfortable riding with clipless pedals. This resulted in such a small dataset that there was no meaningful way of presenting kinetic data and, again, is an area which should be addressed in future investigations.

Finally, this thesis has been intentionally limited in terms of the cycling events studied. The selection of a time trial ensures the most controlled event where the cyclist performs in isolation from any others and has the sole aim of completing the prescribed distance in the shortest time possible. From a dynamical systems perspective this removes a number of potentially perturbating factors but, in doing so, it allows a more manageable investigation to be run. Time trials, however, represent a very small proportion of the competitive events available within the cycling calendar and therefore limits the understanding of the movement variability in a wider context. Many other road cycling events are more complex in terms of the task perturbations a cyclist may experience (for example the interactions between riders within a road race peloton or sprint event or the influence of team tactics in a multi-stage grand tour event) and this is before other disciplines of cycle sport are considered such as BMX, off road cycling or even the multi-sport demands of a triathlon. All of these events offer opportunity for further investigation and a growth of understanding in terms of the functional role of intra-individual movement variability in cycling. As such, it is fair to say that this thesis has only scratched the surface of an area which presents great opportunity for further investigation.

### 7.5 Conclusion

The complexities of cycling and cycling literature are numerous but this thesis presents evidence that, contrary to the historical assumption, intra-individual movement variability may play a functional role within the performance of cycling time trial events. There is a suggestion here that skilled performers employ a greater level of kinematic movement variability than their less skilled counterparts and that this relates to higher performance levels as reflected by the faster completion of time trial events. Future studies should continue to investigate both the origin and implications of such movement variability through the medium of in-depth quantitative studies using a combination of electromyographic and kinetics focussed datasets alongside the kinematic measurement techniques demonstrated throughout this thesis.

Such studies should, wherever possible, replicate “real world” performance conditions and ultimately progress beyond the limits of time trial performance into the full range of cycling activities available across multiples bicycle types and disciplines.

## 8. REFERENCES

### A

Abbiss, C. R., Quod, M. J., Levin, G., Martin, D. T., & Laursen, P. B. (2009). Accuracy of the Velotron ergometer and SRM power meter. *International journal of sports medicine*, *30*(02), 107-112.

Abbiss, C. R., Peiffer, J. J., & Laursen, P. B. (2009). Optimal cadence selection during cycling. *International SportMed Journal*, *10*(1), 1-15.

Abdi, H. (2010). Coefficient of variation. *Encyclopedia of research design*, *1*(5).

Adams, J. A. (1971). A closed-loop theory of motor learning. *Journal of motor behaviour*, *3*(2), 111-150.

Afsharipour, B., Soedirdjo, S., & Merletti, R. (2019). Two-dimensional surface EMG: The effects of electrode size, interelectrode distance and image truncation. *Biomedical Signal Processing and Control*, *49*, 298-307.

Allen, T. R., Brookham, R. L., Cudlip, A. C., & Dickerson, C. R. (2013). Comparing surface and indwelling electromyographic signals of the supraspinatus and infraspinatus muscles during submaximal axial humeral rotation. *Journal of Electromyography and Kinesiology*, *23*(6), 1343-1349.

Álvarez, G., & Vinyolas, J. (1996). A new bicycle pedal design for on-road measurements of cycling forces. *Journal of applied biomechanics*, *12*(1), 130-142.

Amoroso, A., Sanderson, D. J., & Henning, E. M. (1993). Kinematic and kinetic changes in cycling resulting from fatigue. In *Proceedings of the 17th meeting of the American society of biomechanics* (Vol. 17, pp. 157-158).

Anderson, J. R. (1982). Acquisition of cognitive skill. Psychological Review, 89, 369–406.

Arendt, E., & Dick, R. (1995). Knee injury patterns among men and women in collegiate basketball and soccer. *American Journal of Sports Medicine*, 23: 694-701.

Arkesteijn, M., Hopker, J., Jobson, S. A., & Passfield, L. (2013). The effect of turbo trainer cycling on pedalling technique and cycling efficiency. *International journal of sports medicine*, *34*(06), 520-525.

Arkesteijn, M., Jobson, S. A., Hopker, J., & Passfield, L. (2013). Effect of gradient on cycling gross efficiency and technique. *Medicine and science in sports and exercise*, *45*(5), 920-926.

Arutyunyan, GH., Gurfinkwl, VS. & Mirskii, ML. (1968) Investigation of aiming at a target. *Biophysics.* 14: 1162-7.

Arokoski, J. P., Kankaanpää, M., Valta, T., Juvonen, I., Partanen, J., Taimela, S., ... & Airaksinen, O. (1999). Back and hip extensor muscle function during therapeutic exercises. *Archives of physical medicine and rehabilitation*, *80*(7), 842-850.

Atkinson, G., & Nevill, A. M. (1998). Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports medicine*, *26*, 217-238.

**B**

Bailey, C. A., Uchida, T. K., Nantel, J., & Graham, R. B. (2021). Validity and sensitivity of an inertial measurement unit-driven biomechanical model of motor variability for gait. *Sensors*, *21*(22), 7690.

Bailey, M., Maillardet, F., & Messenger, N. (2003). Kinematics of cycling in relation to anterior knee pain and patellar tendinitis. *Journal of sports sciences*, *21*(8), 649-657.

Baron R. Aerobic and anaerobic power characteristics of off-road cyclists. *Med Sci Sports Exerc* 2001;33:1387–93.

Baron R, Bachl N, Petschnig R, Tschan H, Smekal G, Pokan R. Measurement of maximal power output in isokinetic and nonisokinetic cycling. A comparison of two methods. *Int J Sports Med* 1999;20:532–7.

Bartaguiz, E., Dindorf, C., Dully, J., Becker, S., & Fröhlich, M. (2023). Effects of increasing physical load and fatigue on the biomechanics of elite cyclists. *Scientific Journal of Sport and Performance*, *2*(1), 59-69.

Bartlett, R., Bussey, M., & Flyger, N. (2006). Movement variability cannot be determined reliably from no-marker conditions. *Journal of Biomechanics*, 39, 3076–3079.

Bartlett, R., Wheat, J., & Robins, M. (2007). Is movement variability important for sports biomechanists? *Sports Biomechanics*, 6, 224–243.

BBC News. (2020, March 5). *Coronavirus: Woman in 70s becomes first virus fatality in UK*. https://www.bbc.co.uk/news/uk-51759602

Bedeian, A. G., & Mossholder, K. W. (2000). On the use of the coefficient of variation as a measure of diversity. *Organizational Research Methods*, *3*(3), 285-297.

Beek, P. J., Peper, C. E., & Daffertshofer, A. (2002). Modeling rhythmic interlimb coordination: Beyond the Haken–Kelso–Bunz model. Brain and cognition, 48(1), 149-165.

Bernstein, NA. (1967) *The coordination and regulation of movements*. Oxford: Pergamon Press.

Bertucci, W., Grappe, F., & Groslambert, A. (2007). Laboratory versus outdoor cycling conditions: differences in pedaling biomechanics. *Journal of applied biomechanics*, *23*(2), 87-92.

Bertucci, W., Grappe, F., Girard, A., Betik, A., & Rouillon, J. D. (2005). Effects on the crank torque profile when changing pedalling cadence in level ground and uphill road cycling. *Journal of biomechanics*, *38*(5), 1003-1010.

Bertucci, W., Grappe, F., & Groslambert, A. (2007). Laboratory versus outdoor cycling conditions: differences in pedalling biomechanics. *Journal of applied biomechanics*, 23(2), 87-92.

Bieuzen, F., Lepers, R., Vercruyssen, F., Hausswirth, C., & Brisswalter, J. (2007). Muscle activation during cycling at different cadences: effect of maximal strength capacity. *Journal of Electromyography and Kinesiology*, *17*(6), 731-738.

Billaut, F., Basset, F. A., & Falgairette, G. (2005). Muscle coordination changes during intermittent cycling sprints. *Neuroscience letters*, *380*(3), 265-269.

Bini, R. R., & Carpes, F. P. (Eds.). (2014). *Biomechanics of cycling*. Basel, Switzerland: Springer.

Bini, R. R., & Carpes, F. P. (2014). Introduction to biomechanical analysis for performance enhancement and injury prevention. In *Biomechanics of Cycling* (pp. 1-11). Springer, Cham.

Bini, R. R., & Carpes, F. P. (2014). Muscle activity. In *Biomechanics of cycling* (pp. 23-31). Springer, Cham.

Bini, R. R., & Diefenthaeler, F. (2010). Kinetics and kinematics analysis of incremental cycling to exhaustion. *Sports Biomechanics*, *9*(4), 223-235.

Bini, R. R., Diefenthaeler, F., & Mota, C. B. (2010). Fatigue effects on the coordinative pattern during cycling: Kinetics and kinematics evaluation. *Journal of Electromyography and Kinesiology*, *20*(1), 102-107.

Bini, R. R., Hume, P. A., & Cerviri, A. (2011). A comparison of cycling SRM crank and strain gauge instrumented pedal measures of peak torque, crank angle at peak torque and power output. *Procedia Engineering*, *13*, 56-61.

Bini, R., Hume, P. A., & Croft, J. L. (2011). Effects of bicycle saddle height on knee injury risk and cycling performance. *Sports medicine*, *41*(6), 463-476.

Bini, R. R., Hume, P. A., Lanferdini, F. J., & Vaz, M. A. (2014). Effects of body positions on the saddle on pedalling technique for cyclists and triathletes. *European journal of sport science*, *14*(1), 413-420.

Bini, R. R., & Rossato, M. (2014). Kinetics and Pedalling Technique. In *Biomechanics of Cycling* (pp. 43-53). Springer, Cham.

Bini, R. R., Senger, D., Lanferdini, F., & Lopes, A. L. (2012). Joint kinematics assessment during cycling incremental test to exhaustion. *Isokinetics and Exercise Science*, *20*(2), 99-105.

Bini, R. R., Tamborindeguy, A. C., & Mota, C. B. (2010). Effects of saddle height, pedalling cadence, and workload on joint kinetics and kinematics during cycling. *Journal of sport rehabilitation*, *19*(3).

Bolgla, L. A., & Uhl, T. L. (2007). Reliability of electromyographic normalization methods for evaluating the hip musculature. *Journal of electromyography and kinesiology*, *17*(1), 102-111.

Bouillod, A., Pinot, J., Soto-Romero, G., Bertucci, W., & Grappe, F. (2017). Validity, sensitivity, reproducibility, and robustness of the PowerTap, Stages, and Garmin Vector power meters in comparison with the SRM device. *International Journal of Sports Physiology and Performance*, *12*(8), 1023-1030.

Bradshaw, E., & Aisbett, B. (2006). Visual guidance during competition performance and run-through training in long jumping. *Sports Biomechanics*, 5(1): 1–14.

Bradshaw, E., Maulder, P. & Keogh, J. (2007) Biological movement variability during the sprint start: Performance enhancement or hindrance? *Sports Biomechanics*. 6(3): 246–260.

Bradshaw, E. J., Keogh, J. W. L., Hume, P. A., Maulder, P. S., Nortje, J. & Marnewick, M. (2009) The effect of biological movement variability on the performance of the golf swing in the high-and-low-handicapped players. *Research quarterly for exercise and sport*, 80(2), 185.

Brisson, T. A., & Alain, C. (1996). Should common optimal movement patterns be identified as the criterion to be achieved? *Journal of Motor Behavior*, 28, 211–223.

Britishcyclingorguk. (2015). *British Cycling*. Retrieved 7 October, 2015, from https://www.britishcycling.org.uk/road/article/roadst_road-categories_classifications.

Broker, J. P. (2003). Cycling biomechanics: road and mountain. *High Tech Cycling. Champaign, IL: Human Kinetics*, 147-175.

Brooks, V. B. (1986). The neural basis of motor control. *Posture and Locomotion*, 160-180.

Brown, J., & Kirk-Wade, E. (2021). Coronavirus: A History of 'Lockdown Laws' in England. *London: House of Commons Library*, 44.

Burden, A. (2007). Surface electromyography. In *Biomechanical evaluation of movement in sport and exercise* (pp. 91-116). Routledge.

Burden, A., & Bartlett, R. (1999). Normalisation of EMG amplitude: an evaluation and comparison of old and new methods. *Medical engineering & physics*, *21*(4), 247-257.

Burden, A.M., Trew, M. and Baltzopoulos, V. (2003) 'Normalisation of gait EMGs: a re-examination', *Journal of Electromyography and Kinesiology*, 13: 519–532.

Burke, E. R. (1994). Proper fit of the bicycle. *Clinics in Sports Medicine*, 13(1), 1–14.

Burgess-Limerick, R., Abernethy, B., & Neal, R.J. (1993). Relative phase quantifies interjoint coordination. *Journal of Biomechanics*, 26, 91-94.

Button, C., Davids, K., & Schollhorn, W. (2006). Coordination profiling of movement systems. In K. David, S. Bennet, and K. Newell (Eds.), Movement system variability (pp. 133–152). Champaign, IL: Human Kinetics.

Button, C., Macleod, M., Sanders, R. & Coleman, S. (2003) Examining movement variability in the basketball free-throw action at different skill levels, *Research Quarterly for Exercise and Sport*, 74(3): 257-269.

**C**

Caldwell, G. E., Hagberg, J. M., McCole, S. D., & Li, L. (1999). Lower extremity joint moments during uphill cycling. *Journal of Applied Biomechanics*, 15, 166–181.

Cangley, P., Passfield, L., Carter, H., & Bailey, M. (2011). The effect of variable gradients on pacing in cycling time-trials. *International journal of sports medicine*, *32*(02), 132-136.

Candotti CT, Loss JF, Bagatini D, Soares DP, da Rocha EK, de Oliveira AR, Guimares ACS (2009) Co-contraction and economy of triathletes and cyclists at different cadences during cycling motion. Journal of Electromyography and Kinesiology 19 (5):915-921.

Cannon, D. T., Kolkhorst, F. W., & Cipriani, D. J. (2007). Effect of pedalling technique on muscle activity and cycling efficiency. *European Journal of Applied Physiology*, 99, 659–664.

Carpes, F. P., Bini, R. R., & Quesada, J. I. P. (2014). Joint kinematics. In *Biomechanics of cycling* (pp. 33-42). Springer, Cham.

Carpes, F. P., Dagnese, F., Bini, R. R., Diefenthaeler, F., Rossato, M., Mota, C., & Guimarães, A. (2006). Pedalling kinematics characteristics of competitive cyclists of different disciplines. *Portuguese Journal of Sports Sciences*, *6*(1), 7-14.

Carpes, F. P., Diefenthaeler, F., Bini, R. R., Stefanyshyn, D. J., Faria, I. E., & Mota, C. B. (2011). Influence of leg preference on bilateral muscle activation during cycling. *Journal of Sports Sciences*, *29*(2), 151-159.

Carpes, F. P., Mota, C. B., & Faria, I. E. (2010). On the bilateral asymmetry during running and cycling–A review considering leg preference. *Physical therapy in sport*, *11*(4), 136-142.

Carson, R. G., Goodman, D., Kelso, J. A. S., & Elliott, D. (1995). Phase transitions and critical fluctuations in rhythmic coordination of ipsilateral hand and foot. *Journal of motor behaviour*, *27*(3), 211-224.

Castroflorio, T., Farina, D., Bottin, A., Piancino, M. G., Bracco, P., & Merletti, R. (2005). Surface EMG of jaw elevator muscles: effect of electrode location and inter-electrode distance. *Journal of oral rehabilitation*, *32*(6), 411-417.

Cavanagh, P. R. (1986). The biomechanics of cycling studies of the pedalling mechanics of elite pursuit rider. *Science of cycling, Human Kinetics*.

Chaffin, M. E., Berg, K., Zuniga, J., & Hanumanthu, V. S. (2008). Pacing pattern in a 30-minute maximal cycling test. *The Journal of Strength & Conditioning Research*, *22*(6), 2011-2017.

