Man and Machine: Assessing the Efficacy of Athlete Monitoring Tools in Highly Trained Swimmers

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by

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CERTIFICATE OF AUTHORSHIP AND ORIGINALITY OF THESIS

I certify that the work contained in this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Health, Sport and Exercise Discipline at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

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Early into my time as a PhD student an Uber driver told me…

"Man will always beat machine" as he referred to a GPS monitor.

….. after that statement he quickly corrected himself and said… "The right man"

I thought about it for a long time.

Five years later, I think I have some data to support that (with context of course).

PREFACE

This thesis for the degree of Doctor of Philosophy is in the format of thesis by compilation and abides by the 'Procedures for Presentation and Submission of Theses for Higher Degrees – University of Technology, Sydney; Policies and Directions of the University'.

From the research design and data collection by the candidate, four manuscripts have been submitted to peer reviewed journals for publication. These papers are initially brought together by an Introduction. This provides a background, research problem, the purpose and significance of each of the studies. A literature review follows which provides an overview of athlete monitoring tools and coach decision-making. The manuscripts are then presented in a logical sequence following the development of research ideas within this thesis. Each manuscript has a similar structure of introduction, methodology, results, discussion, practical applications and conclusion. Figures, Tables and reference numbers have been retained. The summary chapter integrates all studies research ideas, concludes each study and provides direction for future research.

LIST OF ARTICLES SUBMITTED FOR PUBLICATION

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1. **Crowcroft, S.,** McCleave, E., Slattery, K., & Coutts, A. J. (2017). Assessing the measurement sensitivity and diagnostic characteristics of athlete-monitoring tools in national swimmers. *International Journal of Sports Physiology and Performance*, *12* (Suppl. 2), S2-95.
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4. **Crowcroft, S.,** Slattery, K., McCleave, E. & Coutts, A. J. (Under review). Do athlete monitoring tools improve a coach's understanding of performance change? *International Journal of Sports Physiology and Performance*.

Conference Proceedings & Abstracts

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ABSTRACT

High performance sporting programs make substantial investments to develop and implement athlete monitoring systems to assist coaches understand how their athletes are responding to training. Despite the extensive reviews supporting the usefulness of athlete monitoring systems, it is still unknown if these systems contribute to a coaches' subjective assessment of how an athlete will perform. Therefore, the overall aim of this thesis was to assess the efficacy of an athlete monitoring system and a coach subjective assessment to identify performance changes and athlete training responses in nationally competitive swimmers. To achieve this, a series of four studies were conducted. Study 1 determined the signal-to-noise ratio and diagnostic accuracy of athlete monitoring tools to identify both improvements and decrements in performance. These findings showed clear week-to-week fluctuations of numerous monitoring tools that represented an athlete's acute changes in fitness and fatigue. However, this study also highlighted the poor diagnostic accuracy of athlete monitoring tools to identify performance change. Therefore, Study 2 examined the efficacy of a multi-factorial monitoring system to assess both short-term or longitudinal changes in performance. These findings identified an improved accuracy of a multi-factorial monitoring approach to assess longitudinal performance changes. However, the weaker diagnostic accuracy assessing short-term performance changes limits the practicality of this approach to assess an athlete's readiness to perform in training or competition. Study 3 aimed to compare a coach's expected perceived fatigue, recovery, training intensity and performance outcomes to actual athlete measures in well-trained swimmers. These findings showed a very strong association of coach predicted to actual athlete race results. However, there was a consistent discrepancy of coach expected to athlete reported training intensity and responses to subjective questionnaires. Finally, Study 4 assessed if the use of athlete monitoring tools could improve on a coach's prediction to identify performance changes. The findings from this study demonstrated the high diagnostic accuracy of a coach's subjective assessment of their athlete's performance. Although, no monitoring tools improved on a coach's

subjective assessment of performance. Collectively, this thesis provides initial support of the high accuracy of a swim coach's subjective assessment of their athlete's performances. However, the use of athlete monitoring tools may assist a coach to have a more comprehensive understanding of their athlete's responses to training.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ASCTA	Australian Swim Coaches Teaching Association
AUC	Area under the curve
CI	Confidence interval
CL	Confidence limits
CDM	Classical decision-making
CMJ	Counter movement jump
CV%	Co-efficient of variation as a percentage
Exp.(B)	Exponential of unstandardised beta co-efficient
$Fatigue_{7d}$	The 7-day rolling average of perceived fatigue
FINA	Fédération Internationale de Natation
GEE	Generalised estimating equation
HR	Heart Rate
HRR	Heart rate recovery
HRV	Heart rate variability
KM	Kilometres
Ln rMSSD	The log transformed root mean squared sum of the consecutive R-R intervals
Ln $rMSSD_{7d}$	The 7-day rolling average of the log transformed root mean squared sum of the consecutive R-R intervals
LnRMSSD:RR	The ratio of the log transformed root mean squared sum of the consecutive R-R intervals to R-R interval
LnRMSSD:RR_{7d}	The 7-day rolling average of the ratio of the log transformed root mean squared sum of the consecutive R-R intervals to R-R interval
NDM	Naturalistic decision-making
POMS	Profile of mood state
QIC	Quasi Likelihood under Independence Model Criterion
ROC	Receiver operating characteristics
S.E.	Standard error
SD	Standard deviation
SMC	Smallest meaningful change
sRPE	Session rating of perceived exertion
TE	Technical error
TL	Training load
TQR	Total quality recovery
TQR_{7d}	The 7-day rolling average of both total quality recovery
Wellness%	Total wellness score and expressed as a percentage of highest possible total
$Wellness\%_{7d}$	The 7-day rolling average of total wellness score and expressed as a percentage of highest possible total
β	Unstandardised beta co-efficient

Chapter 1

General Introduction

BACKGROUND

To enhance performance, athletes training programs must achieve a balance between providing a training dose that maximises adaptations (i.e. fatigue inducing) and obtaining appropriate recovery to allow performance in competition [1]. Therefore, to better understand how athletes respond and perform in training, athlete monitoring systems are now commonly used [2]. These systems typically comprise of measures of an athlete's training load and the assessment of an athlete's acute and adaptive responses to training, including physiological assessments (e.g. heart rate derived indices or vertical jump measures) and psychometric (subjective) questionnaires [3-6]. Due to the perceived benefits, high performance sporting organisations now make substantial investments to the development and running of these systems [7]. However, it is currently not known if athlete monitoring systems are able to identify an athlete's readiness to perform beyond that of expert coaches' subjective assessment of athletic performance.

Following a coach-led approach to training, the manipulating of training sessions can be determined from coaches' professional judgements, skilled intuition or 'gut feel'. These perceptions are developed through coaching expertise and prior learnings, following the subjective assessment of an athletes readiness to perform or training 'status' [8,9]. Accordingly, for coaches to optimise training prescription, they must acquire the necessary expertise and skilled intuition to assess their athletes readiness to perform in training or competition [10]. However, a limitation of a coach-led approach is that coaching or skilled intuitions have the potential to be incorrect or hindered by inherent biases [10]. These situations can arise when there is a lack (or absence) of skilled intuition, or when an unfamiliar environment or experience presents [11]. Due to these issues, there is warranted scepticism in subjective decision-making [12]. However, no studies have assessed a coaches' subjective assessment of their athlete's response to training or readiness to perform in both training and competition.

RESEARCH PROBLEM

Despite the ubiquitous nature of athlete monitoring tools in high performance sport, it is currently unknown if these systems can be used to assess an athlete's readiness to perform in training or competition. Furthermore, no studies have assessed the accuracy of coach observations and subjective assessments to identify an athlete's readiness to performance. Finally, it is also unknown if the decision-making process in athlete preparation is improved if athlete monitoring tools are integrated with coach expertise.

RESEARCH OBJECTIVES

This thesis aimed to assess the accuracy of an athlete monitoring system and coach predictions to identify performance changes in highly trained swimmers. This thesis builds upon the knowledge and practical application of athlete monitoring systems in high performance sport. Specifically, providing evidence for how athlete monitoring tools may assist with a coach's subjective assessment of an athlete's readiness to perform in training or competition. Therefore, through a series of four studies this thesis aimed to address the following:

- Can athlete monitoring tools identify performance changes?
    - Chapter 3 *(Study 1)* and Chapter 4 *(Study 2)*
- How do athlete monitoring tools compare to coach expected results in training and competition?
    - Chapter 5 *(Study 3)*
- Does combining athlete monitoring tools with a coach's subjective assessment improve the accuracy of identifying performance changes?
    - Chapter 6 *(Study 4)*

Chapter 3 (Study 1) - **Assessing the measurement sensitivity and diagnostic characteristics of athlete monitoring tools in national swimmers**

Purpose

To report the week-to-week variability, reliability and signal-to-noise ratio in common athlete monitoring tools. Secondly, to assess the diagnostic accuracy of these monitoring tools to identify improvements and decrements in performance.

Significance

Currently, there is limited evidence supporting methods to interpret changes in athlete monitoring tools and relate them to a performance outcome [2,13]. In high performance sport, common methods used to identify these meaningful changes include variation outside of an arbitrary cut-off value, changes beyond normal day-to-day variation or through the visual analysis of trends where data is subjectively reviewed [2]. However, few studies have assessed the diagnostic accuracy of these approaches to assess performance changes in highly trained athletes [14,15]. Therefore, the purpose of this study was to improve interpretation of meaningful changes in non-invasive athlete monitoring tools through the assessment of both the reliability and typical weekly variation. Secondly, this study assessed the diagnostic accuracy (i.e. sensitivity: true positive rate and specificity: true negative rate) of any single monitoring variable to identify both improvements and decrements in performance. The results from this study will improve understanding of interpreting variation in athlete monitoring tools and relate these to performance changes.

Chapter 4 (Study 2) - **Can a multi-factorial athlete monitoring system identify performance change in swimmers?**

Purpose

To assess the accuracy of a multi-factorial athlete monitoring system to identify improvements and decrements in performance of highly trained swimmers.

Significance

No study has contextualised multiple athlete monitoring tools into a single model to identify both improvements and decrements in performance. This study provides a novel approach combining multiple variables including changes in heart rate measures, subjective questionnaires and training volume. These results may support a coach understand an athlete's readiness to perform in training or competition using non-invasive athlete monitoring tools.

Chapter 5 (Study 3) - **Man vs. Monitoring: Assessing a coach's expectations of athletic performance, training intensity, perceived fatigue and recovery.**

Purpose

To compare coach expected perceived fatigue, recovery, training intensity and performance outcomes to actual athlete measures in well-trained swimmers. Secondly, to assess if the use of athlete reported subjective monitoring tools could identify a likely difference between coach planned to athlete reported training intensity.

Significance

Little is known how a coach assesses an athlete's readiness to perform in training or competition. This is the first study to assess a coach prediction of their athlete's race results. Furthermore, this study aimed to assess if the use of subjective questionnaires could identify a difference between the coach planned to athlete reported training intensity. The findings from this study aimed to improve the understanding of a coach's skilled intuition and subjective assessment of athletic performance. Secondly to provide insight of how athlete monitoring tools may assist to refine coach expertise and inform decision-making in the prescription of training intensity.

***Chapter 6 (Study 4)* - Coach and Athlete Monitoring: Do athlete monitoring tools improve a coach's understanding of performance change?**

Purpose

To assess a coach's subjective assessment of their athlete's performance. Secondly, to assess if the use of athlete monitoring tools could improve on a coach's prediction to identify performance changes.