Chao, E.Y.; An, K.N.; Askew, L.J.; Morrey, B.F. Electrogoniometer for the Measurement of Human Elbow Joint Rotation. *J. Biomech. Eng.* **1980**, *102*, 301–310.

Chapman, A. R., Vicenzino, B., Blanch, P., & Hodges, P. W. (2008). Patterns of leg muscle recruitment vary between novice and highly trained cyclists. *Journal of Electromyography and Kinesiology*, *18*(3), 359-371.

Chapman, A., Vicenzino, B., Blanch, P., & Hodges, P. (2009). Do differences in muscle recruitment between novice and elite cyclists reflect different movement patterns or less skilled muscle recruitment? *Journal of Science and Medicine in Sport*, *12*(1), 31-34.

Chapman, A. R., Vicenzino, B., Blanch, P., Knox, J. J., & Hodges, P. W. (2006). Leg muscle recruitment in highly trained cyclists. *Journal of sports sciences*, *24*(2), 115-124.

Christiansen, C., Bradshaw, E. J., & Wilson, C. (2008). Optimal crank arm length and body position for road sprint cycling performance. In *ISBS-Conference Proceedings Archive*.

Clarys, J. P., & Cabri, J. (1993). Electromyography and the study of sports movements: a review. *Journal of sports sciences*, *11*(5), 379-448.

Coakley, S. L., & Passfield, L. (2018). Cycling performance is superior for time-to-exhaustion versus time-trial in endurance laboratory tests. *Journal of sports sciences*, *36*(11), 1228-1234.

Cockcroft, S. J. (2011). *An evaluation of inertial motion capture technology for use in the analysis and optimization of road cycling kinematics* (Doctoral dissertation, Stellenbosch: University of Stellenbosch).

Cooper, G., Sheret, I., McMillian, L., Siliverdis, K., Sha, N., Hodgins, D., ... & Howard, D. (2009). Inertial sensor-based knee flexion/extension angle estimation. *Journal of biomechanics*, *42*(16), 2678-2685.

Coyle, E. F., Feltner, M. E., Kautz, S. A., Hamilton, M. T., Montain, S. J., Baylor, A. M., ... & Petrek, G. W. (1991). Physiological and biomechanical factors associated with elite endurance cycling performance. *Medicine and science in sports and exercise*, *23*(1), 93-107.

Cruse, H., Dean, J., Heuer, H., & Schmidt, R. A. (1990). Utilization of sensory information for motor control. In *Relationships between perception and action* (pp. 43-79). Springer, Berlin, Heidelberg.

Cudejko, T., Button, K., & Al-Amri, M. (2022). Validity and reliability of accelerations and orientations measured using wearable sensors during functional activities. *Scientific reports*, *12*(1), 1-12.

*Cycling UK's cycling statistics.* (2019) Retrieved from Cycling UK's website https://www.cyclinguk.org/statistics

*Cycling participation England 2016-20*. (2022). Statista. https://www.statista.com/statistics/899206/cycling-participation-uk/

Czajkowski, M., Bouillod, A., Dauriannes, A., Soto-Romero, G., & Grappe, F. (2016). Validity and reproducibility of the Powertap P1 power meter when compared with SRM device. *Journal of Science and Cycling*, *5*(2).

**D**

Dankaerts, W., O'Sullivan, P. B., Burnett, A. F., Straker, L. M., & Danneels, L. A. (2004). Reliability of EMG measurements for trunk muscles during maximal and sub-maximal voluntary isometric contractions in healthy controls and CLBP patients. *Journal of Electromyography and Kinesiology*, *14*(3), 333-342.

Davids, K., Bennett, S., & Newell, K. (2006). Movement system variability. Champaign, IL: Human Kinetics.

Davids, K., Glazier, P., & Bartlett, R. (2003) *Dynamical systems theory: A relevant framework for performance-oriented sports biomechanics research.* Retrieved from http://www.sportsci.org/jour/03/psg.htm

Davids, K., Glazier, P., Araújo, D. & Bartlett, R. (2003) Movement systems as dynamical systems: The functional role of variability and its implications for sports medicine. *Sports Medicine.* 33(4): 245-260.

Davids, K., Shuttleworth, R., Button, C., Renshaw, I. & Glazier, P. (2004) ''Essential noise'' – enhancing variability of informational constraints benefits movement control: a comment on Waddington and Adams (2003) *Br J Sports Med*, 38: 601–605.

Davis, R. R., & Hull, M. L. (1981). Measurement of pedal loading in bicycling: II. Analysis and results. *Journal of biomechanics*, *14*(12), 857-872.

De Baets, L., Vanbrabant, S., Dierickx, C., van der Straaten, R., & Timmermans, A. (2020). Assessment of scapulothoracic, glenohumeral, and elbow motion in adhesive capsulitis by means of inertial sensor technology: A within-session, intra-operator and inter-operator reliability and agreement study. *Sensors*, *20*(3), 876.

De Bot, K., Lowie, W., & Verspoor, M. (2007). A dynamic systems theory approach to second language acquisition. *Bilingualism: Language and cognition*, *10*(1), 7-21.

De Leo, A. T., Dierks, T. A., Ferber, R., & Davis, I. S. (2004). Lower extremity joint coupling during running: a current update. *Clinical Biomechanics*, 19(10), 983-991.

De Luca, C. J. (1984). Myoelectrical manifestations of localized muscular fatigue in humans. *Critical reviews in biomedical engineering*, *11*(4), 251-279.

De Luca, C. J. (1997). The use of surface electromyography in biomechanics. *Journal of applied biomechanics*, *13*(2), 135-163.

De Marchis, C., Schmid, M., Bibbo, D., Bernabucci, I., & Conforto, S. (2013). Inter-individual variability of forces and modular muscle coordination in cycling: A study on untrained subjects. *Human movement science*, *32*(6), 1480-1494.

Den Hartog, D., van der Krogt, M. M., van der Burg, S., Aleo, I., Gijsbers, J., Bonouvrié, L. A., ... & Haberfehlner, H. (2022). Home-Based Measurements of Dystonia in Cerebral Palsy Using Smartphone-Coupled Inertial Sensor Technology and Machine Learning: A Proof-of-Concept Study. *Sensors*, *22*(12), 4386.

Diefenthaeler, F., Bini, R. R., Laitano, O., Guimarães, A. C. S., Nabinger, E., Carpes, F. P., ... & Guimarães, A. C. (2006). Assessment of the effects of saddle position on cyclists pedalling technique. *Med Sci Sports Exerc*, *38*(5), S181.

Diefenthaeler, F., Coyle, E. F., Bini, R. R., Carpes, F. P., & Vaz, M. A. (2012). Muscle activity and pedal force profile of triathletes during cycling to exhaustion. *Sports Biomechanics*, *11*(1), 10-19.

Dingwell, J. B., Joubert, J. E., Diefenthaeler, F., & Trinity, J. D. (2008). Changes in muscle activity and kinematics of highly trained cyclists during fatigue. *IEEE Transactions on Biomedical Engineering*, *55*(11), 2666-2674.

Dorel, S., Couturier, A., & Hug, F. (2009). Influence of different racing positions on mechanical and electromyographic patterns during pedalling. *Scandinavian journal of medicine & science in sports*, *19*(1), 44-54.

Dorel, S., Couturier, A., Lacour, J. R., Vandewalle, H., Hautier, C., & Hug, F. (2009). Force-velocity relationship in cycling revisited: benefit of two-dimensional pedal forces analysis. *Medicine and science in sports and exercise*, *42*(6), 1174-1183.

Dorel, S., Drouet, J. M., Couturier, A., Champoux, Y., & Hug, F. (2009). Changes of pedalling technique and muscle coordination during an exhaustive exercise. *Medicine and Science in Sports and Exercise*, *41*(6), 1277.

Dorel, S., Drouet, J. M., Hug, F., Lepretre, P. M., & Champoux, Y. (2008). New instrumented pedals to quantify 2D forces at the shoe-pedal interface in ecological conditions: Preliminary study in elite track cyclists. *Computer Methods in Biomechanics and Biomedical Engineering*, *11*(S1), 89-90.

Driller, M. W., Argus, C. K., Bartram, J. C., Bonaventura, J., Martin, D. T., West, N. P., & Halson, S. L. (2014). Reliability of a 2-bout exercise test on a wattbike cycle ergometer. *International Journal of Sports Physiology and Performance*, *9*(2), 340-345.

Duc, S., Betik, A. C., & Grappe, F. (2005). EMG activity does not change during a time trial in competitive cyclists. *International journal of sports medicine*, *26*(02), 145-150.

**E**

Ebert, T. R., Martin, D. T., Stephens, B., & Withers, R. T. (2006). Power output during a professional men's road-cycling tour. *International journal of sports physiology and performance*, *1*(4), 324-335.

Eckardt, F., Münz, A., & Witte, K. (2014). Application of a full body inertial measurement system in dressage riding. *Journal of Equine Veterinary Science*, *34*(11-12), 1294-1299.

Edwards, R. G., & Lippold, O. C. J. (1956). The relation between force and integrated electrical activity in fatigued muscle. *The Journal of physiology*, *132*(3), 677.

Ekstrom, R. A., Soderberg, G. L., & Donatelli, R. A. (2005). Normalization procedures using maximum voluntary isometric contractions for the serratus anterior and trapezius muscles during surface EMG analysis. *Journal of Electromyography and Kinesiology*, *15*(4), 418-428.

Emanuele, U., Horn, T., & Denoth, J. (2012). The relationship between freely chosen cadence and optimal cadence in cycling. *International journal of sports physiology and performance*, *7*(4), 375-381.

Enoka, R. M. (2000). As bases neuromecânicas da cinesiologia. In *As bases neuromecânicas da cinesiologia* (pp. 450-450).

Ericson, M. (1986). On the biomechanics of cycling. A study of joint and muscle load during exercise on the bicycle ergometer. *Scandinavian journal of rehabilitation medicine. Supplement*, *16*, 1-43.

Ericson, M. O. (1988). Mechanical muscular power output and work during ergometer cycling at different work loads and speeds. *European journal of applied physiology and occupational physiology*, *57*(4), 382-387.

Ericsson, K. A. (2007). Toward a science of expert and exceptional performance in sport: A reply to the commentaries. International Journal of Sport Psychology, 38, 109–123.

Ericsson, K. A. (2013). Training history, deliberate practice and elite sports performance: an analysis in response to Tucker and Collins review—what makes champions? *British Journal of Sports Medecine, Vol 47 (9).* [Editorial]

Ericsson, K. A., Roring, R. W., & Nandagopal, K. (2007). Giftedness and evidence for reproducibly superior performance: An account based on the expert performance framework. *High ability studies*, *18*(1), 3-56.

Ericson, M. O., & Nisell, R. (1988). Efficiency of pedal forces during ergometer cycling. *International journal of sports medicine*, *9*(02), 118-122.

Ettema, G., & Lorås, H.W. (2009). Efficiency in cycling: a review. *European Journal of Applied Physiology*, 106, 1–14.

Ettema, G., Lorås, H., & Leirdal, S. (2009). The effects of cycling cadence on the phases of joint power, crank power, force and force effectiveness. *Journal of Electromyography and Kinesiology*, *19*(2), 94-101.

**F**

Farago, E., Macisaac, D., Suk, M., & Chan, A. D. C. (2022). A Review of Techniques for Surface Electromyography Signal Quality Analysis. *IEEE Reviews in Biomedical Engineering*.

Faria, I., & Cavanagh, P. R. (1978). *The physiology and biomechanics of cycling*. John Wiley & Sons.

Faria, E. W., Parker, D. L., & Faria, I. E. (2005). The science of cycling. *Sports medicine*, *35*(4), 285-312.

Farina, D., Merletti, R., Indino, B., & Graven-Nielsen, T. (2004). Surface EMG crosstalk evaluated from experimental recordings and simulated signals. *Methods of information in medicine*, *43*(01), 30-35.

Farina, D., Merletti, R., Indino, B., Nazzaro, M., & Pozzo, M. (2002). Surface EMG crosstalk between knee extensor muscles: experimental and model results. *Muscle & Nerve: Official Journal of the American Association of Electrodiagnostic Medicine*, *26*(5), 681-695.

Favre, J., Jolles, B. M., Aissaoui, R., & Aminian, K. (2008). Ambulatory measurement of 3D knee joint angle. *Journal of biomechanics*, *41*(5), 1029-1035.

Ferber, R., Davis, I. M., & Williams III, D. S. (2005). Effect of foot orthotics on rearfoot and tibia joint coupling patterns and variability. *Journal of biomechanics*, 38(3), 477-483.

Fernández-Pena, E., Lucertini, F., & Ditroilo, M. (2009). A maximal isokinetic pedalling exercise for EMG normalization in cycling. *Journal of electromyography and kinesiology*, *19*(3), e162-e170.

Ferrer-Roca, V., Roig, A., Galilea, P., & García-López, J. (2012). Influence of saddle height on lower limb kinematics in well-trained cyclists: static vs. dynamic evaluation in bike fitting. *The Journal of Strength & Conditioning Research*, *26*(11), 3025-3029.

Fitts, P. M., & Posner, M. I. (1967). Human performance. Belmont, CA: Brooks/Cole.

Fleming, B. C., Beynnon, B. D., Renstrom, P. A., Peura, G. D., Nichols, C. E., & Johnson, R. J. (1998). The strain behavior of the anterior cruciate ligament during bicycling. *The American journal of sports medicine*, *26*(1), 109-118.

Fonda, B., & Sarabon, N. (2010). Biomechanics of cycling. *Sport Science Review*, *19* (1-2), 187-210.

Fonda, B., & Šarabon, N. (2012). Biomechanics and energetics of uphill cycling: A review. *Kinesiology*, *44*(1.), 5-17.

Fonda, B., Sarabon, N., & Li, F. X. (2014). Validity and reliability of different kinematics methods used for bike fitting. *Journal of sports sciences*, *32*(10), 940-946.

Frigo, C., & Shiavi, R. (2004). Applications in movement and gait analysis. *Electromyography: Physiology, engineering, and noninvasive applications. Hoboken (NJ): John Wiley & Sons, Inc*, 381-402.

Fuchs, A., & Jirsa, V. K. (2008). JA Scott Kelso's contributions to our understanding of coordination. In *Coordination: Neural, behavioural and social dynamics* (pp. 327-346). Springer, Berlin, Heidelberg.

**G**

García-López, J., Díez-Leal, S., Ogueta-Alday, A., Larrazabal, J., & Rodríguez-Marroyo, J. A. (2016). Differences in pedalling technique between road cyclists of different competitive levels. *Journal of sports sciences*, *34*(17), 1619-1626.

Gardner, A. S., Stephens, S., Martin, D. T., Lawton, E., Lee, H., & Jenkins, D. (2004). Accuracy of SRM and power tap power monitoring systems for bicycling. *Medicine & Science in Sports & Exercise*, *36*(7), 1252-1258.

Gates, D.H. and Dingwell, J.B., 2011. The effects of muscle fatigue and movement height on movement stability and variability. *Experimental brain research*, *209*(4), pp.525-536.

Geissinger, J. H., & Asbeck, A. T. (2020). Motion inference using sparse inertial sensors, self-supervised learning, and a new dataset of unscripted human motion. *Sensors*, *20*(21), 6330.

Gentile, A. M. (1972). A working model of skill acquisition with application to teaching. Quest, 17, 3–23.

Glazier, P. (2011) Movement variability in the golf swing: Theoretical, methodological, and practical issues. *Research Quarterly for Exercise and Sport, 82(2):157-161.*

Gonzalez, H., & Hull, M. L. (1989). Multivariable optimization of cycling biomechanics. *Journal of biomechanics*, *22*(11-12), 1151-1161.