Significance

While sports scientists have dedicated considerable time and resources to develop athlete monitoring systems, no studies have assessed how this information contributes to a coach's assessment of athletic performance. This study aimed to identify how athlete monitoring tools could be integrated with a coach prediction to assess an athlete's performance changes. The results from this study would build on the evidence assessing skilled intuition and professional judgements within swim coaching and targeted reporting of athlete monitoring tools to coaches.

REFERENCES

1. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, Raglin J, Rietjens G, Steinacker J, Urhausen A. Prevention, diagnosis and treatment of the overtraining syndrome: Joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). *Eur J Sport Sci.* 2013;13(1):1-24.
2. Taylor K, Chapman DW, Cronin JB, Newton MJ, Gill N. Fatigue monitoring in high performance sport: A survey of current trends. *J Aus Strength Cond.* 2012;20(1):12-23.
3. Lambert M, Borresen J. A theoretical basis of monitoring fatigue: a practical approach for coaches. *Int J Sports Sci Coach.* 2006;1(4):371-388.
4. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
5. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Front Physiol.* 2014;5(73).
6. Claudino JG, Cronin J, Mezêncio B, McMaster DT, McGuigan M, Tricoli V, Amadio AC. The countermovement jump to monitor neuromuscular status: A meta-analysis. *J Sci Med Sport.* 2017;20(4):397-402.
7. Coutts AJ, Crowcroft S, Kempton T. Developing athlete monitoring systems. In: Kellmann M, Beckmann J, eds. *Sport, Recovery, and Performance: Interdisciplinary Insights* London 2017.
8. Kiely J. Periodization paradigms in the 21st century: evidence-led or tradition-driven. *Int J Sports Physiol Perform.* 2012;7(3):242-250.
9. Borresen J, Lambert MI. The quantification of training load, the training response and the effect on performance. *Sports Med.* 2009;9:779-795.
10. Shanteau J. Competence in experts: The role of task characteristics. *Organ Behav Hum Decis Process.* 1992;53:252-262.
11. Bowes I, Jones RL. Working at the edge of chaos: Understanding coaching as a complex, interpersonal system. *Sport Psychol.* 2006;20(2):235-245.
12. Kahneman D, Klein G. Conditions for intuitive expertise: a failure to disagree. *Am Psychol.* 2009;64(6):515-526.
13. Robertson S, Bartlett JD, Gastin PB. Red, Amber or Green? Athlete monitoring in team sport: the need for decision support systems. *Int J Sports Physiol Perform.* 2017;12(2):S2-73.
14. Buchheit M. Sensitivity of monthly heart rate and psychometric measures for monitoring physical performance in highly trained young handball players. *J Sports Med.* 2015;36(5):351-356.
15. Buchheit M, Rabbani A, Beigi HT. Predicting changes in high-intensity intermittent running performance with acute responses to short jump rope workouts in children. *J Sport Sci Med.* 2014;13:476-482.

Chapter 2

Literature Review

Coach expertise and athlete monitoring systems: Assessing an athlete's readiness to perform.

ABSTRACT

Elite athletes can have large inter-individual differences in training adaptations and subsequent performance changes in response to a similar training program [1]. To better understand these differences and optimise the athlete's training, sport scientists use athlete monitoring systems [2,3]. These monitoring systems usually involve measures of training load, and the athletes' fitness and fatigue status [3,4]. Coaches often rely on experiential knowledge, intuition and subjective assessment of an athlete's current performance status to guide decisions on training prescription [5]. Despite the increasing presence of athlete monitoring systems in high performance sport, little is known as to how this information influences decisions made by a coach, or if indeed this information provided is useful.

The purpose of this narrative review is to (i) describe common athlete monitoring tools that have been reported to be useful for guiding training prescription or assessing an athlete's readiness to perform, (ii) examine factors that influence coach decision-making with reference to training prescription and the subjective assessment of athletic performance.

The review demonstrated that there is limited empirical support for the use of athlete monitoring tools to guide training prescription or assess an athlete's readiness to perform. Further research is required to examine the predictive accuracy of athlete monitoring tools to assess an athlete's performance changes. The review also demonstrated that coach's professional judgement and observations may be a learned skill, refined through reflection on an athletes training response. However, skilled intuitions can also have biases leading to poor subjective decision-making. Currently no studies have assessed the accuracy of coach's subjective assessment to identify performance changes. Further research should assess if the decision-making process in athlete preparation is improved if athlete monitoring tools are integrated with coach expertise.

INTRODUCTION

Optimal approaches for planning and implementing training have been of great interest to coaches and sports science practitioners. Historically, coaches personal experience and various periodization theories have formed the basis of how an athlete training program is developed [5]. It is also typical for a coach to prescribe training using external load measures such as time or distance, and manipulate these variables based on the organisation, quality and quantity of work required to elicit a desired physiological response [6,7]. This approach relies largely on the assumption that the physiological responses to a given exercise stimulus precedes a predictable training outcome [5]. However, in contrast to this assumption, athletes show a wide range of responses to a standardised workload due to numerous factors including genetics, training history and age, nutritional and psychological state [1]. More specifically, examples of this between athlete variation includes differing training responses to maximal oxygen update [8], blood pressure [9], aerobic and anaerobic thresholds [10]. Therefore, to have a greater understanding of the training process, sport scientists quantify the internal training load and training response as the key driver for physiological adaptations (see Figure 2:1).

Athlete monitoring systems often incorporate measures used to quantify both external and internal load, along with physiological measures (e.g. heart rate derived indices, submaximal fitness tests and blood lactate testing) and subjective questionnaires to reflect an athlete's current state of fitness and fatigue [3,4,6,11,12]. Through the analysis and reporting of these data, it is suggested that a feedback loop to coaches and support staff can provide more informed decisions in the assessment of an athlete's current athletic ability and assist to guide training prescription [5,13]. Therefore, high performance sporting programs make substantial financial investments to develop and implement monitoring systems based on theoretical models to understand an individual's training response, minimise injury risk, prevent overreaching and improve the training process [3,4,12,14-18]. However, despite the extensive number of reviews and examples of how athlete monitoring systems can be implemented [2-4,6,11,12,14,19-25] , no study has assessed if these systems improve decision making and in turn enhance performance [2].

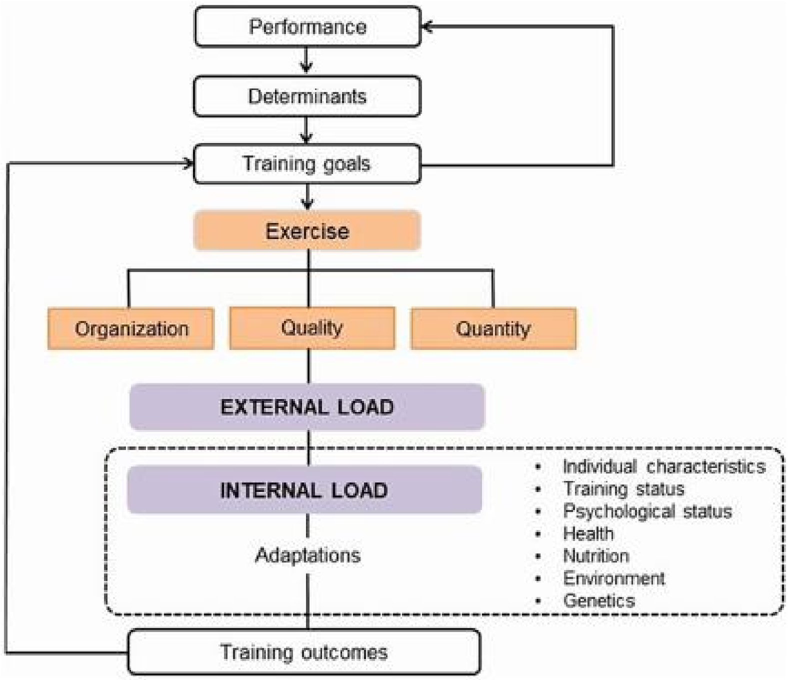

Figure 2:1 Theoretical model of the training process (reproduced from Impellizzeri, et al. [6]).

Decision-making and the subjective assessment of athletic performance from coach observations seem intangible and difficult to quantify [26]. Indeed, skilled intuitive and subjective decision-making in expert coaches can be based upon a multitude of factors (e.g. learning outcomes from the session, environmental considerations and potential risks) often without consideration of all scenarios [27]. In a predictable environment, skilled intuition can be beneficial [26,27]. However, subjective decision-making and professional judgements have received criticisms in medical disciplines as even experienced practitioners can be prone to incorrect diagnosis and biases [28,29], especially in unpredictable environments. Therefore, to prevent these biases, a nested approach where both professional judgements and skilled intuitions are combined with objective monitoring data (to inform decisions) could be applied [30].

At present no studies have examined if athlete monitoring systems provide information that improves training outcomes beyond that of a well-controlled, coach-led training program in isolation [31,32]. Furthermore, there is little evidence to demonstrate the effectiveness of an athlete monitoring system to assess an athlete's readiness to perform within training or competition. As such, the purpose of this narrative review is to consolidate available evidence of athlete monitoring tools that assess an athlete's readiness to perform (in training or competition) or directly guide training prescription. Secondly, to examine existing evidence of factors that influence coach decision-making in training and their subjective assessment of athletic performance.

ATHLETE MONITORING SYSTEMS

Many studies have assessed the relationship of internal and external loads to performance outcomes (for detailed reviews see [12,15-17]) and have contributed to the development of contemporary training theory (see review [5,17]). These studies have guided training theory to improve the understanding of how to manipulate the athlete's training dose. Specifically, these results have reported methods to optimise training to enhance performance and training adaptations [17,33-43] and manage overload and taper periods prior to competitions [38,44-46]. However, modelling the training response from a set training dose assumes a predictable individual training response based upon retrospective data. As such this approach does not account for the daily inter-individual responses that reflect an athlete's current state of readiness to perform in training or competition (e.g. current physiological and or psychological state) [1].

Monitoring Tools to Guide Training Prescription

Athlete monitoring tools may assist to quantify the individual athlete's training response and guide training prescription [47]. The most common athlete monitoring tools include the assessment of the autonomic nervous system through heart rate (HR) derived indices [48,49], neuromuscular status (e.g. jump monitoring) [50] and subjective questionnaires [21]. These tools are relatively non-invasive, can provide immediate feedback, are time efficient and easy to administer for integration into high performance sport programs [2,13,47]. While various athlete monitoring tools appear to be useful to quantify an athletes training response, few examples exist for how monitoring tools can guide training prescription (i.e. used to optimise daily training prescription) or assess an athlete's readiness to perform (i.e. be used to predict real performance changes). Therefore, the following section will review evidence for the use of non-invasive athlete monitoring tools to guide training prescription or assess an athlete's readiness to perform in training or competition.

Subjective Questionnaires

Subjective questionnaires are a simple and effective method to identify how athletes are responding to training [21,51-58]. A recent review of subjective questionnaires has identified an association with athlete responses to changes in both acute and chronic training load [21]. Theoretically, these measures are associated to changes in performance. However, despite numerous reviews supporting the usefulness of subjective monitoring tools in an athlete monitoring system [2-4,6,11,12,14,19-25] , no study has used these tools to guide training prescription.

In addition, few studies have shown how subjective questionnaires can identify performance change performance.

Few investigations have shown how subjective measures can be used to explain changes in athletic performance [21,59,60]. For example, when highly trained swimmers reported subjective levels of fatigue during a taper period, the rating of fatigue could explain up to 53% of the variance in swim performance [59]. Furthermore, when the investigators combined subjective measures of sleep, stress, fatigue and muscle soreness, up to 72% of the variance in performance could be explained [59]. However, interpretation of these results is limited as performance outcomes were reported as “staleness” if there was a performance decrement or no performance change during the swimmer’s taper. Although, limited evidence supports the monthly measurement of the profile of mood states and fatigue to predict changes in physical performance measures (counter movement jump [CMJ], 10-m sprint test and the 30-15 intermittent fitness test) of adolescent handball players. Specifically, the Profile of Mood State (POMS) and total mood score derived from the POMS had a low sensitivity (true positive rate) to identify performance changes in these athletes [60]. As such, while subjective questionnaires may be responsive to training load, there is limited support for these measures in isolation to predict performance changes.

A comprehensive approach to assessing athlete readiness to perform was reported through a case study of a 400-m sprinter (runner) [61]. In this case study, an impulse response model assessed the efficacy of using training load, total quality recovery (TQR) and resting HR to predict performance changes. Training load data was modelled using Banisters “fitness – fatigue” model [39], where modelled performance was regressed against actual performance with a high degree of accuracy (r^2=0.88) [61]. Following analysis of the fitness – fatigue model, resting HR and TQR were reported back to the coach to manipulate the training plan. This approach allowed the coach to make a more informed decision on training prescription and the effect that a training dose would have on a performance outcome. However, the authors recognised the model was not used in the final stages of preparation to guide training prescription or assess the athlete's readiness to perform. Nonetheless, this initial case study has provided evidence that a multi-factorial approach can be used to assess athletic performance. These findings identify the limited evidence for the use of subjective questionnaires in isolation to assess an athlete's readiness to perform. Further research is required to expand upon the usefulness of including subjective questionnaires in multi-factorial models to assess performance changes.

Jump Monitoring

The CMJ is a test that can be used to identify changes in neuromuscular function, the stretch-shorten cycle and central fatigue [50]. Furthermore, CMJ height has been shown to substantially fluctuate during different training phases [62]. Indeed, the within-subject variability in CMJ performance has been shown to be higher during long term overload training phases [62]. As such, the CMJ has been suggested as a useful tool for regular monitoring of an athlete's response to training (see meta-analysis [50]). However, only few studies have used the CMJ to guide training prescription or assess an athletes readiness to perform [63,64].

Initial studies have assessed the efficacy of using CMJ at the commencement of training to guide total plyometric load and optimising performance outcomes. These studies showed that when participant's training was adjusted according to CMJ height, greater improvements in vertical jump performance were observed compared to participants that completed a pre-planned training program [63,64]. The CMJ has also been used to guide decisions around changes in weekly training load during an overload and taper period. This study assigned participants to either a set training program or a group where weekly training load was prescribed following analysis of the athletes CMJ. The CMJ-guided group aimed to induce functional overreaching and a reduction in CMJ during an overload and an increased CMJ following a taper period [64]. The results show that the CMJ-guided training group had greater decrements in CMJ following the overload phase and a greater improvement in CMJ following their taper. However, this study only guided weekly changes in training load and not timing of sessions within the week. Therefore, initial findings support the use of regulating neuromuscular fatigue through the CMJ to improve the desired training responses following an overload and taper phase. However, due to the low level of evidence on this topic, more exploratory studies are required to determine the efficacy of using CMJ to optimise training or as a measure of an athlete's readiness to perform.

Heart Rate Variability

Heart rate variability (HRV) indices have been shown to reflect parasympathetic modulation, is a non-invasive monitoring tool and is economical for longitudinal use with athletes [48,49,65]. Previous studies have related changes in HRV-derived indices to positive or negative training adaptations and to reflect the acute training response [48,49,65-76] (for extensive reviews see [48,49]). Furthermore, HRV-derived measures have also been associated with performance changes in highly trained middle distance and endurance athletes [68-70,77] and reported to identify upper respiratory tract or pulmonary infections and muscular affections in elite level swimmers [78].

Despite these observations, few examples support the efficacy of HR-derived measures to predict changes in performance [60,79]. For example, Buchheit [60] identified the low sensitivity of monthly changes in resting HR and HRV for assessing changes in physical performance measures in adolescent handball players. However, this poor predictive ability may be due to the monthly recording of HRV measures. HRV has also been recommended that daily measurements may explain a greater understanding of an athlete's response to training [48,65,76]. Therefore, although HRV may assist to identify an athlete's responses to training through descriptive studies [48,49,65-68,70,72,74,76], limited evidence currently supports the use of HRV-derived measures to identify an athlete's readiness to perform in training or competition [69,70,77].

Several studies have also examined the efficacy of HRV to guide prescription of intensive endurance training with the purpose of improving cardio-respiratory fitness [80-82]. For example, Kiviniemi, et al. [80] used a four week training period in moderately trained individuals to compare HRV-guided (high frequency measures) training to a fixed training program. In the HRV-guided group, training intensity was reduced when HRV decreased and training intensity increased if HRV measures remained stable or increased. The results demonstrated a larger improvement of maximal workloads at VO_{2max} in the daily HRV-guided group compared to the fixed training schedule.

Following these results, others have used a more complex HRV method to guide training in athletes [83]. In this study an algorithm was developed that used pre-training HRV scores to guide training prescription according to how these variables compared to the normal distribution of daily measures (below 20%= increase in training intensity and or load, 2- between 20-70%= continue with existing training plan, 3- between 70-95%= reduce the training load and focus upon recovery and 4 above 95%= stop training and rest). After the 17-week period of guided training, the results demonstrated a large variance in performance change (-8.8% to +8.5%)

showing no clear benefit of guiding training with HRV in well trained athletes. These findings may not be surprising due to the heterogeneous sample of sports and physiological demands of the athletes (1-decathlete, 1-heptathlete, 2- 400-m hurdlers, 2- 1500-m runner, 1- 110-m hurdler, 1- long jumper, 1- inline skater and 1- fin swimmer). Indeed, high cardiac vagal tone is associated with improved endurance exercise, yet may be detrimental to very short performances (i.e. <30 s) [84]. Therefore, guiding training for very short events and longer duration events based upon the same HRV measures or ANS activity may not be appropriate. Currently, few studies support the use of HRV-training to improve performance. Therefore, future research should examine the use of HRV-guided training towards endurance events of longer duration and its implementation for highly trained athletes.

Heart Rate Recovery

Heart rate recovery (HRR) is the rate at which HR decreases in a set period following exercise (e.g. 60 s following exercise cessation). This reduction is driven by the interaction of cardiac sympathetic withdrawal and the initial cardiac parasympathetic re-activation [85]. Previous studies that have examined the relationship of HRR to performance improvements report inconsistent findings. Specifically, some evidence has identified both a decreased (slower) HRR [86] and increased (faster) HRR [87] may be related to positive performances. These observations suggest that more than one indicator may be required for identifying how athletes are coping with / responding to training. Specifically, a multi-factorial approach where HRR analysed in context of the athlete's psychological state and training phase may be a more appropriate method for monitoring performance changes [86,88].

Several studies have assessed the efficacy of using of both HR and HRR following exercise to identify an athlete's readiness to perform (for detailed review see [89]). However, few studies have used these methods to guide training prescription. For example, Capostagno, et al. [90] assigned cyclists to either a set high-intensity training group or a flexible training group where training was prescribed based on HRR following a standardised submaximal warm up test. The results showed that the HRR-guided group had greater variance in the time taken to complete the required training sessions but had more athletes improve their 40-km time-trial performance compared to the set training group (set: 8 ± 45 s vs. flexible: 48 ± 42 s). Collectively, these findings provide support for a flexible training approach to decrease the likelihood of a poor training response. While initial evidence has supported this approach, these studies are relatively short (2–8 weeks) and no studies have applied this concept over long periods or compared the effectiveness to that of coach-led training.

Summary

The purpose of this section was to review available evidence supporting the use of common athlete monitoring tools for guiding training prescription or assessing an athlete's readiness to perform in trained athletes. The main findings were:

- Modelling internal and external load has developed a theoretical understanding of the training dose to performance relationship, however assumes training adaptations from retrospective data.
- Subjective questionnaires are associated to changes in training load, but limited evidence supports their ability to assess performance changes.
- Little available evidence supports the use of the CMJ to guide training prescription.

- HR-derived indices provide a non-invasive measurement of how an athlete is tolerating and responding to training.
- HR measures may need to be contextualised to training phase and psychological state for more appropriate interpretation of a relationship to performance change.
- Few studies support the use of HRV or HRR measures to guide training prescription or assess an athlete's readiness to perform.

Data Analysis for Athlete Monitoring Systems

Athlete monitoring systems are frequently used in professional sporting teams [25] and by elite endurance athletes [18] to assess an individual's training response. It is commonly accepted that these systems assist to optimise the athlete's training dose while minimising injury risk and illness [14]. To be effective, an athlete monitoring system should report information in an easy to read format, have a short turnaround time in providing feedback and discussion of results should involve coaches, relevant staff and when appropriate with athletes [4,25,91]. The most common analytical methods used in sport to identify a meaningful change in athlete monitoring variables include using [2,14]:

- Arbitrary cut-off values (e.g. if data goes above or below a value).
- Variables observed outside of an athlete's normal day-to-day variation (e.g. 1 standard deviation above/below each individual athlete's mean value).
- Values chosen through a visual analysis of trends (e.g. subjectively chosen from trend in data).

At present however, there is no consensus on the best approach to analyse and interpret monitoring data to guide decision-making for training prescription or assess an athlete's readiness to perform in training or competition. Therefore, the following section will address several key considerations for interpreting changes in athlete monitoring variables for these purposes.

Smallest Meaningful Change

For monitoring tools to be practically used, quantifying a 'true' or meaningful change outside of the normal day-to-day variation must be understood. In monitoring studies this is often reported as a percentage of the typical within-individual co-efficient of variation (CV%) [25,48,92,93]. An individual approach is favoured as it accounts for both the repeated measures structure of athlete monitoring data and the within athlete typical variation of these measures [48]. For example, a comparative study assessed the smallest meaningful change in HR and RPE from a standard warm up using both the inter-individual CV% and the between standard deviation[79]. This study showed that changes in HR and RPE outside of the inter-individual CV% was more sensitive to identify performance changes. However, this approach also identified that specificity was reduced (i.e. accuracy in identifying no performance change).

Methods for detecting meaningful change in performance outcomes have been established [94]. However, there are inconsistencies in how to interpret the smallest meaningful change in athlete monitoring variables dependent upon expected training adaptations, typical variation, and the variable being monitored [48]. For example, CV% for the log transformed root mean squared sum of the consecutive R-R interval differences (Ln rMSSD) measures have been shown to be much smaller than frequency domain indices (~12% resting – Ln rMSSD to ~80% resting Low and High Frequency, for more extensive discussion see [48]). Similarly, the CV% of subjective wellness questionnaires have been reported to range from 12-32% in Australian football players dependent on which day these measures are collected following matches [95]. To interpret the smallest meaningful change, individual athlete differences and the typical variation in monitoring variables should be considered. To improve the practical utility of athlete monitoring tools, a stronger emphasis must be placed on using the smallest meaningful change of each measure to interpret typical variation (noise) from a true change (signal) known as the signal-to-noise ratio [32]. This can be done through assessing the relationship of changes in monitoring tools to the criterion outcome measure (e.g. performance changes, injury or illness).

Diagnostic Accuracy

Once the typical variation of an athlete monitoring measure is established, the next logical progression is to determine its practical utility by quantifying its diagnostic accuracy (i.e. the ability to assess performance change, injury, illness). A common approach to determine diagnostic accuracy of tests is to assess both the sensitivity (true positive rate) and specificity (true negative rate) against a gold standard criterion measure (see Tables 2:1 and 2:2) [96,97]. This confusion matrix (Table 2:1) presents the comparison of identifying a true outcome (e.g. disease, injury or performance change) against a screening or monitoring tool. For example, in the assessment of type 2 diabetes, previous analysis has assessed the diagnostic accuracy of a urinary glucose dipstick for the early detection of type 2 diabetes. To achieve this, the dipstick urine test (screening tool) and gold standard test (glucose tolerance test) were compared to validate the dipsticks diagnostic accuracy [98].