Golden Cheetah [online]. Open-source power analysis cycling software, General public licence. http://www.goldencheetah.org/ (accesses 20/10/2017).

Gregor, R. J., Broker, J. P., & Ryan, M. M. (1991). The Biomechanics of Cycling. *Exercise and sport sciences reviews*, *19*(1), 127-170.

**H**

Hamill, J., Haddad, J. M., & Mcdermott, W. J. (2000). Issues in quantifying variability from a dynamical systems perspective. *Journal of applied Biomechanics.* 16, 407-418.

Hamill, J., Bates, B. T., & Holt, K. G. (1992). Timing of lower extremity joint actions during treadmill running. *Medicine and science in sports and exercise*, *24*(7), 807-813.

Hamill, J., van Emmerik, R. E., Heiderscheit, B. C., & Li, L. (1999). A dynamical systems approach to lower extremity running injuries. *Clinical biomechanics*, *14*(5), 297-308.

Hamley, E. J., & Thomas, V. (1967). Physiological and postural factors in the calibration of the bicycle ergometer. *The Journal of Physiology*, 191(2), 55P–56P.

Hausdorf, J. M., Zemany, L., Peng, C. K. & Goldberger, A. L. (1999) Maturation of gait dynamics: Stride to stride variability and its temporal origin in children. *Journal of applied physiology*, 86, 1040-1047.

Hautier, C. A., Arsac, L. M., Deghdegh, K., Souquet, J. I. M. M. Y., Belli, A. L. A. I. N., & Lacour, J. R. (2000). Influence of fatigue on EMG/force ratio and co-contraction in cycling. *Medicine and science in sports and exercise*, *32*(4), 839-843.

Heiderscheit, B. C., Hamill, J., & van Emmerik, R. E. (2002). Variability of stride characteristics and joint coordination among individuals with unilateral patellofemoral pain. *Journal of applied biomechanics*, *18*(2), 110-121.

Hein, T., Schmeltzpfenning, T., Krauss, I., Maiwald, C., Horstmann, T., & Grau, S. (2012). Using the variability of continuous relative phase as a measure to discriminate between healthy and injured runners. *Human movement science*, *31*(3), 683-694.

Herb, C. C., Chinn, L., Dicharry, J., McKeon, P. O., Hart, J. M., & Hertel, J. (2014). Shank-rearfoot joint coupling with chronic ankle instability. *Journal of applied biomechanics*, *30*(3), 366-372.

Hermens, H. J., Freriks, B., Merletti, R., Stegeman, D., Blok, J., Rau, G., ... & Hägg, G. (1999). European recommendations for surface electromyography. *Roessingh research and development*, *8*(2), 13-54.

Hettinga, F. J., De Koning, J. J., Broersen, F. T., Van Geffen, P., & Foster, C. (2006). Pacing strategy and the occurrence of fatigue in 4000-m cycling time trials. *Medicine & Science in Sports & Exercise*, *38*(8), 1484-1491.

Hoes, M. J. A. J. M., Binkhorst, R. A., Smeekes-Kuyl, A. E. M. C., & Vissers, A. C. A. (1968). Measurement of forces exerted on pedal and crank during work on a bicycle ergometer at different loads. *Internationale Zeitschrift für angewandte Physiologie einschließlich Arbeitsphysiologie*, *26*(1), 33-42.

Hollerbach, J. M. (1978). *A study of human motor control through analysis and synthesis of handwriting* (Doctoral dissertation, Massachusetts Institute of Technology).

Hopker, J., & Jobson, S. (2012). *Performance cycling: the science of success*. A&C Black.

Hopker, J., Myers, S., Jobson, S. A., Bruce, W., & Passfield, L. (2010). Validity and reliability of the Wattbike cycle ergometer. *International journal of sports medicine*, *31*(10), 731-736.

Hopkins, W. G., Schabort, E. J., & Hawley, J. A. (2001). Reliability of power in physical performance tests. *Sports medicine*, *31*, 211-234.

Housh, T. J., Perry, S. R., Bull, A. J., Johnson, G. O., Ebersole, K. T., Housh, D. J., & Devries, H. A. (2000). Mechanomyographic and electromyographic responses during submaximal cycle ergometry. *European journal of applied physiology*, *83*(4), 381-387.

Houtz, S. J., & Fischer, F. J. (1959). An analysis of muscle action and joint excursion during exercise on a stationary bicycle. *JBJS*, *41*(1), 123-131.

Hug, F. (2011). Can muscle coordination be precisely studied by surface electromyography?. *Journal of electromyography and kinesiology*, *21*(1), 1-12.

Dorel, S., Couturier, A., & Hug, F. (2008). Intra-session repeatability of lower limb muscles activation pattern during pedalling. *Journal of Electromyography and Kinesiology*, *18*(5), 857-865.

Hug, F., & Dorel, S. (2009). Electromyographic analysis of pedalling: a review. *Journal of electromyography and Kinesiology*, *19*(2), 182-198.

Hug, F., Drouet, J. M., Champoux, Y., Couturier, A., & Dorel, S. (2008). Interindividual variability of electromyographic patterns and pedal force profiles in trained cyclists. *European journal of applied physiology*, *104*(4), 667-678.

Hug, F., Bendahan, D., Le Fur, Y., Cozzone, P. J., & Grelot, L. (2004). Heterogeneity of muscle recruitment pattern during pedalling in professional road cyclists: a magnetic resonance imaging and electromyography study. *European journal of applied physiology*, *92*(3), 334-342.

Hug, F., Turpin, N. A., Guével, A., & Dorel, S. (2010). Is interindividual variability of EMG patterns in trained cyclists related to different muscle synergies? *Journal of applied physiology*, *108*(6), 1727-1736.

Hull, M. L., & Davis, R. R. (1981). Measurment of pedal loading in bicycling: I. Instrumentation. *Journal of biomechanics*, *14*(12), 843-855.

Hunt, M. A., Sanderson, D. J., Moffet, H., & Inglis, J. T. (2003). Biomechanical changes elicited by an anterior cruciate ligament deficiency during steady rate cycling. *Clinical Biomechanics*, *18*(5), 393-400.

Hunter, A. M., Gibson, A. S. C., Lambert, M., & Noakes, T. D. (2002). Electromyographic (EMG) normalization method for cycle fatigue protocols. *Medicine and science in sports and exercise*, *34*(5), 857-861.

**I**

Iriberri, J., Muriel, X., & Larrazabal, I. (2008). The bike fit of the road professional cyclist related to anthropometric measurements and the torque of the crank. The Engineering of Sport, 7, 483–488.

**J**

James, C. R., Dufek, J. S., & Bates, B. T. (2000). Effects of injury proneness and task difficulty on joint kinetic variability. *Medicine and science in sports and exercise*, *32*(11), 1833-1844.

Jeukendrup, A. E., & Martin, J. (2001). Improving cycling performance. *Sports Medicine*, *31*(7), 559-569.

Jobe, F. W., Moynes, D. R., Tibone, J. E., & Perry, J. (1984). An EMG analysis of the shoulder in pitching: a second report. *The American journal of sports medicine*, *12*(3), 218-220.

Jobson, S. A., Passfield, L., Atkinson, G., Barton, G., & Scarf, P. (2009). The analysis and utilization of cycling training data. *Sports medicine*, *39*(10), 833-844.

Jobson, S.A., Nevill, A.M., Palmer, G.S, Jeukendrup, A.E., Doherty, M. and Atkinson, G. (2010) The ecological validity of laboratory cycling: Does body size explain the difference between laboratory- and field-based cycling performance? *Journal of Sports Sciences*, 25(1): 3 – 9.

Jobson, S.A., Nevill, George, S.R., Jeukendrup, A.E. and Passfields, L. (2008) Influence of body position when considering the ecological validity of laboratory time-trial cycling performance. *Journal of Sports Sciences*, 26(12): 1269–1278.

Jones, S. L. P., & Passfield, L. (1998). The dynamic calibration of bicycle power measuring cranks. *Engineering of Sport*, 265-274.

Jorge, M., & Hull, M. L. (1986). Analysis of EMG measurements during bicycle pedalling. *Journal of biomechanics*, *19*(9), 683-694.

Juker, D., McGILL, S., Kropf, P., & Steffen, T. (1998). Quantitative intramuscular myoelectric activity of lumbar portions of psoas and the abdominal wall during a wide variety of tasks. *Medicine and science in sports and exercise*, *30*(2), 301-310.

**K**

Kautz, S. A., Feltner, M. E., Coyle, E. F., & Baylor, A. M. (1991). The pedalling technique of elite endurance cyclists: changes with increasing workload at constant cadence. *International Journal of Sport Biomechanics*, *7*(1), 29-53.

Keele, S. W. (1968). Movement control in skilled motor performance. *Psychological bulletin*, *70*(6p1), 387.

Keele, S.W. (1998). Programming or planning conceptions of motor control speak to different phenomena than dynamical systems conceptions. In J.P. Piek (Ed.), *Motor behaviour and human skill* (pp. 403-405). Champaign, IL: Human Kinetics.

Keele, S. W., Cohen, A., & Ivry, R. (1990). Motor programs: Concepts and issues. In M. Jeannerod (Ed.) *Attention and performance XIII* (pp.77-110) Hillsdale, NJ: Erlbaum.

Kelso, J. A. S. (1981). On the oscillatory basis of movement. In *Bulletin of the psychonomic society* (Vol. 18, No. 2, pp. 63-63).

Kelso, J. A., & Jeka, J. J. (1992). Symmetry breaking dynamics of human multi-limb coordination. *Journal of experimental psychology: human perception and performance*, *18*(3), 645.

Kenefick, R. W., Mattern, C. O., Mahood, N. V., & Quinn, T. J. (2002). Physiological variables at lactate threshold under-represent cycling time-trial intensity. *Journal of Sports Medicine and Physical Fitness*, *42*(4), 396-402.

Knight, C. A. (2004) Neuromotor issues in the learning and control of golf skill. *Research quarterly for exercise and sport*, 75, 9-15.

Ko, J. H., Han, D. W., & Newell, K. M. (2017). Skill level constrains the coordination of posture and upper-limb movement in a pistol-aiming task. *Human movement science*, *55*, 255-263.

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of chiropractic medicine*, *15*(2), 155-163.

Kollmitzer J, Ebenbichler GR, Kopf A. Reliability of surface electromyographic measurements. *Clin Neurophysiol* 1999;110:725–34

Konczak, J., Vander Velden, H., & Jaeger, L. (2009). Learning to play the violin: motor control by freezing, not freeing degrees of freedom. *Journal of motor behavior*, *41*(3), 243-252.

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of chiropractic medicine*, *15*(2), 155-163.

Kornatz, K.W., Christou, E.A. and Enoka, R.M. (2005) *Practice reduces motor unit discharge variability in a hand muscle and improves manual dexterity in old adults.* Journal of Applied Physiology. 98(6), 2072-2080.

Kugler, P. N., Kelso, J. S., & Turvey, M. T. (1982). On the control and coordination of naturally developing systems. *The development of movement control and coordination*, *5*, 1-78.

Kurz, M. J., & Stergiou, N. (2002). Effect of normalization and phase angle calculations on continuous relative phase. *Journal of biomechanics*, *35*(3), 369-374.

Kurz, M. J., Stergiou, N., Buzzi, U. H., & Georgoulis, A. D. (2005). The effect of anterior cruciate ligament reconstruction on lower extremity relative phase dynamics during walking and running. *Knee Surgery, Sports Traumatology, Arthroscopy*, *13*(2), 107-115.

Kyle, C. R. (1990). Chain friction, windy hills and other quick calculations. *Cycling Sci*, *2*, 23-26.

**L**

Lambert, M. I., & Borresen, J. (2010). Measuring training load in sports. *International journal of sports physiology and performance*, *5*(3), 406-411.

Lamb, P. F., & Stöckl, M. (2014). On the use of continuous relative phase: Review of current approaches and outline for a new standard. *Clinical Biomechanics*, *29*(5), 484-493.

Langdown, B., Bridge, M. & Li, F. (2012) Movement variability in the golf swing. *Sports Biomechanics*, 11(2): 273–287.

Lanferdini, F. J., Jacques, T. C., Bini, R. R., & Vaz, M. A. (2014). Cyclists and triathletes do not differ in muscle volume, muscle recruitment or pedal force effectiveness. *Isokinetics and Exercise Science*, *22*(4), 279-286.

Lay, B. S., Sparrow, W. A., Hughes, K. M., & O'Dwyer, N. J. (2002). Practice effects on coordination and control, metabolic energy expenditure, and muscle activation. *Human movement science*, *21*(5-6), 807-830.

Lee, J., Wheeler, K., & James, D. A. (2019). *Wearable sensors in sport: a practical guide to usage and implementation*. Springer Singapore.

Lees, A. & Rahnama, N. (2014) Variability and typical error in the kinematics and kinetics of the maximal instep soccer kick. *Sports biomechanics*, 12(3), 283-292.

Legnani, G., Zappa, B., Casolo, F., Adamini, R., & Magnani, P. L. (2000). A model of an electro-goniometer and its calibration for biomechanical applications. *Medical engineering & physics*, *22*(10), 711-722.

Lehman, G. J., & McGill, S. M. (1999). The importance of normalization in the interpretation of surface electromyography: a proof of principle. *Journal of manipulative and physiological therapeutics*, *22*(7), 444-446.

Lepers, R., Maffiuletti, N. A., Rochette, L., Brugniaux, J., & Millet, G. Y. (2002). Neuromuscular fatigue during a long-duration cycling exercise. *Journal of applied physiology*, *92*(4), 1487-1493.

Lindstrom, L. (1970). Muscular fatigue and action potential conduction velocity changes studied with frequency analysis of EMG signals. *Electromyography*, *10*(4), 341-356.

Lucía, A., Hoyos, J., & Chicharro, J. L. (2000). The slow component of VO2 in professional cyclists. *British journal of sports medicine*, *34*(5), 367-374.

Lucia, A., Hoyos, J., & Chicharro, J. (2001). Preferred pedalling cadence in professional cycling. *Medicine and science in sports and exercise*, *33*(8), 1361-1366.

Lobbezoo, F., Van der Glas, H. W., Buchner, R., Van der Bilt, A., & Bosman, F. (1993). Gain and threshold of the jaw-jerk reflex in man during isometric contraction. *Experimental brain research*, *93*(1), 129-138.

**M**

Macintosh, B. R., Neptune, R. R., & Horton, J. F. (2000). Cadence, power, and muscle activation in cycle ergometry. *Medicine and science in sports and exercise*, *32*(7), 1281-1287.

Macnamara, B. N., Hambrick, D. Z., & Oswald, F. L. (2014). Deliberate practice and performance in music, games, sports, education, and professions: A meta-analysis. *Psychological science*, *25*(8), 1608-1618.

MacNeilage, P. F. (1970). Motor control of serial ordering of speech. *Psychological review*, *77*(3), 182.

Magill, R., & Anderson, D. (2010). *Motor learning and control*. New York: McGraw-Hill Publishing.

Martin, J. C., Milliken, D. L., Cobb, J. E., McFadden, K. L., & Coggan, A. R. (1998). Validation of a mathematical model for road cycling power. *Journal of applied biomechanics*, *14*(3), 276-291.

Mavor, M. P., Ross, G. B., Clouthier, A. L., Karakolis, T., & Graham, R. B. (2020). Validation of an IMU suit for military-based tasks. *Sensors*, *20*(15), 4280.

McClay, I., & Manal, K. (1997). Coupling parameters in runners with normal and excessive pronation. *Journal of Applied Biomechanics*, 13(1), 109-124.

McDermott, W. J., van Emmerik, R. E., & Hamill, J. (2000). Coordination between locomotion and breathing during running. *In ISBS-Conference Proceedings Archive* (Vol. 1, No. 1).

McLean, B. D., & Lafortune, M. A. (1989). Variation of mechanical parameters during bicycle pedalling. *Journal of Biomechanics*, *22*(10), 1053.

Merletti, R., Farina, D., Hermens, H., Frericks, B. and Harlaar, J. (1999a) ‘European recommendations for signal processing methods for surface electromyography’, in H.J. Hermens, B. Freriks, R. Merletti, D. Stegeman, J. Blok, G. Rau, C. DisselhorstKlug and G. Hägg (eds), European Recommendations for Surface Electromyography: Results of the SENIAM Project, Enschede: Roessingh Research and Development.

Merletti, R., Knaflitz, M., & De Luca, C. J. (1990). Myoelectric manifestations of fatigue in voluntary and electrically elicited contractions. *Journal of applied physiology*, *69*(5), 1810-1820.

Merletti, R., Wallinga, W., Hermens, H.J. and Freriks, B. (1999b) 'Guidelines for reporting SEMG data', in H.J. Hermens, B. Freriks, R. Merletti, D. Stegeman, J. Blok, G. Rau, C. Disselhorst-Klug and G. Hägg (eds), European Recommendations for Surface Electromyography: Results of the SENIAM Project, Enschede: Roessingh Research and DevelopmentMesin, L. (2020). Crosstalk in surface electromyogram: literature review and some insights. *Physical and Engineering Sciences in Medicine*, *43*(2), 481-492.

Mieras, M. E., Heesch, M. W., & Slivka, D. R. (2014). Physiological and psychological responses to outdoor vs. laboratory cycling. *The Journal of Strength & Conditioning Research*, *28*(8), 2324-2329.

Miller, S. A. (2002). Variability in basketball shooting: Practical implications. In Y. Hong (Ed.), International research in sports biomechanics (pp. 27–34). London: Routledge.

Miller, R. H., Meardon, S. A., Derrick, T. R., & Gillette, J. C. (2008). Continuous relative phase variability during an exhaustive run in runners with a history of iliotibial band syndrome. *Journal of Applied Biomechanics*, *24*(3), 262-270.

Minetti, A. E., Pinkerton, J., & Zamparo, P. (2001). From bipedalism to bicyclism: evolution in energetics and biomechanics of historic bicycles. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, *268*(1474), 1351-1360.

Mirka, G. A. (1991). The quantification of EMG normalization error. *Ergonomics*, *34*(3), 343-352.

Moreno, F. J., & Ordoño, E. M. (2015). Variability and practice load in motor learning. *RICYDE. Revista internacional de ciencias del deporte*, 39(11), 62-78.

Mornieux, G., Stapelfeldt, B., Gollhofer, A., & Belli, A. (2008). Effects of pedal type and pull-up action during cycling. *International journal of sports medicine*, *29*(10), 817-822.

Morris, M. E., Summers, J. J., Matyas, T. A., & Iansek, R. (1994). Current status of the motor program. *Physical therapy*, *74*(8), 738-748.

**N**

Newell K.M., Corcos D.M. Issues in variability and motor control. In: Newell C, ed. Variability and Motor Control. Champaign, IL: Human Kinetics; 1993:1-12.

Newmiller, J., Hull, M. L., & Zajac, F. E. (1988). A mechanically decoupled two force component bicycle pedal dynamometer. *Journal of Biomechanics*, *21*(5), 375-386.

Nigg, B. M. (2007). *Biomechanics of the musculo-skeletal system*. John Wiley & Sons Incorporated.

Norcross, M. F., Blackburn, J. T., & Goerger, B. M. (2010). Reliability and interpretation of single leg stance and maximum voluntary isometric contraction methods of electromyography normalization. *Journal of electromyography and kinesiology*, *20*(3), 420-425.

Nordeen-Snyder, K. S. (1977). The effect of bicycle seat height variation upon oxygen consumption and lower limb kinematics. *Medicine and Science in Sports*, 9(2), 113–117.

Novak, A. R., & Dascombe, B. J. (2016). Agreement of power measures between Garmin Vector and SRM cycle power meters. *Measurement in Physical Education and Exercise Science*, *20*(3), 167-172.

**O**

Ostler, L. M., Betts, J. A., & Gore, C. J. (2008). Gross cycling efficiency is not altered with and without toe-clips. *Journal of Sports Sciences*, 26, 47–55.

**P**

Padulo, J., Ayalon, M., Barbieri, F. A., Di Capua, R., Doria, C., Ardigò, L. P., & Dello Iacono, A. (2023). Effects of Gradient and Speed on Uphill Running Gait Variability. *Sports Health*, *15*(1), 67-73.

Palmer, G. S., Dennis, S. C., Noakes, T. D., & Hawley, J. A. (1996). Assessment of the reproducibility of performance testing on an air-braked cycle ergometer. *International journal of sports medicine*, *17*(04), 293-298.

Parro, J. (2014). Relationship between Surface and Indwelling EMG Spike Shape Measures.

Patterson, R. P., & Moreno, M. I. (1990). Bicycle pedalling forces as a function of pedalling rate and power output. *Medicine and science in sports and exercise*, *22*(4), 512-516.

Paton, C. D., & Hopkins, W. G. (2006). Variation in performance of elite cyclists from race to race. *European Journal of Sport Science*, *6*(01), 25-31.

Pearson, K. (1897). *On the scientific measure of variability*. McMillan and Company.

Peiffer, J. J., & Abbiss, C. R. (2010). The influence of elliptical chainrings on 10 km cycling time trial performance. *International Journal of Sports Physiology and Performance*, *5*(4), 459-468.

Perry, J., & Davids, J. R. (1992). Gait analysis: normal and pathological function. *Journal of Pediatric Orthopaedics*, *12*(6), 815.

Petrofsky, J. S. (1979). Frequency and amplitude analysis of the EMG during exercise on the bicycle ergometer. *European Journal of Applied Physiology and Occupational Physiology*, *41*(1), 1-15.

Payton, C. J., & Burden, A. (Eds.). (2017). *Biomechanical evaluation of movement in sport and exercise: the British Association of Sport and Exercise Sciences guide*. Routledge.

Peterson, C., Pyne, D., Portus, M., Karppinen, S. & Dawson, B. (2009). Variability in Movement Patterns During One Day Internationals by a Cricket Fast Bowler. *International Journal of Sports Physiology and Performance,* 4: 278-281.

Pearce, J. M. (2018). Lord Adrian, MD, PRS, OM. *European Neurology*, *79*(1-2), 64-67.

Pfau, T., Bruce, O., Edwards, W. B., & Leguillette, R. (2022). Stride frequency derived from GPS speed fluctuations in galloping horses. *Journal of Biomechanics*, 111364.

Phillips, K. E., & Hopkins, W. G. (2020). Determinants of cycling performance: a review of the dimensions and features regulating performance in elite cycling competitions. *Sports medicine-open*, *6*(1), 1-18.

Pollard, C., Heiderscheit, B., Van Emmerik, R. & Hamill, J. (2005) Gender differences in lower extremity coupling variability during an unanticipated cutting manoeuvre. *Journal of applied biomechanics*, 21**:** 143-152.

PowerTap Advanced pedal metrics explained. Available online: https://www.powertap.com/post/blog-16-powertap-advanced-pedal-metrics-explained (accessed on 3/2/2018).

Prilutsky, B. I., Gregor, R. J., & Ryan, M. M. (1998). Coordination of two-joint rectus femoris and hamstrings during the swing phase of human walking and running. *Experimental Brain Research*, *120*(4), 479-486.

Prilutsky, B. I., Herzog, W., & Leonard, T. (1996). Transfer of mechanical energy between ankle and knee joints by gastrocnemius and plantaris muscles during cat locomotion. *Journal of biomechanics*, *29*(4), 391-403.

Prins, L., Terblanche, E., & Myburgh, K. H. (2007). Field and laboratory correlates of performance in competitive cross-country mountain bikers. *Journal of Sports Sciences*, *25*(8), 927-935.

Purtsi, J., Vihko, V., Kankaanpää, A., & Havas, E. (2012). The motor-learning process of older adults in eccentric bicycle ergometer training. *Journal of aging and physical activity*, *20*(3), 345-362.

**Q**

Queen's Printer of Acts of Parliament. (n.d.). *The Health Protection (Coronavirus, Restrictions) (England) Regulations 2020*. https://www.legislation.gov.uk/uksi/2020/350/contents/made/data.htm

**R**

Raibert, M. H. (1977). *Motor control and learning by the state space model* (Doctoral dissertation, Massachusetts Institute of Technology).

Ramsey, D. K., & Wretenberg, P. F. (1999). Biomechanics of the knee: methodological considerations in the in vivo kinematic analysis of the tibiofemoral and patellofemoral joint. *Clinical biomechanics*, *14*(9), 595-611.

Rana, M., & Mittal, V. (2020). Wearable sensors for real-time kinematics analysis in sports: a review. *IEEE Sensors Journal*, *21*(2), 1187-1207.

Reeves, J., Starbuck, C., & Nester, C. (2020). EMG gait data from indwelling electrodes is attenuated over time and changes independent of any experimental effect. *Journal of Electromyography and Kinesiology*, *54*, 102461.

Robins, M., Wheat, J., Irwin, G., and Bartlett, R. (2006). The effect of shooting distance on movement variability in basketball*. Journal of Human Movement Studies*, 20: 218–238.

Rodano, R. and Squadrone, R. (2002) Stability of selected lower limb joint kinetic parameters during vertical jump. *Journal of Applied Biomechanics,* 18, 83-89.

Rosenbaum, D., Becker, H. P., Wilke, H. J., & Claes, L. E. (1998). Tenodeses destroy the kinematic coupling of the ankle joint complex: a three-dimensional in vitro analysis of joint movement. *The Journal of bone and joint surgery. British volume*, *80*(1), 162-168.

Rouffet, D. M., & Hautier, C. A. (2008). EMG normalization to study muscle activation in cycling. *Journal of Electromyography and Kinesiology*, *18*(5), 866-878.

Ryan, M. M., & Gregor, R. J. (1992). EMG profiles of lower extremity muscles during cycling at constant workload and cadence. *Journal of Electromyography and Kinesiology*, *2*(2), 69-80.

## S

Sanderson, D. J., & Black, A. (2003). The effect of prolonged cycling on pedal forces. *Journal of Sports Sciences*, 21, 191–199.

Sanderson, D. J. (1991). The influence of cadence and power output on the biomechanics of force application during steady-rate cycling in competitive and recreational cyclists. *Journal of Sports Sciences*, 9, 191–203. doi:10.1080/02640419108729880

Sanderson DJ, Amoroso AT (2009) The influence of seat height on the mechanical function of the triceps surae muscles during steady-rate cycling. Journal of Electromyography and Kinesiology 19 (6):e465-e471.

Sanderson, D. J., Hennig, E. M., & Black, A. H. (2000). The influence of cadence and power output on force application and in shoe pressure distribution during cycling by competitive and recreational cyclists. *Journal of Sports Sciences*, 18, 173–181. doi:10.1080/026404100365072

Sargeant AJ, Hoinville E, Young A. Maximum leg force and power output during short-term dynamic exercise. *J Appl Physiol* 1981;51:1175–82

Saunders, M. J., Evans, E. M., Arngrimsson, S. A., Allison, J. D., Warren, G. L., & Cureton, K. J. (2000). Muscle activation and the slow component rise in oxygen uptake during cycling. *Medicine and science in sports and exercise*, *32*(12), 2040-2045.

Savelberg HHCM, Van de Port IGL, Willems PJB (2003) Body Configuration in Cycling Affects Muscle Recruitment and Movement Pattern. Journal of Applied Biomechanics 19 (4):310-324

Schlage, N., Kitzig, A., Stockmanns, G., & Naroska, E. (2021). Development of a mobile, cost-effective and easy to use inertial motion capture system for monitoring in rehabilitation applications. *Current Directions in Biomedical Engineering*, *7*(2), 586-589.

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological review*, *82*(4), 225.

Schmidt, R.A. (1988) Motor and action perspectives on motor behaviour. In Meijer, O. G., & Roth, K. (Eds.). *Complex movement behaviour: 'The' motor-action controversy* (Vol. 50). Elsevier.

Schmidt, A. (1998). *Handbook of competitive cycling: Training, keep fit, tactics*. Meyer & Meyer Sport.

Schmidt, R. A. (2003). Motor schema theory after 27 years: Reflections and implications for a new theory. *Research quarterly for exercise and sport*, *74*(4), 366-375.

Schmidt, R. A., & Lee, T. D. (2018). *Motor learning and performance: from principles to application*. Human Kinetics.

Schmidt, R. A., Lee, T., Winstein, C., Wulf, G., & Zelaznik, H. (2018). *Motor Control and Learning: A Behavioural Emphasis, 6E*. Champaign, IL: Human kinetics.

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. *Anesthesia & Analgesia*, *126*(5), 1763-1768.

Scholz, J. P. (1990). Dynamic pattern theory – some implications for therapeutics. *Physical Therapy*, 70, 827–843.

Scholz, JP., Schöner, G. & Latash, ML. (2000) Identifying the control structures of multijoint coordination during pistol shooting. *Exp Brain Res*, 135: 382-404.

Schorer, J., Baker, J., Fath, F., & Jaitner, T. (2007). Identification of interindividual and intraindividual movement patterns in handball players of varying expertise levels. *Journal of motor behavior*, *39*(5), 409-421.

Schot, P. K., Hart, B. A. & Mueller, M. (2002) Within participant variation in landing kinetics: Movement behaviour trait or transient? *Research quarterly for exercise and sport,* 73, 450-456.

Seay, J. F., Van Emmerik, R. E., & Hamill, J. (2011). Low back pain status affects pelvis-trunk coordination and variability during walking and running. *Clinical biomechanics*, *26*(6), 572-578.

Seel, T., Raisch, J., & Schauer, T. (2014). IMU-based joint angle measurement for gait analysis. *Sensors*, *14*(4), 6891-6909.

Shamsi, M., Mirzaei, M., & Khabiri, S. S. (2019). Universal goniometer and electro-goniometer intra-examiner reliability in measuring the knee range of motion during active knee extension test in patients with chronic low back pain with short hamstring muscle. *BMC Sports Science, Medicine and Rehabilitation*, *11*(1), 1-5.

Shanker, S. & King, B. (2002). *The emergence of a new paradigm in ape language research. B*ehavioural and Brain Sciences, 25 (5), 605–656.

Shapiro, D.C (1977). A preliminary attempt to determine the duration of a motor program In D.M. Landers & R.W. Christina (Eds.), *Psychology of motor behaviour and sport.* (p. 17-24) Champaign, IL: Human Kinetics.

Sides, D., & Wilson, C. (2012). Intra-limb coordinative adaptations in cycling. *Sports biomechanics*, *11*(1), 1-9.

Simpson, G. G., Roe, A., & Lewontin, R. C. (2003). *Quantitative zoology*. Courier Corporation.

Smit, I., Parmentier, J. I. M., Spoormakers, T., Rovel, T., te Moller, N., & Braganca, F. S. (2022, June). Electrode positioning in the horse: towards standardisation of surface EMG measurements. In *11th International Conference on Equine Exercise Physiology 2022*.

Smith, M. F., Davison, R. C. R., Balmer, J., & Bird, S. R. (2001). Reliability of mean power recorded during indoor and outdoor self-paced 40 km cycling time-trials. *International journal of sports medicine*, *22*(04), 270-274.

Smith J, Padgett DJ, Dahm DL, Kaufman KR, Harrington SP, Morrow DA, et al. Electromyographic activity in the immobilized shoulder girdle musculature during contralateral upper limb movements. *J Shoulder Elbow Surg.* 2004;13:583–8.

So, R. C., Ng, J. K. F., & Ng, G. Y. (2005). Muscle recruitment pattern in cycling: a review. *Physical therapy in sport*, *6*(2), 89-96.

Soden, P. D., & Adeyefa, B. A. (1979). Forces applied to a bicycle during normal cycling. *Journal of Biomechanics*, *12*(7), 527-541.