Table 2:1 Confusion matrix and explanation of diagnostic metrics adopted from Greenhalgh [96] as a method to assess monitoring tools against a criterion measure.

	Results of gold standard test	
Screening tool	**Positive (Disease) (A+C)**	**Negative (No disease) (B+D)**
Test Positive (A+B)	True Positive (A)	False Positive (B)
Test Negative (C+D)	False Negative (C)	True Negative (D)

In sport, this approach has been used to examine training load measures to predict non-contact injuries in football players across multiple seasons [99]. While high training loads were associated with injury, there was poor diagnostic accuracy, shown by the high false positive rate of injuries predicted during “very-high” training loads. In players assessed in this study, the false positive rate ranged from 273-653 occurrences (i.e. the number of times an injury was predicted from training load, and no injury occurred). As such, the authors cautioned the interpretation of these results when making decisions on individual players training prescription due to the low sensitivity (12.5 to 43.1%) and the high number of false positives.

Table 2:2 Explanation of outcomes from confusion matrix adopted from Greenhalgh [79].

Feature of the test	Alternative name	Question addressed	Formula *(Table 2:1)*
Sensitivity	True positive rate	How good is this test at picking up people who have the condition?	A / (A + C)
Specificity	True negative rate	How good is this test at correctly excluding people without the condition?	D / (B + D)
Diagnostic Accuracy	-	What proportion of all tests have given the correct result? (True positives and true negatives as a proportion of all results).	(A + D) / (A + B + C + D)

Despite the widespread use in other fields, very few scientific reports have assessed the diagnostic accuracy of an athlete monitoring system to highlight (a probability of) performance change [14]. It is important to understand the diagnostic accuracy of monitoring tools for interpretation of data. This information can assist coaches’ and support staff to inform decision-making on training prescription and the assessment of athletic performance. However, of the few studies that have assessed non-invasive athlete monitoring tools, few have shown positive results. For example, Buchheit [60] identified the low sensitivity of resting HR, HRV and subjective questionnaires to assess changes in physical performance measures in adolescent handball players. Surprisingly, despite the prevalence of monitoring systems in high performance sport [2], there is no strong evidence to support highlighting 'red flags' (e.g. an arbitrary or set cut off value within monitoring tools) to improve training prescription or its ability to determine an athlete's readiness to perform [2]. Therefore, future research should aim to identify changes in athlete training status through non-invasive monitoring systems and their diagnostic accuracy to better inform training prescription utilising the increased availability of data and more advanced statistical techniques [48].

Contextualising Monitoring Tools

Several studies have highlighted the importance of contextualising monitoring variables such as HR-derived indices and subjective questionnaires to the athlete's training load, particularly during intensified training periods (for detailed example see [48]) to understand how an athlete will perform [86,88,89,100-103]. For example, Bellenger et al., [101] observed a moderate increase in vagal mediated time domain HRV indices, reduced training tolerance and performance following a 14-d intensified training phase in endurance athletes. However, during a subsequent 10-d taper, HRV indices remained elevated and this occurred concomitantly with improvements in both ratings of training tolerance and time-trial performance. These results highlight the importance of contextualising changes in HRV measures relevant to both the training phase and athlete's psychological state. Otherwise, changes in HRV measures to assess an athlete's readiness to perform may be misinterpreted. Similarly, increases in both HRR and perceived fatigue following an overload training phase in triathletes has been related to functional overreaching [100]. It was described that this elevated HRR response aligned with a large increase in subjective reporting of fatigue and reflects an athlete's shift to parasympathetic hyperactivity. This shift to parasympathetic hyperactivity suppresses HR responses and oxygen delivery during maximal exercise [104]. Collectively, these examples highlight the need to contextualise changes in monitoring tools (usually physiological measures and subjective questionnaires) to performance changes. However, beyond these types of observational or descriptive studies, no study has attempted to contextualise multiple non-invasive athlete monitoring tools into a single statistical model to predict the likelihood of a performance change or assess an athlete's readiness to perform.

Summary

The purpose of this section was to discuss to role of data analysis for the practical application of an athlete monitoring system. The main findings were:

- The smallest meaningful change and the signal-to-noise ratio of monitoring variables should be determined specific to the sport, athlete and training context.
- Very few studies have assessed the sensitivity, specificity and diagnostic accuracy of athlete monitoring tools to highlight performance changes or an athlete's readiness to perform.
- Changes in physiological measures and subjective questionnaires contextualised relevant to training phase have been associated with performance changes.
- Few studies have contextualised multiple athlete monitoring tools into a single statistical model to assess a performance change.

COACH EXPERTISE

Successful coaches have self-reported that event specific knowledge, experience, continuing education, observation, willingness to learn, commitment, competence, consistency and mastery are critical for success [105]. Accordingly, it seems logical that coaches should engage in experiential learning and reflective practices to refine these qualities and in turn improve their performance [28,30,106,107]. The following section will summarise evidence on the current models of how coaches may develop expertise and use this information to guide coach decision-making on training prescription or the subjective assessment of athletic performance.

Coach Observation and Reflection

Coach observations of their athletes performances provides vital information that informs decision-making around future training [12]. Classical decision-making (CDM) can be used to explain how expert coaches make informed decisions, through both observation and experiential learning [106]. Through an iterative process of observation, experiences and reflection, coaches can develop their expertise that is then used to inform decision-making (see Figure 2:2).

It is logical that coaches gain expertise through repeated observation of athletes during the training process. It has also been shown that the ability to discern important information from the insignificant details is an important characteristic that separates novice to expert coaches [108]. Having access to pertinent information around athlete training such as the training dose and the athlete's response to that load may facilitate an in-depth reflection (i.e. where the coach compares their subjective observations with objective information recorded in training) and learning. This is important as a mismatch between coach planned and athlete reported session rating of perceived exertion (sRPE) has been reported consistently with various levels of athletes and sports. This mismatch suggests that without feedback coaches may be mis-informed of the true training intensity their athletes completed [7,109-113]. Through receiving feedback on these measures, coaches may refine their understanding of how individual athletes are coping or responding to training. Therefore, athlete monitoring systems can assist in developing a feedback loop where coaching observations are compared with objective information. This comparison may then lead to detailed reflections and allow coaches to develop expertise in understanding and controlling the training process [12]. However, despite a logical basis for this concept, there have been surprisingly few examples that have shown how athlete monitoring tools are used and contextualised against coach observations. Furthermore, there is little understanding how this information related to the assessment of an athlete readiness to perform in training or competition.

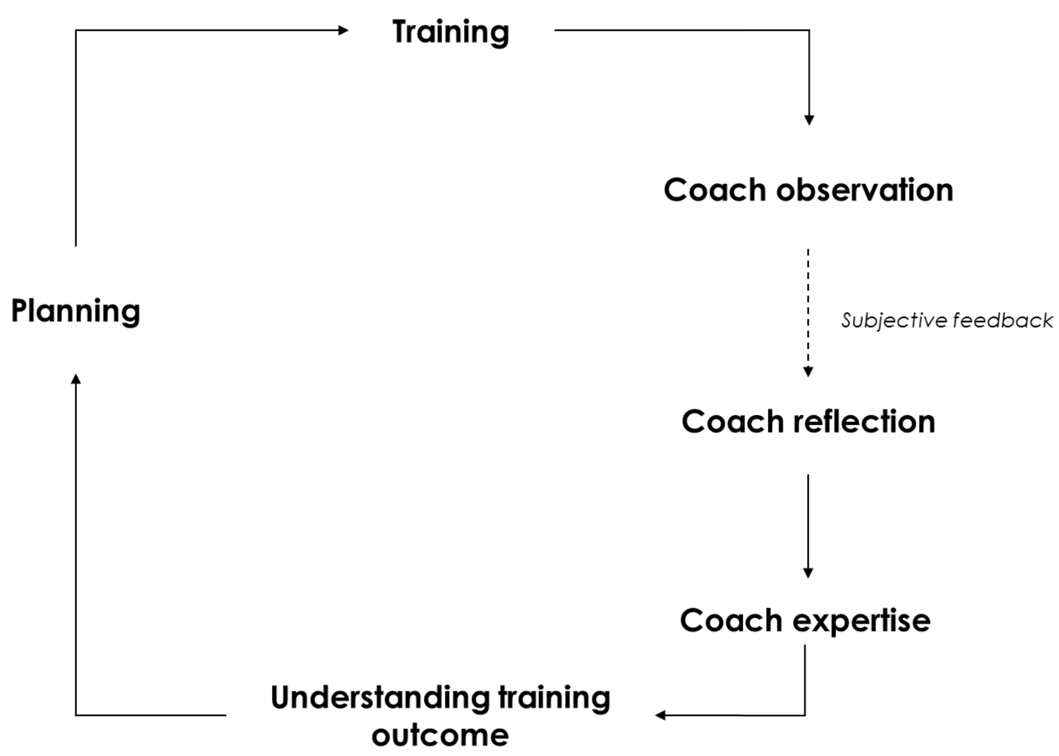

Figure 2:2 Conceptual model of coach observation and reflection to develop expertise and guide the training process.

Skilled Intuition

One of the key responsibilities of high performance coaches is to understand how their athletes are responding to training and infer their readiness to perform. There are a myriad of confounding factors that influence an athlete's response to training (e.g. age, genetics, nutritional status, psychological state, etc.) [1,106]. Accordingly, it is likely that coaches with greater expertise can accurately identify positive or negative training responses and manipulate sessions or plans to optimise training outcomes for their athletes. Quite often coaches refer to this ability as their intuition, but the academic literature suggest that this ability is developed through Naturalistic Decision-making (NDM) [106,114]. NDM ability occurs where experts regularly make complex decisions in time demanding real-world situations [106,114]. Therefore, when coaches develop greater expertise, the NDM processes and subjective assessments of the environment can seem intangible [26], and this ability is referred to as skill intuition.

Expert sport coaches have shown intuitive decision-making in training prescription based on a multitude of factors including the: pedagogical focus (learning outcomes, content of the session, potential goals), environmental context (risk to athletes from physical and social environment); and, learning environment (coach decision-making formed through experience, knowledge and audit of their decision-making) [27]. Therefore, intuition has been described as a recognition of patterns stored in memory [30] before applying an apparent intuitive solution without consideration of all possibilities [115,116]. Skilled intuition (at least within a professional setting) is therefore likely semi-conscious, learned, or if unconscious at the point of decision-making, could be quickly brought into a conscious space and reviewed [27].

For skilled intuition to be developed within coaching, the training and competition environment must provide regular and valid cues to an outcome. In a sporting context, this validity could be described as the relevant information (e.g. execution of specific tasks in training or psychological state) that would influence a performance outcome [28]. Characteristics of skilled intuitive decision makers include:

- Working in an environment which has high predictability of an outcome.
- The practitioner has many years of experience.
- The sport or work environment has good feedback of outcome measures [28].

Within the sporting domain, individual physiological and skill-based sports such as swimming or track and field have a very consistent performance environment. Due to this, performance outcomes can be easily quantified and there is consistent feedback available to the coach through direct observations [12,33]. This provides an ideal environment for investigating the development of NDM and skilled intuition. However, no studies have assessed the accuracy of coach intuition or subjective assessment of how their athletes will perform in training or competition. This information could guide sport scientists to complement coaches skilled intuition with objective data to allow for a more comprehensive assessment of athletic performance.