Soderberg, G. L., & Knutson, L. M. (2000). A guide for use and interpretation of kinesiologic electromyographic data. *Physical therapy*, *80*(5), 485-498.

Solomonow, M., Baratta, R., Bernardi, M., Zhou, B., Lu, Y., Zhu, M., & Acierno, S. (1994). Surface and wire EMG crosstalk in neighbouring muscles. *Journal of Electromyography and Kinesiology*, *4*(3), 131-142.

Sparrow, W. A., Donovan, E., Van Emmerik, R., & Barry, E. B. (1987). Using relative motion plots to measure changes in intra-limb and inter-limb coordination. *Journal of motor behavior*, 19(1), 115-129.

Sporns, O., & Edelman, G. M. (1993). Solving Bernstein's problem: A proposal for the development of coordinated movement by selection. *Child development*, *64*(4), 960-981.

Stagni, R., Fantozzi, S., Cappello, A., & Leardini, A. (2005). Quantification of soft tissue artefact in motion analysis by combining 3D fluoroscopy and stereophotogrammetry: a study on two subjects. *Clinical biomechanics*, *20*(3), 320-329.

Stapelfeldt, B., Mornieux, G., Oberheim, R., Belli, A., & Gollhofer, A. (2007). Development and evaluation of a new bicycle instrument for measurements of pedal forces and power output in cycling. *International journal of sports medicine*, *28*(04), 326-332.

Stevens, C. J., & Dascombe, B. J. (2015). The reliability and validity of protocols for the assessment of endurance sports performance: an updated review. *Measurement in Physical Education and Exercise Science*, *19*(4), 177-185.

Summers, J. J., & Anson, J. G. (2009). Current status of the motor program: Revisited. *Human Movement Science*, *28*(5), 566-577.

Swain, D. P. (1997). A model for optimizing cycling performance by varying power on hills and in wind. *Medicine and science in sports and exercise*, *29*(8), 1104-1108.

**T**

Taylor, P., Landeo, R. & Coogan, J. (2014) Intra-individual movement variability within the 5 m water polo shot. *Journal of Applied Biomechanics*, 30: 477-482.

Thelen, E. & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action.* Cambridge, MA: MIT Press.

Too, D. (1990). Biomechanics of cycling and factors affecting performance. *Sports medicine*, *10*(5), 286-302.

Trezise, J., Bartlett, R., & Bussey, M. (2011). Coordination variability changes with fatigue in sprinters. *International Journal of Sports Science & Coaching*, *6*(3), 357-363.

Tucker, C., Anderson, R. & Kenny, I. (2013) Is outcome related to movement variability in golf? *Sports Biomechanics*, 12(4): 343-354.

Tucker, R., Rauch, L., Harley, Y. X., & Noakes, T. D. (2004). Impaired exercise performance in the heat is associated with an anticipatory reduction in skeletal muscle recruitment. *Pflügers Archiv*, *448*(4), 422-430.

Turpin, N. A., & Watier, B. (2020). Cycling biomechanics and its relationship to performance. *Applied Sciences*, *10*(12), 4112.

Turvey, M. T. (1977). Preliminaries to a theory of action with reference to vision. *Perceiving, acting and knowing*, *2*.

**U**

Umberger, B. R., & Martin, P. E. (2001). Testing the planar assumption during ergometer cycling. *Journal of Applied Biomechanics*, *17*(1), 55-62.

**V**

Van Bolhuis, B. M., & Gielen, C. C. A. M. (1999). A comparison of models explaining muscle activation patterns for isometric contractions. *Biological cybernetics*, *81*(3), 249-261.

Van den Noort, J. C., Scholtes, V. A., & Harlaar, J. (2009). Evaluation of clinical spasticity assessment in cerebral palsy using inertial sensors. *Gait & posture*, *30*(2), 138-143.

Van Emmerik, R., Hamill, J. & McDermott, W. (2005) Variability and Coordinative Function in Human Gait. *QUEST (National Association for Kinesiology and Physical Education in Higher Education).* 57: 102-123.

Van Emmerik, R. E., Rosenstein, M. T., McDermott, W. J., & Hamill, J. (2004). A nonlinear dynamics approach to human movement. *Journal of Applied Biomechanics*, *20*(4), 396-420.

Van Emmerik, R. E., & Van Wegen, E. E. (2000). On variability and stability in human movement. *Journal of Applied Biomechanics*, *16*(4), 394-406.

Van Gelder, T. (1998). *The dynamical hypothesis in cognitive science*. Behavioural and Brain Sciences, 21, 615–656.

van Ingen Schenau, G. J., Boots, P. J. M., De Groot, G., Snackers, R. J., & Van Woensel, W. W. L. M. (1992). The constrained control of force and position in multi-joint movements. *Neuroscience*, *46*(1), 197-207.

Vereijken, B. Whiting, H.T.A. Newell, K.M. (1992) Free(z)ing degrees of freedom in skill acquisition. *Journal of Motor Behaviour.*24 (1). 133-142.

Von Tscharner, V. (2002). Time–frequency and principal-component methods for the analysis of EMGs recorded during a mildly fatiguing exercise on a cycle ergometer. *Journal of Electromyography and Kinesiology*, *12*(6), 479-492.

**W**

Wagner, H., Pfusterschmied, J., Klous, M., von Duvillard, S. P., & Müller, E. (2012). Movement variability and skill level of various throwing techniques. *Human movement science*, *31*(1), 78-90.

Wagoner, B. (2013). Bartlett's concept of schema in reconstruction. *Theory & Psychology*, *23*(5), 553-575.

Wainwright, B., Cooke, C. B., & O'Hara, J. P. (2017). The validity and reliability of a sample of 10 Wattbike cycle ergometers. *Journal of sports sciences*, *35*(14), 1451-1458.

Wei, W., Kurita, K., Kuang, J., & Gao, A. (2021, November). Real-Time Limb Motion Tracking with a Single IMU Sensor for Physical Therapy Exercises. In *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 7152-7157). IEEE.

Wheeler, J. B., Gregor, R. J., & Broker, J. P. (1995). The effect of clipless float design on shoe/pedal interface kinetics and overuse knee injuries during cycling. *Journal of applied biomechanics*, *11*(2), 119-141.

*WHO statement on cases of COVID-19 surpassing 100 000*. (2020, March 7). https://www.who.int/news/item/07-03-2020-who-statement-on-cases-of-covid-19-surpassing-100-000

Williams, AM., Davids, K. & Williams, JG. (1999). *Visual perception and action in sport*. London: Routledge, Taylor & Francis.

Wilson, C., & Bush, T. R. (2007). Interface forces on the seat during a cycling activity. *Clinical Biomechanics*, *22*(9), 1017-1023.

Wilson, C., Simpson, S., Van Emmerik, R. & Hamill, J. (2008) Coordination variability and skill development in expert triple jumpers. *Sports Biomechanics*, 7(1): 2–9.

Wozniak-Timmer, C. A. (1991). Cycling biomechanics: a literature review. *Journal of Orthopaedic & Sports Physical Therapy*, *14*(3), 106-113.

Wright, B. O. (2021, January 29). *Coronavirus: How the UK dealt with its first Covid case*. BBC News. https://www.bbc.co.uk/news/uk-england-55622386

Wu, W.F.W, Porter, J.M., Partridge, J.A., Young, M.A. & Newman, N. (2012) Practice Variability and Training Design: Strategies of Elite Horizontal Jump Coaches. *Sport Science Review*, 21(5): 113 – 127.

**X**

Xu, Y., Wang, K., Jin, Y., Qiu, F., Yao, Y., & Xu, L. (2022). Influence of electrode configuration on muscle-fiber-conduction-velocity estimation using surface electromyography. *IEEE Transactions on Biomedical Engineering*, *69*(8), 2414-2422.

**Y**

Yang, C., Bouffard, J., Srinivasan, D., Ghayourmanesh, S., Cantú, H., Begon, M., & Côté, J. N. (2018). Changes in movement variability and task performance during a fatiguing repetitive pointing task. *Journal of biomechanics*, *76*, 212-219.

**Z**

Zommers, A. (2000). *Variations in pedalling technique of competitive cyclists: the effect on biological efficiency* (Doctoral dissertation, Victoria University of Technology).

## 9. APPENDIX I

sports

**Chris Whittle [1], Neal Smith [2] and Simon A. Jobson [1,*]**

[1] Department of Sport, Exercise and Health, University of Winchester, Sparkford Road, Winchester SO22 4NR, UK; Chris.Whittle@winchester.ac.uk

[2] Department of Sport & Exercise Sciences, University of Chichester, College Lane, Chichester PO19 6PE, UK; N.Smith@chi.ac.uk

* Correspondence: Simon.Jobson@winchester.ac.uk; Tel.: +44-(0)1962-827516

Received: 1 August 2018; Accepted: 30 August 2018; Published: 5 September 2018

**Abstract:** The use of mobile power measuring devices has become widespread within cycling, with a number of manufacturers now offering power measuring pedals. This study aimed to investigate the validity of PowerTap P1 pedals by comparing them with the previously validated Wattbike ergometer. Ten trained cyclists performed three simulated 10-mile (16-km) time trials on a Wattbike,

while using PowerTap P1 pedals. There were no statistically significant differences ($p > 0.05$) between PowerTap P1 pedals and a Wattbike for maximum, minimum, and mean power output, or for maximum, minimum, and mean cadence. There were good to excellent levels of agreement between the PowerTap P1 pedals and Wattbike (ICC > 0.8) for all measured variables except minimum cadence

(ICC = 0.619). This suggests that PowerTap P1 pedals provide a valid measurement of power output.

**Keywords:** power output; cadence; power meter; mobile dynamometer

---

### 1. Introduction

Laboratory-based testing must be conducted upon the assumption of accurate and reliable data collection. To this end, a number of cycle ergometers have been validated for use within laboratory settings, including the Wattbike (Wattbike Ltd., Nottingham, UK), which has been shown to be both valid and reliable across a range of testing protocols.

For trained cyclist populations, the Wattbike has been reported to have a coefficient of variation (CV) of 2.6% [1] and to afford “highly reproducible” results during 30-s sprint and 4-min performance test protocols [2]. In addition, the Wattbike demonstrates high levels of intra-day and inter-day reliability [2] and no significant difference between measures of power output recorded in test–retest conditions [3]. As such, the Wattbike is considered to be an accurate and reliable tool for training and performance assessments, but there is a growing acknowledgement that laboratory-based research may not possess adequate levels of ecological validity [4–11].

Researchers have reported differences of up to 8% between indoor cycling performance and an equivalent outdoor event [8–11]. This would suggest that, despite the validity of the Wattbike, laboratory protocols do not accurately replicate “real-world” performance. As such, it has become increasingly important to be able to measure power output during outdoor cycling events using a range of devices designed to be fitted to the athlete’s own bicycle rather than relying only on laboratory-based measures.

The Schoberer Rad Messtechnik (SRM) device, which consists of a number of rotational strain gauges housed between the crank spindle and chain ring interface, has become the “gold standard” device for mobile power measurement applications due to its high validity and reliability [12–15] and the ability to collect valid and reliable data during actual sporting performance while using the cyclist’s bicycle. This is not to say that it is without limitations as the SRM device remains prohibitively expensive for most recreational-level participants and there are also potential compatibility issues due to the wide range of bottom bracket standards currently employed by bicycle manufacturers. In addition, the device itself requires a certain level of mechanical competency to install correctly and requires manufacturer-based servicing for battery replacements [16]. These issues, along with the suggestion that when using this style of device there may be potential distortion of the crank arms, which would lead to systematic error in torque measurement [17], have led to the development of alternative mobile power measurement devices.

One example of this is power measuring pedals, such as Garmin Vector pedals (Garmin, Schaffhausen, Switzerland), which, instead of containing strain gauges in the crank arms, house them within each pedal body. Not only does this allow power measurement to be differentiated between right and left—something that is only possible with additional computation modules when using the SRM device—it also removes the potential influence of crank distortion. In addition, pedals-based devices are almost universally compatible, regardless of the individual bicycle componentry, which affords the potential to transfer between bicycles, with limited mechanical experience required for installation or maintenance.

Garmin Vector pedals have been compared with the SRM device and have been shown to report non-statistically significant differences in power output [16] and to give reproducible results across a range of power outputs and various cycling efforts, such as sub-maximal incremental tests, sub-maximal 30-min continuous tests and sprint tests [18]. It has been noted, however, that they increasingly overestimate at higher power outputs, whilst underestimating during sprints with a low gear ratio and during a 2-h road cycling session on hilly terrain [18]. This would suggest that data from Garmin Vector pedals should be treated with some caution.

One, largely unresearched, alternative to the Garmin Vector pedals is the P1 pedals system by PowerTap (Madison, WI, USA). The PowerTap P1 pedals have four pairs of strain gauges per pedal to measure applied force at the pedal body in both the vertical and horizontal planes and Hall effect sensors attached to the pedal axle, which results in a claimed 40 measurement points per pedal stroke [19]. In addition, the PowerTap P1 pedals have a temperature sensor at the point of force measurement. This allows for automatic accommodation for changes in temperature in an effort to avoid measurement error due to changes in environmental conditions during data collection and is something which, to the best of the authors' knowledge, is not present in any of the other devices mentioned here.

Despite the popularity of power measuring pedals and the number of papers examining the validity of the Garmin Vector pedals, there has been little published on the validity of the PowerTap P1 pedals with, to the authors' knowledge, only one study comparing PowerTap P1 pedals with the SRM device [20]. These researchers evaluated the pedals during both sub-maximal incremental test and sprint test protocols in a small ($n$ = 5) experimental cohort. Though such protocols can provide valuable insight, it has been observed that "constant work" or "time trial" type tests, where the cyclist is required to complete a set distance in the shortest time possible, provide more appropriate simulations of the bioenergetics of most competitive events lasting several minutes or more [21].

The aim of this study, therefore, was to assess the validity of the PowerTap P1 pedals by comparing them with the previously validated Wattbike cycle ergometer during self-paced, simulated time trials.

## 2. Materials and Methods

### 2.1. Participants

Ten trained cyclists (9 male, 1 female) (mean ± standard deviation (SD): 31 ± 10 years; 1.80 ± 0.10 m; 72 ± 9 kg, maximum power output 366 ± 69 W) volunteered to take part in the study. All cyclists held a current British Cycling Race Licence and maintained their normal diet and daily activity patterns throughout the test period. All participants gave written informed consent before taking part in the study, which had local ethics committee approval.

### 2.2. Procedure

Participants visited the laboratory on 3 separate occasions, separated by a minimum of 48 h to allow full recovery from the previous trial. Each visit consisted of a self-directed warm up followed by a simulated 10-mile (16-km) time trial and self-directed cool down. Time trials were conducted from a standing start and participants were given free choice of gearing and cadence throughout. All trials were conducted in an air-conditioned laboratory using a standard Wattbike Pro cycle ergometer (Wattbike Ltd., Nottingham, UK), with PowerTap P1 pedals (CycleOps, Madison, WI, USA),

which were zeroed before each ride, in line with manufacturer recommendations. Participants used their own cycling shoes and those who normally rode with cleats incompatible with the PowerTap pedals had their cleat position replicated with 3 bolt Kéo cleats (Look cycle international, Nevers, France). The ergometer was set to, as closely as possible, replicate the dimensions of each participant's own bicycle.

### 2.3. Data Analysis

Power output and cadence were recorded for the duration of the time trials by a Garmin Edge 1000 head unit (Garmin, Schaffhausen, Switzerland) and the ergometer's display unit for the PowerTap pedals and Wattbike respectively. The Garmin data were then exported to third party open source analysis software, Golden Cheetah [22], and Wattbike data was analysed using Wattbike Expert software (Wattbike Ltd., Nottingham, UK), where it was displayed as a single value per second.

Technical issues during some testing sessions meant that a small number of incomplete data sets were recorded by the Wattbike. Affected trials were removed from the study, which did not alter the number of participants tested but did result in only 20 of the 30 trials performed being analysed.

Mean, maximum, and minimum power outputs and mean, maximum, and minimum cadences were calculated, checked for normality and compared between equipment using paired samples T-tests. Effect sizes were calculated for these tests by calculating the mean difference between the two measures and then dividing the result by the pooled standard deviation.

A Bland and Altman 95% limits of agreement (LoA) analysis quantified the agreement (bias and random error) between measurement equipment. In accordance with recommendations for carrying out LoA analysis [19,23], the data were checked for heteroscedasticity via a Levene's test and LoA analysis was followed by intra-class correlation coefficients (ICC) via the two-way mixed model to quantify the consistency of the power and cadence measurements between PowerTap P1 pedals and Wattbike.

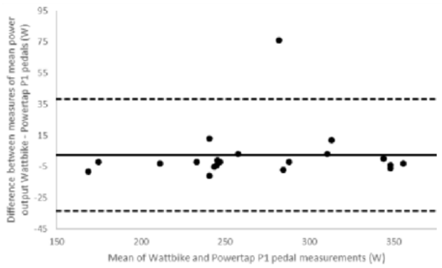
All statistical testing was performed using IBM SPSS statistics version 24 (IMB Corporation, New York, NY, USA), with a significance level set at $p < 0.05$.

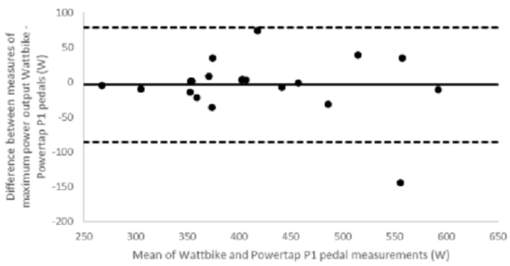
**3. Results**

Levene's test revealed a lack of heteroscedasticity ($p > 0.05$) and the results of paired samples T-tests showed no statistically significant differences between the PowerTap P1 pedals and the Wattbike in any of the measured variables: mean power output, minimum power output, maximum power output, mean cadence, minimum cadence or maximum cadence ($p > 0.05$).

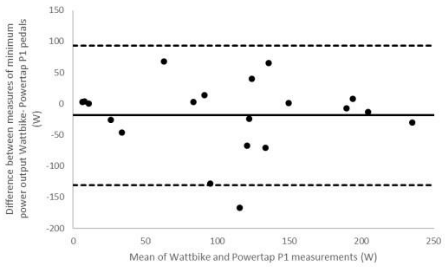
For the purpose of clarity, limits of agreement (LoA) results are reported in the format: Bias ± SD (upper confidence interval (CI), lower CI), where the bias represents the mean difference between the measurement methods and the lower and upper confidence intervals were calculated as Bias ± 1.96 × SD. This is followed by a value for the intraclass correlation coefficient (ICC).

Limits of Agreement analyses resulted in values of: 2.35 ± 18.3 W (CI: 33.5 and 38.2) and an ICC of 0.973 for mean power output (Figure 1a); −3.95 ± 41.8 W (CI: 86.0 and 78.1) and an ICC of 0.944 for maximum power output (Figure 1b) and −18.65 ± 57.2 W (CI: 130.7 and 93.4) and an ICC of 0.816 for minimum power output (Figure 1c). Cadence analysis showed 0.25 ± 3.8 rev·min$^{-1}$ (CI: 7.2 and 7.7) and an ICC of 0.864 for mean cadence (Figure 2a); 1.05 ± 2.6 rev·min$^{-1}$ (CI: 4.1 and 6.2) and an ICC of 0.960 for maximum cadence (Figure 2b); and −1.00 ± 23.9 rev·min$^{-1}$ (CI: 47.8 and 45.9) and an ICC of 0.619 for minimum cadence (Figure 2c).



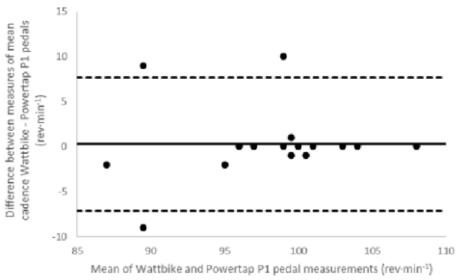



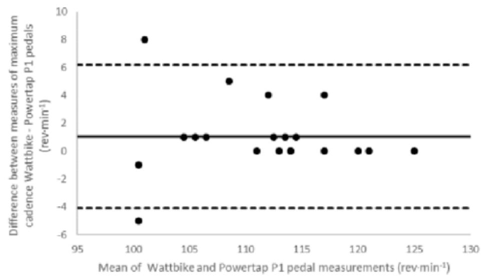

(**a**) (**b**)



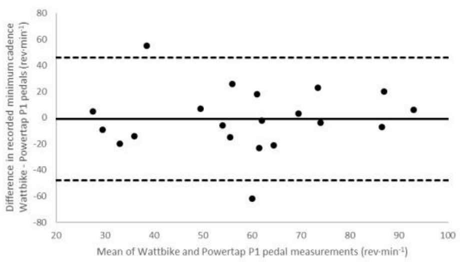

(**c**)

**Figure 1.** Bland-Altman plots for (**a**) mean power output (**b**) maximum power output and (**c**) minimum power output. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in power output reported between the two measurement methods).




(**a**) (**b**)




(**c**)

**Figure 2.** Bland-Altman plots for (**a**) mean cadence (**b**) maximum cadence and (**c**) minimum cadence. Dashed lines represent the high and low 95% confidence intervals, the solid line shows the bias (the mean difference in cadence reported between the two measurement methods).

## 4. Discussion

The aim of this study was to assess the validity of measurements by PowerTap P1 pedals during simulated time trial performances. Difference testing suggested no statistically significant differences between the PowerTap P1 pedals and the Wattbike ergometer for any of the recorded variables.

The PowerTap P1 pedals underreported maximum power output values by 3.95 W, while overestimating mean power output values by 2.35 W in comparison to the previously validated Wattbike [1]. This represents a −0.94% difference for maximum power output and 0.88% difference for mean power output, both of which are lower than the −1.5% difference reported by Czajkowski et al. [20]. Although it is important to note that Czajkowski et al. [20] conducted both sub-maximal incremental test and sprint test protocols—in contrast to the simulated time trial used here—it would appear that there is a greater level of agreement between the Wattbike and PowerTap P1 pedals investigated in the current study than was reported between the PowerTap P1 pedals and the SRM by Czajkowski et al. [20].

In contrast, the PowerTap P1 pedals appear to have underreported minimum power output by an average of 18.65 W, a 16.03% difference between the two measurement methods. Although this appears to be a large difference, it is statistically non-significant and this variable is likely to be of little interest to cyclists in the field.

The levels of agreement shown in this study compare favourably with previously reported values [18] gathered during both submaximal incremental and continuous 30-min testing protocols to compare the data produced by Garmin Vector pedals and the SRM device. During incremental tests, non-significant differences in mean power output between devices were found [18], with LoA analysis highlighting a bias of 13.7 ± 12.4 W and 0.6 ± 6.2 W between the SRM and Stages systems and the SRM and Vector pedals, respectively. The 30-min continuous test more closely resembles the time trial effort evaluated in the current study and also produced no significant difference between the mean power outputs recorded. It was noted, however, that the Garmin Vector underestimated mean power output by 16.5% compared to the SRM. Given that a 0.88% difference for mean power output was recorded in the current study, it would appear that the PowerTap P1 pedals agree more closely with the Wattbike than do Garmin Vector pedals with the SRM.

Further support for the validity of the PowerTap P1 pedals is provided by consideration of ICC results. ICC values less than 0.5, between 0.5 and 0.75, between 0.75 and 0.9, and greater than 0.90 are suggested to be indicative of poor, moderate, good, and excellent levels of agreement between measures, respectively [24]. As such, it can be suggested that there are excellent levels of agreement between the PowerTap P1 pedals and the Wattbike for maximum cadence (0.960), maximum power output (0.944) and mean power output (0.973). These are followed by good reliability for mean cadence (0.864) and minimum power output (0.816) and moderate reliability for minimum cadence (0.619).

The differences between systems seen in this study in terms of minimum power output may be the result of a lack of synchronisation at their point of measurement as the Powertap P1 pedals claim 40 measurement points per pedal stroke [19], compared to two measurement points by the Wattbike [1]. Alternatively, the discrepancy may be the result of differences in how the two systems measure force.

The Wattbike calculates force via the use of chain tension over a load cell, whereas the PowerTap P1 pedals have four pairs of strain gauges per pedal to measure applied force at the pedal body in both the vertical and horizontal planes. Regardless of the reason for this variation in measurements, these results suggest that caution should be employed when investigating minimum power output values using the PowerTap P1 pedals, although the authors would repeat that this variable is likely to be of little interest to cyclists or researchers using the PowerTap P1 pedals in the future.

It is acknowledged that the sample size for the current study ($n$ = 10) could be viewed as a potential limitation. It is worth noting, however, that mean calculated effect sizes for this study were 0.11 for power output variables and 0.08 for cadence variables. With such small differences between measures it was calculated that 896 participants would be required for power output variables and 1693 for cadence variables before the level of difference seen here became statistically significant at an alpha level of $p < 0.05$.

In addition, although all participants were experienced cyclists who held a British cycling race licence, none were time trial specialists. This may have led to issues with pacing strategy and power production during the testing protocol as it has previously been shown 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 [11]. In the current study this was not a significant concern due to the concurrent nature of the measurements. As such, the results described here would suggest that the PowerTap P1 pedals are a viable alternative to the SRM device for mobile power measurement applications.

**5. Conclusions**

There are no statistically significant differences between PowerTap P1 pedals and a Wattbike when measuring maximum, minimum, and mean power output or when measuring maximum, minimum, and mean cadence during a laboratory-based time trial. In addition, there are good to excellent levels of agreement between the PowerTap P1 pedals and Wattbike (ICC > 0.8) for all variables except minimum cadence. This study suggests that PowerTap P1 pedals are valid for measurement applications within a laboratory setting but further investigation is needed during real cycling locomotion in the field to assess their usage in outdoor applications.

**Author Contributions:** Conceptualisation, C.W., N.S. and S.A.J.; data curation, C.W.; formal analysis, C.W.; investigation, C.W.; methodology, C.W., N.S. and S.A.J.; project administration, C.W.; validation, N.S. and S.A.J.; writing-original draft, C.W.; writing-review & editing, N.S. and S.A.J.

**Funding:** This research received no external funding.

**Acknowledgments:** The authors would like to thank all the participants who volunteered their time to take part.

**Conflicts of Interest:** The authors declare no conflict of interest.

## 5. References

1. Hopker, J.; Myers, S.; Jobson, S.A.; Bruce, W.; Passfield, L. Validity and reliability of the Wattbike cycle ergometer. *Int. J. Sports Med.* **2010**, *31*, 731–736. [CrossRef] [PubMed]
2. Driller, M.W.; Argus, C.K.; Bartram, J.C.; Bonaventura, J.; Martin, D.T.; West, N.P.; Halson, S.L. Reliability of a 2-bout exercise test on a Wattbike cycle ergometer. *Int. J. Sports Physiol. Perform.* **2014**, *9*, 340–345. [CrossRef] [PubMed]
3. Wainwright, B.; Brian Cooke, C.; Paul O'Hara, J. The validity and reliability of a sample of 10 Wattbike cycle ergometers. *J. Sports Sci.* **2016**, *35*, 1451–1458. [CrossRef] [PubMed]
4. Bertucci, W.; Grappe, F.; Groslambert, A. Laboratory versus outdoor cycling conditions: Differences in pedaling biomechanics. *J. Appl. Biomech.* **2007**, *23*, 87–92. [CrossRef] [PubMed]
5. Mieras, M.E.; Heesch, M.W.; Slivka, D.R. Physiological and psychological responses to outdoor vs. laboratory cycling. *J. Strength Cond. Res.* **2014**, *28*, 2324–2329. [CrossRef] [PubMed]
6. Prins, L.; Terblanche, E.; Myburgh, K.H. Field and laboratory correlates of performance in competitive cross-country mountain bikers. *J. Sports Sci.* **2007**, *25*, 927–935. [CrossRef] [PubMed]
7. Stevens, C.J.; Dascombe, B.J. The reliability and validity of protocols for the assessment of endurance sports performance: An updated review. *Meas. Phys. Educ. Exerc. Sci.* **2015**, *19*, 177–185. [CrossRef]
8. Jobson, S.A.; Nevill, A.M.; Palmer, G.S.; Jeukendrup, A.E.; Doherty, M.; Atkinson, G. The ecological validity of laboratory cycling: Does body size explain the difference between laboratory-and field-based cycling performance? *J. Sports Sci.* **2007**, *25*, 3–9. [CrossRef] [PubMed]
9. Palmer, G.S.; Dennis, S.C.; Noakes, T.D.; Hawley, J.A. Assessment of the reproducibility of performance testing on an air-braked cycle ergometer. *Int. J. Sports Med.* **1996**, *17*, 293–298. [CrossRef] [PubMed]
10. Smith, M.F.; Davison, R.C.R.; Balmer, J.; Bird, S.R. Reliability of mean power recorded during indoor and outdoor self-paced 40 km cycling time-trials. *Int. J. Sports Med.* **2001**, *22*, 270–274. [CrossRef] [PubMed]
11. Coakley, S.L.; Passfield, L. Cycling performance is superior for time-to-exhaustion versus time-trial in endurance laboratory tests. *J. Sports Sci.* **2017**, *36*, 1228–1234. [CrossRef] [PubMed]
12. Abbiss, C.R.; Quod, M.J.; Levin, G.; Martin, D.T.; Laursen, P.B. Accuracy of the Velotron ergometer and SRM power meter. *Int. J. Sports Med.* **2009**, *30*, 107–112. [CrossRef] [PubMed]
13. Gardner, A.S.; Stephens, S.; Martin, D.T.; Lawton, E.; Lee, H.; Jenkins, D. Accuracy of SRM and power tap power monitoring systems for bicycling. *Med. Sci. Sports Exerc.* **2004**, *36*, 1252–1258. [CrossRef] [PubMed] 14. Jones, S.M.;

Passfield, L. The dynamic calibration of bicycle power measuring cranks. *Eng. Sport* **1998**, 265–274. Available online: https://kar.kent.ac.uk/27863/ (accessed on 1 July 2017).