Subjective Decision-making and Biases

Intuitions have the potential to be incorrect or hindered by inherent biases. These situations arise when there is a lack of skilled intuition, or when an unfamiliar environment or situation presents [117]. For example, in a large-scale analysis in human health and behaviours (medicine and psychiatry) mechanical judgements (statistical and algorithm predictions) could equal or outperform professional judgments (subjective decision-making from data and subjective measures) [29]. This analysis reported that professional judgements performed worse when a practitioner interview was included as a predictor variable. This may be due to:

- Unexplained intuition.
- If the practitioner has not developed expertise.
- The practitioner's overreliance on irrelevant cues.

However, recognition of these situations allows for further development and the refinement of coach expertise (if reflected on and reviewed) [117,118]. Although, without recognition of the decision-making process or over confidence, there is a missed opportunity for coach development and increased risk of establishing biases [30]. These findings provide warranted scepticism of professional judgements and subjective decision-making [30]. Therefore, in high performance sport objective data (e.g. athlete monitoring data) could present information unbeknown to the coach and open opportunities for reflective and more informed decision-making. However, to date no studies have attempted to compare or combine a coach's subjective assessment or professional judgements and athlete monitoring systems (mechanical predictions) to assess performance outcomes in elite sport.

Summary

The purpose of this section was to discuss how coaches develop expertise and use this information to guide coach decision-making with reference to training prescription. The main findings from this section were:

- CDM improves expertise through experienced based learning providing there is an opportunity to reflect.

- NDM and skilled intuition can be learned in controllable environments.
- Evidence supports algorithm-based decision-making has outperformed subjective and intuitive decision-making.
- Subjective biases can be formed if coaches don't reflect on intuitive decisions.
- No studies have examined coaches' subjective assessments to predict how their athletes will perform.

AN INTEGRATED APPROACH

Guidelines for the development and practical application of athlete monitoring systems have previously been provided [14,32]. These reports suggest an athlete monitoring system would complement training prescription through objective feedback to inform coaches decision-making. A recent survey reported coaches want directly measured physiological parameters and self-reported athlete information, within a system that only provides relevant facts, can learn from previous events and is not too invasive in the training process [13]. However, the implementation of algorithms or decision-making aids may encounter opposition or problems if algorithms outperform human judgement [30]. This could be cited as lack of skill or ability of a coach's professional judgment to make an informed decision if not reported appropriately [30].

Conceptually, the use of objective data would provide a more comprehensive approach to the assessment of athletic performance and assist a coach to understand the training process. Currently, no studies have assessed if athlete monitoring tools improve the training process or assess athletic performance beyond that of experiences coaches' observations and expertise. Despite numerous studies providing examples of the implementation of athlete monitoring systems [2-4,6,11,12,14,19-25], no research has assessed if these systems enhance the training process or improve on a coach's subjective assessment of an athletes readiness to perform in training or competition [2].

SUMMARY

The purpose of this review was to consolidate evidence on athlete monitoring tools that has guided training prescription or assessed an athlete's readiness to perform. A second aim was to summarise factors that influence coach decision-making and the subjective assessment of athletic performance. The main points from this review included:

- HR-derived indices, subjective questionnaires and CMJ provide a non-invasive measurement of an athletes training responses yet limited support exists to identify performance changes.
- Descriptive studies suggest changes in physiological and perceptual measures contextualised relevant to training phase are associated with performance changes.
- Few studies have combined multiple athlete monitoring tools into a single model to assess a performance change.
- The sensitivity, specificity and diagnostic accuracy of athlete monitoring tools to highlight performance changes or an athlete's readiness to perform is unknown.
- CDM can improve coach expertise through experienced based learning providing there is an opportunity to reflect.
- NDM and skilled intuition can be learned in controllable environments.
- Subjective biases can be formed if coaches don't reflect on intuitive decisions.
- Evidence supports algorithm-based decision-making can outperform subjective decision-making.
- No studies have examined coaches' subjective assessment of their athlete's performance.

- No studies have assessed the use of athlete monitoring tools to improve a coaches' assessment of an athlete's readiness to perform.

REFERENCES

1. Mann TN, Lamberts RP, Lambert MI. High responders and low responders: Factors associated with individual variation in response to standardized training. *Sports Med.* 2014;44(8):1113-1124.
2. Taylor K, Chapman DW, Cronin JB, Newton MJ, Gill N. Fatigue monitoring in high performance sport: A survey of current trends. *J Aus Strength Cond.* 2012;20(1):12-23.
3. Bourdon PC, Cardinale M, Murray A, Gastin P, Kellmann M, Varley MC, Gabbett TJ, Coutts AJ, Burgess DJ, Gregson W, Cable NT. Monitoring athlete training loads: consensus statement. *Int J Sports Physiol Perform.* 2017;12(Suppl 2):S2-161.
4. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med.* 2014;44(2):139-147.
5. Kiely J. Periodization paradigms in the 21st century: evidence-led or tradition-driven. *Int J Sports Physiol Perform.* 2012;7(3):242-250.
6. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and external training load: 15 years on. *Int J Sports Physiol Perform.* 2019(00):1-4.
7. Wallace LK, Slattery KM, Coutts AJ. The ecological validity and application of the session-RPE method for quantifying training loads in swimming. *J Strength Cond Res.* 2009;23(1):33-38.
8. Bouchard C, An P, Rice T, Skinner JS, Wilmore JH, Gagnon J, Pérusse L, Leon AS, Rao DC. Familial aggregation of VO_2 max response to exercise training: results from the HERITAGE Family Study. *J Appl Physiol.* 1999;87(3):1003-1008.
9. Wilmore JH, Stanforth PR, Gagnon J, Rice T, Mandel S, Leon AS, Rao DC, Skinner JS, Bouchard C. Heart rate and blood pressure changes with endurance training: the HERITAGE Family Study. *Med Sci Sports Exerc.* 2001;33(1):107-116.
10. Scharhag-Rosenberger F, Walitzek S, Kindermann W, Meyer T. Differences in adaptations to 1 year of aerobic endurance training: individual patterns of nonresponse. *Scand J Med Sci Sports.* 2012;22(1):113-118.
11. Lambert M, Borresen J. A theoretical basis of monitoring fatigue: a practical approach for coaches. *Int J Sports Sci Coach.* 2006;1(4):371-388.
12. Borresen J, Lambert MI. The quantification of training load, the training response and the effect on performance. *Sports Med.* 2009;9:779-795.
13. Roos L, Taube W, Brandt M, Heyer L, Wyss T. Monitoring of daily training load and trianing load responses in endurance sports: What do coaches want? *Schweizerische Zeitschrift für Sportmedizin und Sporttraumatologie.* 2013;61(4):30-36.
14. Robertson S, Bartlett JD, Gastin PB. Red, Amber or Green? Athlete monitoring in team sport: the need for decision support systems. *Int J Sports Physiol Perform.* 2017;12(2):S2-73.
15. Jobson SA, Passfield L, Atkinson G, Barton G, Scarf P. The analysis and utilization of cycling training data. *Sports Med.* 2009;39(10):833-844.
16. Foster C, Daines E, Hector L, Snyder AC, Welsh R. Athletic performance in relation to training load. *Wis Med J.* 1996;95(6):370-374.
17. Mujika I. Quantification of training and competition loads in endurance sports: methods and applications. *Int J Sports Physiol Perform.* 2017;12(2):2-9.
18. Saw A, Halson S, Mujika I. Monitoring athletes during training camps: Observations and translatable strategies from elite road cyclists and swimmers. *Sports.* 2018;6(63).
19. Lambert MI, Borresen J. Measuring training load in sports. *Int J Sports Physiol Perform.* 2010;5:406-411.
20. Morgan WP, Brown DR, Raglin JS, O'connor PJ, Ellickson KA. Psychological monitoring of overtraining and staleness. *Br J Sports Med.* 1987;21(3):107-114.

21. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
22. Vanrenterghem J, Nedergaard NJ, Robinson MA, Drust B. Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Med.* 2017;47(11):2135-2142.
23. Hooper SL, MacKinnon LT. Monitoring overtraining in athletes. Recommendations. *Sports Med.* 1995;20(5):321-327.
24. Coyne JC, Haff GG, Coutts A, Newton RU, Nimphius S. The current state of subjective training load monitoring—a practical perspective and call to action. *Sports Med - Open.* 2018;4(1):58.
25. Ward P, Coutts AJ, Pruna R, McCall A. Putting the 'i' back in team. *Int J Sports Physiol Perform.* 2018:1-14.
26. Hinds PJ, Patterson M, Pfeffer J. Bothered by abstraction: The effect of expertise on knowledge transfer and subsequent novice performance. *J Appl Psychol.* 2001;86(6):1232-1243.
27. Collins D, Collins L, Carson HJ. "If it feels right, do it": Intuitive decision making in a sample of high-level sport coaches. *Front Psychol.* 2016;7(504).
28. Shanteau J. Competence in experts: The role of task characteristics. *Organ Behav Hum Decis Process.* 1992;53:252-262.
29. Grove WM, Zald DH, Lebow BS, Snitz BE, Nelson C. Clinical versus mechanical prediction: a meta-analysis. *Psychol Assess.* 2000;12(1):19-30.
30. Kahneman D, Klein G. Conditions for intuitive expertise: a failure to disagree. *Am Psychol.* 2009;64(6):515-526.
31. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, Raglin J, Rietjens G, Steinacker J, Urhausen A. Prevention, diagnosis and treatment of the overtraining syndrome: Joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). *Eur J Sport Sci.* 2013;13(1):1-24.
32. Coutts AJ. In the age of technology, occam's razor still applies. *Int J Sports Physiol Perform.* 2014;9(5):2014-0353.
33. Taha T, Thomas S. Systems modelling of the relationship between training and performance. *Sports Med.* 2003;33(14):1061-1073.
34. Calvert TW, Banister EW, Savage MV, Bach T. A systems model of the effects of training on physical performance. *IEEE Trans Syst Man Cybern Syst.* 1976;2:94-102.
35. Busso T. Variable dose-response relationship between exercise training and performance. *Med Sci Sports Exerc.* 2003;35:1188-1195.
36. Busso T, Häkkinen K, Pakarinen A, Carasso C, Lacour JR, Komi PV, Kauhanen H. A systems model of training responses and its relationship to hormonal responses in elite weight-lifters. *Eur J Appl Physiol Occup Phys.* 1990;61(1):48-54.
37. Busso T, Hakkinen K, Pakarinen A, Kauhanen H, Komi PV, Lacour JR. Hormonal adaptations and modelled responses in elite weightlifters during 6 weeks of training. *Eur J Appl Physiol Occup Phys.* 1992;64(4):381-386.
38. Mujika I, Busso T, Lacoste L, Barale F, Geyssant A, Chatard JC. Modelled responses to training and taper in competitive swimmers. *Med Sci Sports Exerc.* 1996;28(2):251-258.
39. Morton RH, Fitz-Clarke JR, Banister EW. Modeling human performance in running. *J Appl Physiol.* 1990;69(3):1171-1177.
40. Clarke DC, Skiba PF. Rationale and resources for teaching the mathematical modeling of athletic training and performance. *Adv Physiol Educ.* 2013;37(2):134-152.
41. Hellard P, Scordia C, Avalos M, Mujika I, Pyne DB. Modelling of optimal training load patterns during the 11 weeks preceding major competition in elite swimmers. *Appl Physiol Nutr Metab.* 2017;42(10):1106-1117.