15. Martin, J.C.; Milliken, D.L.; Cobb, J.E.; McFadden, K.L.; Coggan, A.R. Validation of a mathematical model for road cycling power. *J. Appl. Biomech.* **1998**, *14*, 276–291. [CrossRef] [PubMed]
16. Novak, A.R.; Dascombe, B.J. Agreement of power measures between Garmin vector and SRM cycle power meters. *Meas. Phys. Educ. Exerc. Sci.* **2017**, *20*, 167–172. [CrossRef]
17. Kyle, C.R. Chain friction, windy hills and other quick calculations. *Cycl. Sci.* **1990**, *2*, 23–26.
18. Bouillod, A.; Pinot, J.; Soto-Romero, G.; Bertucci, W.; Grappe, F. Validity, Sensitivity, Reproducibility, and Robustness of the PowerTap, Stages, and Garmin Vector Power Meters in Comparison With the SRM Device. *Int. J. Sports Physiol. Perform.* **2017**, *12*, 1023–1030. [CrossRef] [PubMed]
19. PowerTap Advanced Pedal Metrics Explained. Available online: https://www.powertap.com/post/blog16-powertap-advanced-pedal-metrics-explained (accessed on 3 February 2018).
20. Czajkowski, M.; Bouillod, A.; Dauriannes, A.; Soto-Romero, G.; Grappe, F. Validity and reproducibility of the Powertap P1 power meter when compared with SRM device. *J. Sci. Cycl.* **2016**, *5*, 9–10.
21. Hopkins, W.G.; Schabort, E.J.; Hawley, J.A. Reliability of power in physical performance tests. *Sports Med.* **2001**, *31*, 211–234. [CrossRef] [PubMed]
22. Golden Cheetah. Open Source Power Analysis Cycling Software, General Public Licence. Available online: http://www.goldencheetah.org/ (accesses on 20 October 2017).
23. Atkinson, G.; Nevill, A.M. Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Med.* **1998**, *26*, 217–238. [CrossRef] [PubMed]
24. Koo, T.K.; Li, M.Y. A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *J. Chiropr. Med.* **2016**, *15*, 155–163. [CrossRef] [PubMed]

# 10. APPENDIX II

sensors

*Communication*

# Validity of Calculating Continuous Relative Phase during Cycling from Measures Taken with Skin-Mounted Electro-Goniometers †

Chris Whittle 1,*, Simon A. Jobson 1 and Neal Smith 2

check for updates

**Citation:** Whittle, C.; Jobson, S.A.; Smith, N. Validity of Calculating Continuous Relative Phase during Cycling from Measures Taken with Skin-Mounted Electro-Goniometers. *Sensors* **2022**, *22*, 4371. https:// doi.org/10.3390/s22124371

Academic Editors: Giuseppe Vannozzi, Zimi Sawacha and Andrea Merlo

Received: 21 March 2022 Accepted: 29 May 2022
Published: 9 June 2022



[1] School of Sport, Health and Community, University of Winchester, Winchester SO22 4NR, UK; simon.jobson@winchester.ac.uk
[2] Chichester Institute of Sport, University of Chichester, Chichester PO19 6PE, UK; n.smith@chi.ac.uk
* Correspondence: chris.whittle@winchester.ac.uk

† This paper is an extended version of our paper published in Book of Abstracts. In Proceedings of the 25th Annual Congress of the European College of Sport Science, Seville, Spain, 28–30 October 2020.

**Abstract:** The aim of this study was to assess the validity of electro-goniometers as a tool for recording continuous relative phase data at two joint couplings during cycling tasks at a range of cadences. Seven participants (4 male, 3 female, age: 29 ± 7 years, height: 1.76 ± 0.10 m, mass: 71.97 ± 11.57 kg) performed exercise bouts of 30 s at four prescribed cadences (60, 80, 100, 120 rev·min$^{-1}$) on a stationary ergometer (Wattbike, Nottingham, UK). Measures were synchronously recorded by bi-axial electro-goniometers (Biometrics, UK) and a 12-camera motion-capture system (Qualisys, Gothenburg, Sweden), with both systems sampling at 500 Hz. Sagittal plane joint angle and joint angular velocity were recorded at the hip, knee and ankle and analysed for ten complete pedal revolutions per participant per condition. Data were interpolated to 100 time points and used to calculate mean continuous relative phase (CRP) per pedal revolution at two intra-limb couplings: (i) knee flexion/extension– ankle plantarflexion/dorsiflexion (KA) and (ii) hip flexion/extension–knee flexion/extension (HK). At the KA coupling, significant differences in mean CRP were found between measurement systems at 120 rev·min$^{-1}$ ($p = 0.006$). At the HK coupling, significant differences in mean CRP were found between measurement systems at 80 rev·min$^{-1}$ ($p = 0.043$) and 100 rev·min$^{-1}$ ($p = 0.028$). ICC values for most comparisons were below 0.5, suggesting poor levels of agreement between systems. Significant differences in mean CRP per pedal revolution and poor levels of agreement between systems suggests that electro-goniometers are not a suitable alternative to motion-capture systems when attempting to record CRP during cycling.

**Keywords:** electro-goniometers; validity; continuous relative phase; cycling

## 1. Introduction

Historically, cycling kinematics research has tracked joint and segment positions in an effort to calculate joint ranges of motion [1]. These joints are then, most commonly, analysed in isolation [2–5]. Although this is the most widely replicated approach, it has been criticised for not effectively capturing the complexity of coordinated motion [6].

As an alternative, it has been suggested that the continuous, multi-joint nature of the cycling task [7] lends itself best to a continuous relative phase (CRP) method of analysis, whereby the influence of one segment's motion upon an adjacent segment can be more readily acknowledged. This is achieved by calculating the joint angle at each joint across the entire motion cycle and then using angle–angle plots. These plots can then be quantified using vector coding techniques to establish the relative motion of two adjacent joints [8].

CRP values can range from 0° to 360°, where 0° shows the respective movements of the coupled joints perfectly in-phase, and 180° indicates that they are perfectly anti-phase. Any value between these indicates a relative amount of in-phase or anti-phase movement.

Inconsistencies with this reporting convention have been identified [9], with some authors choosing to report values only between 0° and 180°, given that the values −180° and 180° both indicate anti-phase behaviour, whilst others utilise both the positive and negative values because they have qualitative meaning that should be preserved. For example, it has been suggested that preserving the negative values is important because if the phase angle of the proximal segment is subtracted from the phase angle of the distal segment, then positive continuous relative phase values indicate that the distal segment is ahead of the proximal segment in phase space, therefore providing a clearer image of the coupling's interaction [10].

The level of detail offered by CRP analysis allows a more detailed evaluation of the interactions along the kinematic chain and has been suggested to be especially important where one end of the segmental chain is effectively fixed, in the case of cycling through its attachment to the pedal. The consideration of the coupling relationship between segments has been therefore suggested to be especially crucial in the analysis of cycling motion [11]. Additionally, CRP analysis has been deemed to be more sensitive to changes in coordination [12] and could offer greater insight into the changing techniques employed in response to learning environmental changes such as wind speed or road surface or other independent variables [13].

CRP has traditionally been measured using motion-capture systems in a laboratory setting [14–16]. This requires the duplication of a cyclist's equipment using an ergometer due to the amount of distance covered during a cycling bout and the inability to calibrate such an extensive capture volume for kinematic analysis. There is, however, a readily available body of literature that focusses on the lack of ecological validity of such an approach. Studies have shown that there is a significant difference in cycling speed and power output between laboratory and road conditions during time trial events [17,18], whilst others have shown that crank torque profiles are significantly different when comparing laboratory and outdoor cycling conditions [19]. This has prompted calls to move towards a testing environment where riders can use their own bikes to accurately replicate "real-world" performance [1], an approach which may be facilitated by the use of electro-goniometers during field testing.

Electro-goniometers have long been used for the measurement of lower extremity joint motion [20], and their physical characteristics make them suitable for practical applications within biomechanics [21]. The lightweight equipment and non-invasive methods of data collection, coupled with the ability to record offline data logging systems, makes them a potentially excellent choice for field-based assessments within cycling. Indeed, they have already been assessed in terms of their suitability for use in professional bike-fitting services [22] and have been found to be more accurate and valid for use within laboratory studies than manual methods of measuring knee joint range of motion [23]. Despite this, to the best of the authors' knowledge, electro-goniometers have yet to be used to calculate CRP during cycling efforts.

The aim of this study, therefore, was to extend the initial findings reported at the ECSS 25th Annual congress [24] in an effort to investigate whether electro-goniometers offer a valid method for the calculation of CRP values during cycling performance. If this is the case, investigations into cycling techniques can move to a more ecologically valid setting, whilst considering the interconnected nature of joint movements which occur during the movement.

## 2. Materials and Methods

### 2.1. Participants

Seven participants (4 male, 3 female, age: 29 ± 7 years, height: 1.76 ± 0.10 m, mass: 71.97 ± 11.57 kg) volunteered to take part in the study. Participants were recreationally active and free from injury at the time of testing but were not trained cyclists. All participants provided written informed consent before taking part in this study, which had local ethics committee approval in accordance with the rules of the Declaration of Helsinki of 1975, revised in 2013.

### 2.2. Procedure

Participants were invited to adjust the cycle ergometer (Wattbike Pro cycle ergometer, Wattbike, UK) to their comfort. This configuration was maintained throughout the testing session. Reflective markers (Qualisys, Sweden) were attached to the participant's right leg at the greater trochanter, lateral femoral condyle and lateral malleolus. A marker was also attached to the lateral side of the participant's shoe, with placement determined by palpation to establish the positioning of the base of the 5th metatarsal. Bi-axial electrogoniometers (Biometrics, UK) were attached at the hip, knee and ankle. The electrogoniometer at the hip was aligned vertically with the strain gauge running immediately posterior to the greater trochanter marker and the terminals positioned equidistant superior and inferior to the marker. The electro-goniometer at the knee was positioned on the medial aspect of the knee, aligned vertically with the strain gauge running directly over the medial femoral condyle and the terminals equidistant superior and inferior to this landmark. The electro-goniometer at the ankle was attached so that the superior terminal was aligned vertically above the medial malleolus, the strain gauge ran over the medial malleolus and the inferior terminal was positioned horizontally on the participant's shoe so that the electro-goniometer recorded an angle of 90$^{\circ}$ with the participant standing in the anatomical reference position. Goniometers were "zeroed" before application and applied to achieve values close to 0$^{\circ}$, 0$^{\circ}$ and 90$^{\circ}$, respectively.

Participants performed exercise bouts of 30 s at four prescribed cadences (60, 80, 100, 120 rev·min$^{-1}$) on the stationary ergometer (Wattbike, UK), with freely chosen resistance. Participants were given free choice of riding posture but asked to maintain the same position across all conditions.

### 2.3. Data Analysis

Measures were synchronously recorded by the bi-axial electro-goniometers (Biometrics, UK) and a 12-camera motion-capture system (Qualisys, Sweden), with both systems recording at 500 Hz. Raw marker trajectories were used to calculate sagittal plane joint angle and joint angular velocity, which were recorded at the hip, knee and ankle and analysed for 10 complete pedal revolutions per participant per condition. Data were interpolated to 100 time points and used to calculate mean continuous relative phase (CRP) per pedal revolution at two intra-limb couplings: (i) knee flexion/extension–ankle plantarflexion/dorsiflexion (KA) and (ii) hip flexion/extension–knee flexion/extension (HK).

Following checks for normal distribution, a combination of repeated measures T-tests and Wilcoxon signed rank tests were used to check for significant differences between measurement systems, followed by intra-class correlation coefficients (ICC) via the two-way mixed model to quantify the consistency of the CRP values produced by the two systems.

All statistical testing was performed using IBM SPSS statistics (IMB Corporation, Armonk, NY, USA), with an alpha level set at $p < 0.05$.

## 3. Results

When comparing the mean CRP values produced by the two systems (Table 1), there were statistically significant differences ($p < 0.05$) at 80 and 100 rev·min$^{-1}$ for the Hip–Knee coupling and at 120 rev·min$^{-1}$ for the Knee–Ankle coupling.

The goniometers appeared to report consistently higher mean values at the Hip–Knee coupling across all cadences. This is also true for 80, 100 and 120 rev·min$^{-1}$ for the Knee–Ankle coupling, with the goniometers apparently under-reporting at 60 rev·min$^{-1}$, compared to the previously validated camera system (Table 1).

**Table 1.** Comparisons between mean continuous relative phase values produced across a complete pedal revolution.

| Coupling | Cadence (rev·min$^{-1}$) | Mean CRP Value (Mean ± SD) | | Sig. | ICC |
|---|---|---|---|---|---|
| | | Camera System | Goniometers | | |
| Hip–Knee | 60 | 3.57 (±1.94) | 5.55 (±1.05) | 0.080 | −0.413 |
| Hip–Knee | 80 | 3.33 (±2.36) | 6.81 (±1.84) | 0.043 * | −0.272 |
| Hip–Knee | 100 | 2.48 (±1.76) | 7.19 (±1.73) | 0.028 * | −0.103 |
| Hip–Knee | 120 | 7.81 (±6.57) | 13.59 (±5.23) | 0.191 | −0.418 |
| Knee–Ankle | 60 | 11.43 (±4.83) | 8.71 (±3.36) | 0.066 | 0.749 |
| Knee–Ankle | 80 | 12.31 (±6.13) | 13.17 (±6.67) | 0.691 | 0.664 |
| Knee–Ankle | 100 | 12.26 (±6.70) | 18.95 (±13.11) | 0.176 | 0.346 |
| Knee–Ankle | 120 | 11.29 (±5.10) | 29.22 (±16.25) | 0.009 * | 0.376 |

* Denotes a significant difference between systems at $p < 0.05$.

Intra-class correlation coefficients were created via the two-way mixed model to quantify the consistency of the CRP values produced by the two systems (see Table 1 The majority of these coefficients were below 0.5, suggesting poor levels of reliability between systems. The only exceptions to this were seen at 80 and 100 rev·min$^{-1}$ at the Knee–Ankle coupling, where values of 0.749 and 0.664, respectively, were recorded. This would suggest, at best, a moderate level of agreement between systems, and predicated further investigation into the basic joint position data produced by each system to ascertain the reason for such discrepancies.

Comparing positional data between systems using Wilcoxon signed rank tests, it became apparent that there were significant differences ($p < 0.05$) at all cadences when comparing mean maximum hip angle and mean minimum hip angle (Table 2). The only exception to this was at 80 rev·min$^{-1}$ ($p = 0.197$), where there was no statistically significant difference between the two systems; however, the large standard deviation value (±18.95) in the goniometer dataset does offer some cause for concern.

**Table 2.**Comparison of mean maximum and mean minimum hip angle recorded across 10 pedal revolutions.

| **Cadence (rev·min$^{-1}$)** | 60 | | 80 | | 100 | | 120 | |
|---|---|---|---|---|---|---|---|---|
| **Measurement System** | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer |
| **Maximum Hip Angle (°)** | 73.25 (±2.10) | 84.08 (±13.70) | 73.56 (±2.00) | 82.22 (±17.30) | 73.37 (±2.42) | 82.88 (±15.85) | 71.80 (±2.75) | 83.52 (±16.89) |
| **Sig.** | <0.001 * | | <0.001 * | | <0.001 * | | <0.001 * | |
| **Minimum Hip Angle (°)** | 33.49 (±5.21) | 40.79 (±17.71) | 33.87 (±5.65) | 36.30 (±18.95) | 33.21 (±5.60) | 37.11 (±19.25) | 31.02 (±5.92) | 39.24 (±17.70) |
| **Sig.** | 0.010 * | | 0.197 | | 0.044 * | | <0.001 * | |

* Denotes a significant difference between systems at $p < 0.05$.

When comparing the mean maximum knee angle, there was further evidence that the two systems did not agree, with statistically significant differences ($p < 0.05$) being seen at all cadences (see Table 3). This was also the case when comparing the mean minimum knee angle (see Table 3). Again, statistically significant differences ($p < 0.05$) were recorded at all cadences.

Levels of reported ankle flexion/extension were also statistically significantly different ($p < 0.05$) between the two measurement systems at all cadences with regards to both maximum and minimum mean reported values (see Table 4).

In summary, positional data suggested that the goniometer systems consistently overreported both maximum and minimum values for hip and knee flexion/extension, while simultaneously under-reporting the corresponding values at the ankle.

**Table 3.** Comparison of mean maximum and mean minimum knee angle recorded across 10 pedal revolutions.

| **Cadence (rev·min⁻¹)** | 60 | | 80 | | 100 | | 120 | |
|---|---|---|---|---|---|---|---|---|
| **Measurement System** | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer |
| | 138.75 (±8.66) | 165.24 (±6.36) | 138.52 (±9.39) | 166.99 (±6.07) | 138.61 (±8.87) | 170.04 (±5.36) | 140.26 (±9.74) | 173.62 (±8.19) |
| | <0.001 * | | <0.001 * | | <0.001 * | | <0.001 * | |
| | 70.75 (±4.17) | 113.25 (±13.35) | 70.42 (±4.44) | 116.62 (±14.08) | 69.81 (±4.40) | 117.41 (±13.29) | 70.17 (±4.92) | 121.00 (±15.70) |
| | <0.001 * | | <0.001 * | | <0.001 * | | <0.001 * | |

* Denotes a significant difference between systems at $p < 0.05$.

**Table 4.** Comparison of mean maximum and mean minimum ankle angle recorded across 10 pedal revolutions.

| **Cadence (rev·min⁻¹)** | 60 | | 80 | | 100 | | 120 | |
|---|---|---|---|---|---|---|---|---|
| **Measurement System** | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer | Camera | Goniometer |
| **Maximum Ankle Angle (°)** | 120.65 (±11.98) | 102.31 (±9.61) | 117.97 (±5.67) | 102.18 (±8.70) | 118.11 (±6.15) | 104.41 (±13.20) | 119.68 (±5.31) | 114.49 (±48.72) |
| **Sig.** | <0.001 * | | <0.001 * | | <0.001 * | | <0.001 * | |
| **Minimum Ankle Angle (°)** | 100.90 (±13.35) | 83.59 (±7.17) | 95.39 (±7.38) | 83.23 (±7.17) | 94.91 (±6.92) | 83.23 (±6.80) | 94.80 (±5.26) | 79.22 (±12.10) |
| **Sig.** | <0.001 * | | <0.001 * | | <0.001 * | | <0.001 * | |

* Denotes a significant difference between systems at $p < 0.05$.

## 4. Discussion

Results from this investigation suggest that bi-axial electro-goniometers are not a valid method for recording CRP values during simulated cycling efforts. There were statistically significant differences ($p < 0.05$) between measurement systems in two of four tested cadences for the Hip–Knee coupling, and a further significant difference was reported at 120 rev·min$^{-1}$ for the Knee–Ankle coupling. The lack of agreement between systems was further supported by ICC values, which mostly fell below 0.5, showing poor levels of agreement between systems [25] when calculating CRP.

The discrepancy between systems could be because signal values were not normalised. There has been some debate as to whether or not normalisation would avoid the magnitude of values from one segment dominating the CRP pattern [9]. However, multiple studies [9,10] concluded that, in the case of joint kinematics, normalisation is not required because the finite values are unimportant—it is the relative phase that is of interest. Calculation of CRP, therefore, appears to require normalisation of values against time, as performed here, but not normalisation of the original signal values themselves.

As shown above, further investigation into the reason for the lack of agreement revealed statistically significant differences ($p < 0.05$) between systems at the fundamental level of measured angular position. The two systems only agreed in terms of the minimum angle recorded at one joint (the hip), in one condition (80 rev·min$^{-1}$). All other comparisons returned significantly different results. Discrepancies at this level make it almost inevitable that there will be differences between reported CRP values, based, as they are, on differing fundamental measures.

The reason for such discrepancies in basic measures of angular position could, in part, be attributed to poor experimental control in terms of goniometer placement. Although every effort was made to replicate the exact placement described in the Methods Section above, the lack of anatomical landmarks to use for reference means it is possible that there was some variation in placement between participants.

Even if placement was perfectly replicated between participants, it has been suggested that the human body lacks even surfaces and right angles on which to attach sensors of this nature to accurately calculate joint angles [26]. The suggestion being that the lack of flat surfaces means the orientation of a measurement device cannot possibly be aligned with any physiologically meaningful axis. This is especially apparent at the knee, where despite traditionally being described as a single planar hinge joint, there are degrees of freedom relating to flexion/extension, abduction/adduction and internal/external rotation [27,28]. Although abduction/adduction and internal/external rotation angles very rarely exceed a range of ±10° [29], it is possible that this is enough to affect the measurement of angular position when using a system such as the electro-goniometers used here, which assume entirely planar motion.

Related concerns with the placement of the electro-goniometers include the influence of soft-tissue movement artifacts, the suggestion that surface-mounted markers may not adequately represent true anatomical locations and the assumption that markers attached to the skin surface are rigidly connected to the underlying bones [30,31]. It has been reported that skin marker trajectories showed up to a 31 mm error, when compared to a prosthesis-embedded anatomical frame, and up to a 192% root mean square error in abduction/adduction estimations taken from markers placed on the thigh and shank. Although the reflective markers used in this investigation were placed on bony anatomical landmarks (greater trochanter, lateral femoral condyle and lateral malleolus) to remove the influence of such artifacts, it should be noted that it is not possible to mount the electrogoniometers in such a way. The electro-goniometers, therefore, may have been subject to the type of soft-tissue movement artifacts described above, and this could contribute to the lack of agreement between systems in terms of fundamental angular position and CRP.

A potential limitation of the current study relates to the way in which the measures were produced. Although care was taken to match the sampling frequencies of the systems at 500 Hz and the same 10 revolutions were analysed per participant per condition, the systems themselves were not synchronised. It is possible that this may have contributed to the differences seen between systems, but it is worth noting that, even at the highest cadence (120 rev·min$^{-1}$), the chosen sampling rate still provides approximately 250 measures per pedal revolution.

In the current investigation, CRP was reported as a mean value for an entire pedal revolution. The poor agreement between systems shown at this level meant that it was deemed more worthwhile to investigate the root of the discrepancies between systems rather than delve further into the divisions of a pedal revolution, but this is something which would be recommended once a valid measurement system has been established. Reporting a single CRP value averaged across a complete pedal revolution may not offer enough detail throughout the various phases of the revolution to fully exhibit the nuanced kinematics at play. Therefore, it is suggested that future studies should split the pedal revolution into separate power and recovery phases. This approach has been adopted previously [32] and has, at times, been extended to an even more detailed analysis of four "quarters" across the pedal revolution [33–35]. The purpose of such a split would be to effectively separate the power and recovery phases from the areas at the top and bottom of the pedal revolution, which have long been identified as areas where pedalling kinematics are altered due to tangential force being at a minimum [36,37].

## 5. Conclusions

Although it has been suggested that the use of CRP analysis provides information that cannot be obtained through conventional angular position vs. time presentation, the results from this study would suggest that bi-axial electro-goniometers are not a suitable method for recording such values.

Further investigations are recommended to establish a valid alternative to traditional motion-capture systems so that investigations into joint-couple motions during cycling may move to a more ecologically valid setting that accurately replicates the "real-world" performances of athletes.

**Author Contributions:** Conceptualization, C.W., S.A.J. and N.S.; methodology, C.W., S.A.J. and N.S.; validation, C.W., S.A.J. and N.S.; formal analysis, C.W.; investigation, C.W.; resources, C.W.; data curation, C.W.; writing—original draft preparation, C.W.; writing—review and editing, C.W., S.A.J. and N.S.; visualization, C.W. and S.A.J.; supervision, S.A.J.; project administration, C.W. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Ethics Committee of The University of Winchester (Ethical clearance reference (BLS/18/28)).

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the assurance of anonymity given to all participants prior to their involvement in the study.

**Conflicts of Interest:** The authors declare no conflict of interest.

## 6. References

1. Carpes, F.P.; Bini, R.R.; Quesada, J.I.P. Joint kinematics. In *Biomechanics of Cycling*; Springer: Cham, Switzerland, 2014; pp. 33–42.
2. Bailey, M.; Maillardet, F.; Messenger, N. Kinematics of cycling in relation to anterior knee pain and patellar tendinitis. *J. Sports Sci.* **2003**, *21*, 649–657. [CrossRef] [PubMed]
3. Dingwell, J.B.; Joubert, J.E.; Diefenthaeler, F.; Trinity, J.D. Changes in Muscle Activity and Kinematics of Highly Trained Cyclists during Fatigue. *IEEE Trans. Biomed. Eng.* **2008**, *55*, 2666–2674. [CrossRef] [PubMed]
4. Bini, R.R.; Diefenthaeler, F.; Mota, C.B. Fatigue effects on the coordinative pattern during cycling: Kinetics and kinematics evaluation. *J. Electromyogr. Kinesiol.* **2010**, *20*, 102–107. [CrossRef] [PubMed]
5. Cockcroft, S.J. An Evaluation of Inertial Motion Capture Technology for Use in the Analysis and Optimization of Road Cycling Kinematics. Ph.D. Dissertation, University of Stellenbosch, Stellenbosch, South Africa, 2011.
6. Bartlett, R.; Wheat, J.; Robins, M. Is movement variability important for sports biomechanists? *Sports Biomech.* **2007**, *6*, 224–243. [CrossRef]
7. Hug, F.; Drouet, J.M.; Champoux, Y.; Couturier, A.; Dorel, S. Interindividual variability of electromyographic patterns and pedal force profiles in trained cyclists. *Eur. J. Appl. Physiol.* **2008**, *104*, 667–678. [CrossRef]
8. Sparrow, W.A.; Donovan, E.; van Emmerik, R.; Barry, E.B. Using Relative Motion Plots to Measure Changes in Intra-Limb and Inter-Limb Coordination. *J. Mot. Behav.* **1987**, *19*, 115–129. [CrossRef]
9. Lamb, P.F.; Stöckl, M. On the use of continuous relative phase: Review of current approaches and outline for a new standard. *Clin. Biomech.* **2014**, *29*, 484–493. [CrossRef]
10. Kurz, M.J.; Stergiou, N. Effect of normalization and phase angle calculations on continuous relative phase. *J. Biomech.* **2001**, *35*, 369–374. [CrossRef]
11. Chapman, A.; Vicenzino, B.; Blanch, P.; Hodges, P. Do differences in muscle recruitment between novice and elite cyclists reflect different movement patterns or less skilled muscle recruitment? *J. Sci. Med. Sport* **2009**, *12*, 31–34. [CrossRef]
12. Davids, K.; Bennett, S.; Newell, K.M. (Eds.) *Movement System Variability*; Human Kinetics: Champaign, IL, USA, 2006.
13. Burgess-Limerick, R.; Abernethy, B.; Neal, R.J. Relative phase quantifies inter-joint coordination. *J. Biomech.* **1993**, *26*, 91–94. [CrossRef]
14. Miller, R.H.; Meardon, S.A.; Derrick, T.R.; Gillette, J.C. Continuous Relative Phase Variability during an Exhaustive Run in Runners with a History of Iliotibial Band Syndrome. *J. Appl. Biomech.* **2008**, *24*, 262–270. [CrossRef] [PubMed]
15. Seay, J.F.; Van Emmerik, R.E.; Hamill, J. Low back pain status affects pelvis-trunk coordination and variability during walking and running. *Clin. Biomech.* **2011**, *26*, 572–578. [CrossRef] [PubMed]
16. Hein, T.; Schmeltzpfenning, T.; Krauss, I.; Maiwald, C.; Horstmann, T.; Grau, S. Using the variability of continuous relative phase as a measure to discriminate between healthy and injured runners. *Hum. Mov. Sci.* **2011**, *31*, 683–694. [CrossRef] [PubMed]
17. Jobson, S.; Nevill, A.M.; Palmer, G.S.; Jeukendrup, A.E.; Doherty, M.; Atkinson, G. The ecological validity of laboratory cycling:
Does body size explain the difference between laboratory- and field-based cycling performance? *J. Sports Sci.* **2007**, *25*, 3–9. [CrossRef] [PubMed]
18. Jobson, S.A.; Nevill George, S.R.; Jeukendrup, A.E.; Passfields, L. Influence of body position when considering the ecological validity of laboratory time-trial cycling performance. *J. Sports Sci.* **2008**, *26*, 1269–1278. [CrossRef]

19. Bertucci, W.; Grappe, F.; Groslambert, A. Laboratory versus Outdoor Cycling Conditions: Differences in Pedaling Biomechanics.
*J. Appl. Biomech.* **2007**, *23*, 87–92. [CrossRef]
20. Chao, E.Y.; An, K.N.; Askew, L.J.; Morrey, B.F. Electrogoniometer for the Measurement of Human Elbow Joint Rotation. *J. Biomech. Eng.* **1980**, *102*, 301–310. [CrossRef]
21. Legnani, G.; Zappa, B.; Casolo, F.; Adamini, R.; Magnani, P.L. A model of an electro-goniometer and its calibration for biomechanical applications. *Med. Eng. Phys.* **2000**, *22*, 711–722. [CrossRef]
22. Fonda, B.; Sarabon, N.; Li, F.-X. Validity and reliability of different kinematics methods used for bike fitting. *J. Sports Sci.* **2014**, *32*, 940–946. [CrossRef]
23. Shamsi, M.; Mirzaei, M.; Khabiri, S.S. Universal goniometer and electro-goniometer intra-examiner reliability in measuring the knee range of motion during active knee extension test in patients with chronic low back pain with short hamstring muscle. *BMC Sports Sci. Med. Rehabil.* **2019**, *11*, 4. [CrossRef]
24. Whittle, C. Validity of electro-goniomters as a method of measuring continuous relative phase during cycling. In Proceedings of the European College of Sport Science 25th Anniversary Congress, Online, 28–30 October 2020.
25. Koo, T.K.; Li, M.Y. A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. *J. Chiropr. Med.* **2016**, *15*, 155–163. [CrossRef] [PubMed]
26. Seel, T.; Raisch, J.; Schauer, T. IMU-Based Joint Angle Measurement for Gait Analysis. *Sensors* **2014**, *14*, 6891–6909. [CrossRef] [PubMed]
27. Favre, J.; Jolles, B.; Aissaoui, R.; Aminian, K. Ambulatory measurement of 3D knee joint angle. *J. Biomech.* **2008**, *41*, 1029–1035. [CrossRef] [PubMed]
28. Cooper, G.; Sheret, I.; McMillan, L.; Siliverdis, K.; Sha, N.; Hodgins, D.; Kenney, L.; Howard, D. Inertial sensor-based knee flexion/extension angle estimation. *J. Biomech.* **2009**, *42*, 2678–2685. [CrossRef]
29. Perry, J.; Davids, J.R. Gait analysis: Normal and pathological function. *J. Pediatric Orthop.* **1992**, *12*, 815. [CrossRef]
30. Ramsey, D.; Wretenberg, P.F. Biomechanics of the knee: Methodological considerations in the in vivo kinematic analysis of the tibiofemoral and patellofemoral joint. *Clin. Biomech.* **1999**, *14*, 595–611. [CrossRef]
31. Stagni, R.; Fantozzi, S.; Cappello, A.; Leardini, A. Quantification of soft tissue artefact in motion analysis by combining 3D fluoroscopy and stereophotogrammetry: A study on two subjects. *Clin. Biomech.* **2005**, *20*, 320–329. [CrossRef]
32. Sides, D.; Wilson, C. Intra-limb coordinative adaptations in cycling. *Sports Biomech.* **2012**, *11*, 1–9. [CrossRef]
33. Dorel, S.; Couturier, A.; Hug, F. Influence of different racing positions on mechanical and electromyographic patterns during pedalling. *Scand. J. Med. Sci. Sports* **2008**, *19*, 44–54. [CrossRef]
34. Dorel, S.; Couturier, A.; Lacour, J.R.; Vandewalle, H.; Hautier, C.; Hug, F. Force-velocity relationship in cycling revisited: Benefit of two-dimensional pedal forces analysis. *Med. Sci. Sports Exerc.* **2009**, *42*, 1174–1183. [CrossRef]
35. Lanferdini, F.J.; Jacques, T.C.; Bini, R.R.; Vaz, M.A. Cyclists and triathletes do not differ in muscle volume, muscle recruitment or pedal force effectiveness. *Isokinet. Exerc. Sci.* **2014**, *22*, 279–286. [CrossRef]
36. Ericson, M.; Nisell, R.; Németh, G. Joint Motions of the Lower Limb during Ergometer Cycling. *J. Orthop. Sports Phys. Ther.* **1988**, *9*, 273–278. [CrossRef] [PubMed]
37. Patterson, R.P.; Moreno, M.I. Bicycle pedalling forces as a function of pedalling rate and power output. *Med. Sci. Sports Exerc.* **1990**, *22*, 512–516. [CrossRef] [PubMed]