42. Mujika I, Chatard JC, Busso TG, A., Barale F, Lacoste L. Use of swim-training profiles and performances data to enhance training effectiveness. *J Swim Res.* 1996;23-29.
43. Hellard P, Avalos-Fernandes M, Lefort G, Pla R, Mujika I, Toussaint J, Pyne D. Elite swimmers' training patterns in the 25 weeks prior to their season's best performances: insights into periodization from a 20-year cohort. *Front Physiol.* 2019;10:363.
44. Hellard P, Avalos M, Hausswirth C, Pyne D, Toussaint JF, Mujika I. Identifying optimal overload and taper in elite swimmers over time. *J Sport Sci Med.* 2013;12(4):668-678.
45. Thomas L, Mujika I, Busso T. A model study of optimal training reduction during pre-event taper in elite swimmers. *J Sports Sci.* 2008;26(6):643-652.
46. Avalos M, Hellard P, Chatard JC. Modeling the training-performance relationship using a mixed model in elite swimmers. *Med Sci Sports Exerc.* 2003;35(5):838-846.
47. Starling LT, Lambert MI. Monitoring rugby players for fitness and fatigue: What do coaches want? *Int J Sports Physiol Perform.* 2017;13:777-782.
48. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Front Physiol.* 2014;5(73).
49. Bellenger CR, Fuller JT, Thomson RL, Davison K, Robertson EY, Buckley JD. Monitoring athletic training status through autonomic heart rate regulation: A systematic review and meta-analysis. *Sports Med.* 2016:1-26.
50. Claudino JG, Cronin J, Mezêncio B, McMaster DT, McGuigan M, Tricoli V, Amadio AC. The countermovement jump to monitor neuromuscular status: A meta-analysis. *J Sci Med Sport.* 2017;20(4):397-402.
51. Coutts AJ, Wallace LK, Slattery KM. Monitoring changes in performance, physiology, biochemistry, and psychology during overreaching and recovery in triathletes. *J Sports Med.* 2007;28(2):125-134.
52. Kellmann M, Klaus-Dietrich G. Changes in stress and recovery in elite rowers during preparation for the Olympic Games. *Med Sci Sports Exerc.* 2000;32(3):676-683.
53. Maestu J, Jurimae J, Kreegipuu K, Jurimae T. Changes in perceived stress and recovery during heavy training in highly trained male rowers. *Sport Psychol.* 2006;20(1):24-39.
54. Kellmann M, Kallus KW. Recovery-stress questionnaire for athletes: User manual. *Human Kinetics Publishers.* 2001.
55. McNair DM, Lorr M, Droppleman LF. Profile of mood state manual. *San Diego (CA): Educational and industrial testing service.* 1971.
56. Terry PC, Lane AM. BRUMS user guide. *University of Southern Queensland.* 2010.
57. Rushall BS. A tool for measuring stress tolerance in elite athletes. *J Appl Sport Psychol.* 1990;2(1):51-66.
58. Kenttä G, Hassmén P. Overtraining and recovery: A conceptual model. *Sports Med.* 1998;26(1):1-16.
59. Hooper SL, Mackinnon LT, Howard A, Gordon RD, Bachmann AW. Markers for monitoring overtraining and recovery. *Med Sci Sports Exerc.* 1995;27(1):106-112.
60. Buchheit M. Sensitivity of monthly heart rate and psychometric measures for monitoring physical performance in highly trained young handball players. *J Sports Med.* 2015;36(5):351-356.
61. Suzuki S, Sato T, Maeda A, Takahashi Y. Program design based on a mathematical model using rating of perceived exertion for an elite Japanese sprinter: a case study. *J Strength Cond Res.* 2006;20(1):36-42.
62. Taylor KL, Hopkins WG, Chapman DW, Cronin JB. The influence of training phase on error of measurement in jump performance. *Int J Sports Physiol Perform.* 2016;11(2):235-239.
63. Claudino JG, Mezêncio B, Soncin R, Ferreira JC, Couto BP, Szmuchrowski LA. Pre vertical jump performance to regulate the training volume. *J Sports Med.* 2012;33(02):101-107.
64. Claudino JG, Cronin JB, Mezêncio B, Pinho JP, Pereira C, Mochizuki L, Amadio AC, Serrão JC. Autoregulating jump performance to induce functional overreaching. *J Strength Cond Res.* 2016;30(8):2242-2249.

65. Plews DJ, Laursen PB, Stanley J, Kilding AE, Buchheit M. Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring. *Sports Med.* 2013;43(9):773-781.
66. Koenig J, Jarczok MN, Wasner M, Hillecke TK, Thayer JF. Heart rate variability and swimming. *Sports Med.* 2014;44(10):1377-1391.
67. Task-Force. Heart rate variability: standards of measurement, physiological interpretation and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. *Circulation.* 1996;93(5):1043-1065.
68. Plews DJ, Laursen PB, Kilding AE, Buchheit M. Evaluating training adaptation with heart rate measures: A methodological comparison. *Int J Sports Physiol Perform.* 2013;6:688-691.
69. Chalencon S, Pichot V, Roche F, Lacour JR, Garet M, Connes P, Barthélémy JC, Claude J, Busso T. Modeling of performance and ANS activity for predicting future responses to training. *Eur J Appl Physiol.* 2015;115(589-596).
70. Chalencon S, Busso T, Lacour JR, Garet M, Pichot V, Connes P, Gabel CP, Roche F, Barthélémy JC. A model for the training effects in swimming demonstrates a strong relationship between parasympathetic activity, performance and index of fatigue. *PloS one.* 2012;7(12):e52636.
71. Esco MR, Flatt AA. Ultra-short-term heart rate variability indexes at rest and post-exercise in athletes: Evaluating the agreement with accepted recommendations. *J Sport Sci Med.* 2014;13(3):535-541.
72. Flatt A, Esco MR. Heart rate variability stabilization in athletes: towards more convenient data acquisition. *Clin Physiol Funct Imaging.* 2016;36(5):331-336.
73. Flatt A, Howells D. Effects of varying training load on heart rate variability and running performance among an olympic rugby sevens team. *J Sci Med Sport.* 2019;22(2):222-226.
74. Flatt AA, Esco MR. Evaluating individual training adaptation with Smartphone-derived heart rate variability in a collegiate female soccer team. *J Strength Cond Res.* 2015.
75. Nakamura FY, Flatt A, Pereira LA, Ramirez-Campillo R, Loturco I, Esco M. Ultra-short-term heart rate variability is sensitive to training effects in team sports players. *J Sport Sci Med.* 2015;14(3):602.
76. Plews DJ, Laursen PB, Le Meur Y, Hausswirth C, Kilding AE, Buchheit M. Monitoring training with heart rate variability: How much compliance is needed for valid assessment? *Int J Sports Physiol Perform.* 2013;9(5):783-790.
77. Wallace LK, Slattery KM, Coutts AJ. A comparison of methods for quantifying training load: relationships between modelled and actual training responses. *Eur J Appl Physiol.* 2014;114(1):11-20.
78. Hellard P, Guimaraes, F., Avalos, M., Houel, N., Hausswirth, C., & Toussaint, J. F. . Modelling the association between HR variability and illness in elite swimmers. *Med Sci Sports Exerc.* 2011;43(6):1063-1070.
79. Buchheit M, Rabbani A, Beigi HT. Predicting changes in high-intensity intermittent running performance with acute responses to short jump rope workouts in children. *J Sport Sci Med.* 2014;13:476-482.
80. Kiviniemi AM, Hautala AJ, Kinnunen H, Tulppo MP. Endurance training guided individually by daily heart rate variability measurements. *Eur J Appl Physiol.* 2007;101(6):743-751.
81. Kiviniemi AM, Hautala AJ, Kinnunen H, Nissilä J, Virtanen P, Karjalainen J, Tulppo M. Daily exercise prescription on the basis of HR variability among men and women. *Med Sci Sports Exerc.* 2010;42(7):1355-1363.
82. Javaloyes A, Sarabia JM, Lamberts RP, Moya-Ramon M. Training prescription guided by heart rate variability in cycling. *Int J Sports Physiol Perform.* 2018;14(1):23-32.

83. Botek M, McKune AJ, Krejci J, Stejskal P, Gaba A. Change in performance in response to training load adjustment based on autonomic activity. *J Sports Med.* 2013.
84. Merati G, Maggioni MA, Invernizzi PL, Ciapparelli C, Agnello L, Veicsteinas A, Castiglioni P. Autonomic modulations of heart rate variability and performances in short-distance elite swimmers. *Eur J Appl Physiol.* 2015;115(825-835).
85. Daanen HA, Lamberts RP, Kallen VL, Jin A, Van Meeteren N. A systematic review on heart rate recovery to monitor changes in training status in athletes. *Int J Sports Physiol Perform.* 2012:251-260.
86. Hug B, Heyer L, Naef N, Buchheit M, Wehrlin JP, Millet GP. Tapering for marathon and cardiac autonomic function. *J Sports Med.* 2014;35(8):676-683.
87. Borresen J, Lambert MI. Autonomic control of heart rate during and after exercise: measurements and implications for monitoring training status. *Sports Med.* 2008;38(8):633-646.
88. Lamberts RP, Swart J, Capostagno B, Noakes TD, Lambert MI. Heart rate recovery as a guide to monitor fatigue and predict changes in performance parameters. *Scand J Med Sci Sports.* 2010;20(3):449-457.
89. Capostagno B, Lambert MI, Lamberts RP. A systematic review of submaximal cycle tests to predict, monitor, and optimize cycling performance. *Int J Sports Physiol Perform.* 2016;11(6):707-714.
90. Capostagno B, Lambert MI, Lamberts RP. Standardized versus customized high-intensity training: effects on cycling performance. *Int J Sports Physiol Perform.* 2014;9(2):292-301.
91. Meyers MC. Enhancing sport performance: Merging sports science with coaching. *Int J Sports Sci Coach.* 2006;1(1):89-100.
92. Hopkins WG. Spreadsheets for analysis of validity and reliability. *Sportscience.* 2015;19:36-42.
93. Buchheit M. The numbers will love you back in return—I promise. *Int J Sports Physiol Perform.* 2016;11(4):551-554.
94. Hopkins WG, Hawley JA, Burke LM. Design and analysis of research on sport performance enhancement. *Med Sci Sports Exerc.* 1999;31(3):472-485.
95. Gastin PB, Meyer D, Robinson D. Perceptions of wellness to monitor adaptive responses to training and competition in elite Australian football. *J Strength Cond Res.* 2013;27(9):2518-2526.
96. Greenhalgh T. How to read a paper. Papers that report diagnostic or screening tests. *Br Med J.* 1997;315(7107):540.
97. Fawcett T. An introduction to ROC analysis. *Pattern Recognit Lett.* 2006;27(8):861-874.
98. Andersson DKG, Lundblad E, Svärdsudd K. A model for early diagnosis of type 2 diabetes mellitus in primary health care. *Diabetic medicine.* 1993;10(2):167-173.
99. Fanchini M, Rampinini E, Riggio M, Coutts AJ, Pecci C, McCall A. Despite association, the acute: chronic work load ratio does not predict non-contact injury in elite footballers. *Science and Medicine in Football.* 2018;2(2):108-114.
100. Aubry A, Hausswirth C, Louis J, Coutts AJ, Buchheit M, Le Meur Y. The development of functional overreaching is associated with a faster heart rate recovery in endurance athletes. *PloS one.* 2015;10(10):e0139754.
101. Bellenger CR, Karavirta L, Thomson RL, Robertson EY, Davison K, Buckley JD. Contextualising parasympathetic hyperactivity in functionally overreached athletes with perceptions of training tolerance. *Int J Sports Physiol Perform.* 2016;11(5):685-692.
102. Le Meur Y, Hausswirth C, Natta F, Couturier A, Bignet F, Vidal PP. A multidisciplinary approach to overreaching detection in endurance trained athletes. *J Appl Physiol.* 2013;114(3):411-420.
103. Le Meur Y, Louis J, Aubry A, Guéneron J, Pichon A, Schaal K, Corcuff JB, Hatem SN, Isnard R, Hausswirth C. Maximal exercise limitation in functionally overreached triathletes: role of cardiac adrenergic stimulation. *J Appl Physiol.* 2014;117(3):214-222.

104. Le Meur Y, Pichon A, Schaal K, Schmitt L, Louis J, Gueneron J, Vidal P, Hausswirth C. Evidence of parasympathetic hyperactivity in functionally overreached athletes. *Med Sci Sports Exerc.* 2013;45(11):2061-2071.
105. Mujika I. Winning the BIG medals. *Int J Sports Physiol Perform.* 2017;12(273-274).
106. Abraham A, Collins D. Taking the next step: Ways forward for coaching science. *Quest.* 2011;63(4):366-384.
107. Côté J, Gilbert W. An integrative definition of coaching effectiveness and expertise. *Int J Sports Sci Coach.* 2009;4(3):307-323.
108. Einhorn HJ, Hogarth RM. Confidence in judgment: Persistence of the illusion of validity. *Psychol Rev.* 1978;85(5):395.
109. Brink MS, Frencken WGP, Jordet G, Lemmink KAPM. Coaches' and players' perceptions of training dose: Not a perfect match. *Int J Sports Physiol Perform.* 2014;9(3):497-502.
110. Brink MS, Visscher C, Arends S, Zwerver J, Post WJ, Lemmink KA. Monitoring stress and recovery: new insights for the prevention of injuries and illnesses in elite youth soccer players. *Br J Sports Med.* 2010;44(11):809-815.
111. Brink MS, Visscher C, Coutts AJ, Lemmink KAPM. Changes in perceived stress and recovery in overreached young elite soccer players. *Scand J Med Sci Sports.* 2012;22(2):285-292.
112. Doeven SH, Brink MS, Frencken WG, Lemmink KA. Impaired player–coach perceptions of exertion and recovery during match congestion. *Int J Sports Physiol Perform.* 2017;12(9):1151-1156.
113. Barroso R, Cardoso RK, do Carmo EC, Tricoli V. Perceived exertion in coaches and young swimmers with different training experience. *Int J Sports Physiol Perform.* 2014;9:212-216.
114. Klein G. Developing expertise in decision making. *Think Reas.* 1997;3(4):337-352.
115. Chase WG, Simon HA, 215-281). Ip. Skill in Chess. *American Scientist.* 1973;61(4):394-403.
116. Nash C, Collins D. Tacit knowledge in expert coaching: Science or art? *Quest.* 2006;58(4):465-477.
117. Bowes I, Jones RL. Working at the edge of chaos: Understanding coaching as a complex, interpersonal system. *Sport Psychol.* 2006;20(2):235-245.
118. Gilbert WD, Trudel P. Learning to coach through experience: Reflection in model youth sport coaches. *J Teach Phys Educ.* 2001;21(1):16-34.

Chapter 3

Study 1

Assessing the measurement sensitivity and diagnostic characteristics of athlete monitoring tools in national swimmers

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ABSTRACT

Purpose: To assess measurement sensitivity and diagnostic characteristics of athlete monitoring tools to identify performance change.

Methods: Fourteen nationally competitive swimmers (11 males, 3 females, age: 21.2 ± 3.2 y) recorded daily monitoring over 15 months. The "Self-report" group (n=7) reported general health, energy levels, motivation, stress, recovery, soreness and wellness. The "Combined" group (n=7) recorded sleep quality, perceived fatigue, total quality recovery (TQR) and heart rate variability measures. The week-to-week change in mean weekly values were presented as the co-efficient of variance (CV%). Reliability was assessed on three occasions and expressed as the typical error CV%. Week-to-week change was divided by the reliability of each measure to calculate the signal-to-noise ratio. The diagnostic characteristics for both groups were assessed with receiver operating curve analysis, where area under the curve (AUC), Youden index, sensitivity and specificity of measures were reported. A minimum AUC of 0.70 and lower confidence interval (CI) >0.50 classified a "good" diagnostic tool to assess performance change.

Results: Week-to-week variability was greater than reliability for soreness (3.1), general health (3.0), wellness% (2.0), motivation (1.6), sleep (2.6), TQR (1.8), fatigue (1.4), R-R interval (2.5) and LnRMSSD:RR (1.3). Only general health was a "good" diagnostic tool to assess decreased performance (AUC-0.70, 95% CI, 0.61-0.80).

Conclusion: Many monitoring variables are sensitive to changes in fitness and fatigue. However, no single monitoring variable could discriminate performance change. As such the use of a multi-dimensional system that may be able to better account for variations in fitness and fatigue should be considered.

Key Words: Subjective questionnaires, Heart rate variability, performance prediction

INTRODUCTION

The primary goal of high performance coaches and sport science staff is to deliver well controlled training programs for achieving peak performance. Traditional approaches to training prescription include increases in both training volume and intensity prior to a taper [1]. However, during such heavy training periods athletes may be at a higher risk of negative training outcomes such as injury, illness and/or overreaching [2]. Indeed, these negative outcomes in training have been associated with a lower chance of achieving success in competition [3]. Therefore, to better understand if athletes are tolerating life stressors and training demands, athletes are monitored through several physiological and subjective measures. Whilst observational studies have shown monitoring tools fluctuate with changes to training load illness and overreaching, no studies are yet to examine the sensitivity, specificity or diagnostic characteristics of these monitoring tools for identifying performance change [2,4,5].

In medicine, a common approach used to assess this characteristic is testing a binary outcome, which yields two discrete functions to infer an unknown, based off a specific cut-off value (e.g. disease or no disease from a specific blood marker). The accuracy for determining these specific cut-off values is assessed using measures of sensitivity (true positive rate, i.e. the percentage of accurately diagnosed disease) and specificity (true negative rate, i.e. the percentage of patients accurately diagnosed with no disease). These values are then assessed using a receiver operating characteristic (ROC) curve to determine the diagnostic accuracy and optimal cut-off values which identify a particular outcome [6]. However, identifying the diagnostic characteristics of monitoring variables on performance change in athletes has yet to be assessed in this manner.

Subjective questionnaires and heart rate variability (HRV) have been assessed for their practicality when monitoring athletes in the daily training environment [4,7]. These measures are used to determine an athlete's fitness and/or fatigue status and inform coaches how their athletes are tolerating training demands. Although numerous validated psychometric tools are available, many athletes prefer using abbreviated questionnaires due to their simplicity and shorter time required for completion [5,7]. Likewise, many physiological measures have been used for monitoring the athlete training response. For example, HRV has been used to monitor athletes fitness or fatigue status and inform future training decisions [4,8]. Changes in HRV reflect the autonomic nervous systems control of cardiovascular function from alterations in parasympathetic modulation that may signify an adaptive or maladaptive training state [4,8]. However, while case studies have identified the positive and negative training responses, whether these variables are sensitive to adjustments in training or performance is unclear. As such, the purpose of this study was to firstly report the week-to-week variability, reliability and signal-to-noise ratio in common athlete monitoring tools, and secondly, assess the diagnostic characteristics of these tools to identify improvements and decrements in performance.

METHODS

Participants

Two groups of seven (n=14) nationally competitive swimmers (11 males, 3 females, age: 21.2 ± 3.2 y, body mass 75.8 ± 6.8 kg, best time in main event as percentage of world record: 93.5 ± 2.2%, mean ± SD), were monitored daily over 15 months. Each swimmer was provided a verbal and written explanation of the investigation before giving signed informed consent to release their data for the purpose of this research. This study was approved by the Human Research Ethics Committee of University of Technology Sydney (REF NO. 2014000842).

Study Design

This longitudinal observational study occurred over a 15-month period. Throughout this period, two commonly used monitoring systems were assessed. Monitoring questions from the "Self-report” group were part of a subjective athlete self-report monitoring system from the national body (Swimming Australia). The “Combined” group provided an alternate system that included both physiological and subjective athlete self-report questions. Two separate groups were used to compare the diagnostic accuracy of a number of commonly used monitoring variables. Swimmers in each group completed a similar training load (average weekly distance; Self report: 41 ± 6km, combined: 42 ± 9km and duration; Self-report: 17 ± 3hr, Combined: 17 ± 2hr). Athletes were asked to complete all monitoring measures daily at a standardized time for each individual and on race days at least 1 h prior to competition. Part one of the analysis investigated the test re-test reliability (i.e. noise) and the week-to-week change (i.e. signal) of all measures. The week-to-week change was then divided by test re-test reliability to calculate the signal-to-noise ratio. Part two assessed the diagnostic ability of the tools from the ROC analysis, using the area under the curve (AUC) and Youden index as diagnostic classifiers. Daily and the 7-day rolling average of monitoring variables that aligned with races were included in this part of the analysis.

Monitoring variables

The Self-report group completed daily subjective questions as ‘how you feel today’ for general health, motivation, energy levels, stress and recovery on 1 to 5 scales (1=Very poor to 5=Excellent) and soreness as a 1 to 10 scale which was inverted prior to analysis (1=No soreness at all, 10=Unbearable pain). The sum of these measures were also calculated for a total wellness score and expressed as a percentage of highest possible total (Wellness%) [9]. These variables were reported on the athlete’s personal smart phone and stored to a cloud-based athlete monitoring software (Smartabase, Fusion Sport, Brisbane, Australia). The 7-day rolling average was included in analysis if at least 3 data points were recorded in the previous 7 days (Wellness%$_{7d}$).

The Combined group completed a customized monitoring system which included resting HRV, sleep quality and fatigue rating (1=Much worse than normal, to 5=Much better than normal) and the total quality recovery scale (TQR; 6-20 scale). Athletes were asked to report all subjective measures with 'how you feel today'. The 7-day rolling average of both fatigue ($Fatigue_{7d}$) and TQR (TQR_{7d}) were analyzed in the ROC curve if at least 3 data points were available for analysis in the previous 7 days. These variables were reported on the athlete's personal smart phone and stored to a cloud-based data management system (Google Docs, USA). Upon waking each morning HRV was recorded for 6 min in a supine position via R-R series using the Polar Team 2 system (1.3.0.3. Polar Electro Oy, Kempele, Finland). Athletes left the heart rate monitor by their bedside each evening to minimise disturbances in the morning. Following recording, data was downloaded and analyzed using Kubios HRV analysis software 2.0 (The Biomedical Signal Analysis Group, University of Kuopio, Kuopio, Finland). Time domain indices selected for analysis as indicators of training adaptation and fatigue included R-R interval, the log transformed root mean squared sum of the consecutive R-R intervals (LnRMSSD) [10] and the LnRMSSD to R-R interval ratio (LnRMSSD:RR) . The LnRMSSD and LnRMSSD:RR were assessed on an isolated day for the signal-to-noise and for ROC analysis as a 7-day rolling average if at least 3 points were available for analysis in the previous 7 days (Ln $rMSSD_{7d}$, $LnRMSSD{:}RR_{7d}$) [11].

Performance Measures

Race performances included in analysis were electronically timed by official swimming governing bodies (Swimming Australia or Fédération Internationale de Natation (FINA)) at sanctioned events in a standard international 50 m pool. Prior to racing, swimmers completed a full race preparation warm up. The performance of each swimmer was tracked in their designated events ranging from 50 to 400 m in freestyle, breaststroke, backstroke, butterfly and individual medley. If multiple races of the same event (e.g. heat and final) were recorded on the same day, the fastest time was recorded for analysis. Each swimmer recorded a minimum of five races of the same event throughout the study period. Times for each athlete's individual events were averaged to give a mean time and the smallest meaningful change (SMC) was determined as 0.3 x within-swimmer standard deviation (SD) of race performance times [12]. Times outside of the SMC were then coded as a dichotomous outcome variable (0= No change, 1= Change) to assess both improvements (change< SMC) and decrements (change> SMC) in performance in separate analysis.

Statistical Analysis

Week-to-week Change

All monitoring measures were converted to mean weekly values, analyzed using a customized spreadsheet and reported as the week-to-week change presented as the coefficient of variance and 90% confidence limits (CV%, ±90% CL) [13]. A minimum of three measures in the week were required for the data to be included in the analysis. To avoid including data at the same time point leading into major competitions in consecutive seasons, only the first 12 months of data were included in the week-to-week analysis.

Test-Retest Reliability

The test-retest reliability was estimated by measurements taken twice within one hour for subjective measures and within 15 min for HRV, on three separate occasions without any physical activity between the two collections. These recordings were completed following a day of no training, low intensity (rating of "somewhat hard" or less) and high intensity training session (rating greater than "hard") using the session rating of perceived exertion [14]. For both measures, athletes were asked to record their answers with 'how they feel today' at the time of entry without consciously attempting to repeat previous results. Data was then entered into a customized spreadsheet as single day variables and presented as the test-retest technical error (TE) CV% [13].

Signal-to-noise Ratio

The signal-to-noise ratio was calculated by dividing the week-to-week change by the reliability of each measure. The signal-to-noise ratio was classified as "Good" if >1, "Ok" =~1 and "Poor" if <1 [15].

Data Normalization

Following the signal-to-noise ratio analysis, monitoring variables were normalised using Z-scores to standardize athlete values. Athlete's Z-scores were calculated by the daily measure subtracted from the individual's mean value from all measures collected through the study and divided by the SD of the mean. All Z-scores were then aligned with dichotomous outcomes (0= No change, 1= Change) for improvements and decrements in performance from separate analysis. Z-scores were used in this analysis to provide a standardized value and cut-off score (meaningful Z-score) to discriminate performance change relevant for each individual.

Receiver Operating Characteristic Curves

Variables with a "good" signal-to-noise ratio and the 7d rolling average of measures were assessed as Z-scores to examine the diagnostic capability to discriminate a change in performance. Sensitivity versus specificity analysis was performed using ROC curves to assess if a monitoring variable can diagnose an improvement (change < SMC) or decrease in performance (change > SMC) in separate analysis. An ROC curve plots the true positive rate (sensitivity) against the true negative rate (specificity) to produce an AUC. An AUC of 1.00 (100%) represents perfect discriminant power, where 0.50 (50%) would represent no discriminatory power. An AUC >0.70 and the lower CI >0.50 was classified as a "good" benchmark [16]. All ROC curve results were presented as AUC ± 95% CI [6]. The Youden Index was calculated (Youden index= sensitivity+specificity−1) from all ROC curve plots (sensitivity and specificity) to determine the point where the Youden index was optimised and considered the score at which a “cut-off’ value presented as a Z-score from each monitoring variable might be acceptable to discriminate a change in performance. The maximum Youden index of 1 would suggest perfect discriminatory value, whilst a score of 0 would reflect no diagnostic value [17]. All ROC analysis was performed using SPSS (Version 21. IBM Company, New York, USA).

RESULTS

Performance

The total number of races included in the analysis, along with the number of improvements (Change < SMC) and decrements (Change > SMC) in performance are reported in Table 3:1 and 3:2 respectively. The Self-report group had a total of 143 performances included in analysis, recording 27 ± 8 races per athlete. The Combined group had a total of 143 performances included in analysis, recording 27 ± 6 races per athlete.

Signal-to-noise Ratio

The week-to-week CV%, Reliability and signal-to-noise ratio is reported in Table 3:3. For both groups a total of 280 training weeks (40 weeks per athlete) were analyzed for the week-to-week CV% respectively. For both groups, 4 weeks were excluded from analysis due to no training. The seven athletes in the Self-report group had a total of 252 athlete training weeks included in analysis. The Combined group had a combined 243 training weeks included for the subjective measures (sleep, fatigue and TQR) and 226 training weeks for HRV across all seven athletes. Of all measures assessed there was a ‘good’ signal-to-noise ratio for the following variables in the Self-report group; soreness (3.1), general health (3.0), wellness% (2.0), motivation (1.6). The Combined group had a ‘good’ signal to noise ratio for sleep (2.6), TQR (1.8), fatigue (1.4), R-R Interval (2.5) and LnRMSSD:RR (1.3).

Table 3:1 Diagnostic characteristics of monitoring variables for improvements in performance.

Group	Variable	Improved	Total Performance	AUC *(95% CI)*	Z-Score	Sensitivity	Specificity	Youden Index
SELF REPORT	***Performance***	*52*	143					
	Gen Health	45	124	0.67 *(0.57 – 0.76)*	> 0.2	78%	51%	0.28
	Motivation	45	124	0.58 *(0.48 – 0.68)*	> 0.4	56%	62%	0.18
	Soreness	45	124	0.61 *(0.51 – 0.71)*	> 1.0	51%	72%	0.23
	Wellness%	45	124	0.62 *(0.51 – 0.72)*	> 0.6	69%	57%	0.26
	Wellness%$_{7d}$	50	136	0.64 *(0.54 – 0.74)*	> 1.0	54%	76%	0.30
COMBINED	***Performance***	*66*	143					
	Sleep	66	142	0.52 *(0.43 – 0.62)*	> 0.1	50%	59%	0.09
	TQR	66	142	0.62 *(0.53 – 0.72)*	> 0.4	59%	65%	0.24
	TQR$_{7d}$	67	143	0.64 *(0.54 – 0.73)*	> 0.9	60%	75%	0.35
	Fatigue	66	142	0.65 *(0.56 – 0.74)*	> 0.1	71%	54%	0.25
	Fatigue$_{7d}$	67	143	0.66 *(0.56 – 0.75)*	> 0.7	61%	71%	0.32
	RR Interval	46	99	0.65 *(0.54 – 0.76)*	< -0.7	54%	79%	0.34
	LnRMSSD:RR$_{7d}$	55	120	0.62 *(0.52 – 0.72)*	> 0.4	60%	66%	0.26

Abbreviations: CI- 95% Confidence intervals, AUC- Area under the curve, Gen health- General health, Wellness%- A sum of all subjective measures expressed as a percentage of highest possible total. Wellness%$_{7d}$- The seven day average of Wellness%, TQR- Total quality recovery scale, TQR$_{7d}$- The seven day rolling average of the total quality recovery scale, Fatigue$_{7d}$- The seven day average of the fatigue, RR Interval- The average R-R interval from morning resting heart rate, LnRMSSD:RR$_{7d}$- The seven day average of the LnRMSSD: R-R interval ratio.

Table 3:2 Diagnostic characteristics of monitoring variables for decrements in performance.

Group	Variable	Decreased	Total Performances	AUC *(95% CI)*	Z-Score	Sensitivity	Specificity	Youden Index
SELF REPORT	***Performance***	***48***	143					
	Gen Health	**47**	**124**	**0.70 *(0.61 – 0.80)***	**< 0.2**	**62%**	**73%**	**0.34**
	Motivation	47	124	0.63 *(0.52 – 0.73)*	< 0.2	66%	58%	0.24
	Soreness	47	124	0.59 *(0.49 – 0.70)*	< -0.1	32%	87%	0.19
	Wellness%	47	124	0.63 *(0.53 – 0.73)*	< 1.3	89%	33%	0.22
	Wellness%$_{7d}$	44	136	0.64 *(0.54 – 0.73)*	< 1.0	84%	45%	0.29
COMBINED	***Performance***	***54***	143					
	Sleep	54	142	0.56 *(0.47 – 0.66)*	< -0.2	37%	74%	0.11
	TQR	54	142	0.62 *(0.52 – 0.71)*	< 0.1	52%	68%	0.20
	TQR$_{7d}$	54	143	0.62 *(0.53 – 0.72)*	< 0.7	67%	61%	0.27
	Fatigue	54	142	0.61 *(0.52 – 0.70)*	< 0.1	56%	66%	0.22
	Fatigue$_{7d}$	54	143	0.63 *(0.53 – 0.72)*	< 1.1	89%	38%	0.27
	RR Interval	38	99	0.59 *(0.48 – 0.70)*	> -0.7	79%	46%	0.25
	LnRMSSD:RR$_{7d}$	46	120	0.59 *(0.48 – 0.70)*	< 0.7	80%	39%	0.19

Abbreviations: CI- 95% Confidence intervals, AUC- Area under the curve Gen health- General health, Wellness%- A sum of all subjective measures expressed as a percentage of highest possible total. Wellness%$_{7d}$- The seven day average of Wellness%, TQR- Total quality recovery scale, TQR$_{7d}$- The seven day rolling average of the total quality recovery scale, Fatigue$_{7d}$- The seven day average of the fatigue, RR Interval- The average R-R interval from morning resting heart rate, LnRMSSD:RR$_{7d}$- The seven day average of the LnRMSSD: R-R interval ratio. ***Bold text****: Highlights diagnostic criteria of area under the curve >= 0.70 and lower CI > 0.50 to be classified as a "good" discriminatory monitoring variable.*

Table 3:3 Week-to-week variation, test-retest and signal-to-noise ratio of monitoring variables.

Monitoring Variable	Week-to-week Change *(90% CL)*	Test- Retest *(90% CL)*	Signal-to-Noise Ratio	Rating
Soreness	8.0 *(7.3 – 8.9)*	2.6 *(2.0 – 3.8)*	3.1	Good
Gen Health	10.6 *(9.6 – 11.8)*	3.5 *(2.7 – 5.2)*	3.0	Good
Wellness%	4.9 *(4.5 – 5.5)*	2.5 *(2.0 – 3.7)*	2.0	Good
Motivation	10.0 *(9.1 – 11.1)*	6.2 *(4.8 – 9.3)*	1.6	Good
Energy Levels	10.6 *(9.7 – 11.9)*	10.4 *(7.9 – 15.5)*	1.0	Ok
Recovery	8.0 *(7.3 – 8.9)*	8.4 *(6.4 – 12.6)*	1.0	Ok
Stress	7.9 *(7.2 – 8.8)*	9.3 *(7.1 – 13.9)*	0.8	Poor
Sleep	11.5 *(10.5 – 12.9)*	4.5 *(3.5 – 6.7)*	2.6	Good
TQR	6.8 *(6.2 – 7.6)*	3.8 *(2.9 – 5.5)*	1.8	Good
Fatigue	14.0 *(12.6 – 15.7)*	10.0 *(7.6 – 15)*	1.4	Good
R-R Interval	8.9 *(8.0 – 10.0)*	3.5 *(2.7 – 5.1)*	2.5	Good
LnRMSSD:RR Ratio	10.1 *(9.1 – 11.4)*	7.7 *(5.9 – 11.4)*	1.3	Good
Ln RMSSD	5.9 *(5.4 – 6.6)*	6.3 *(4.8 – 9.4)*	0.9	Poor

Abbreviations: CV (%)- Coefficient of variance, 90% CL- 90% confidence limits, Signal-to-Noise Ratio- calculated from dividing the week-to-week change by the test retest coefficient of variance. Rating- ratings of the signal-to-noise ratio "Good" if > 1, "Ok" = ~ 1 and "Poor" if < 1, Gen Health- General health, Wellness%- sum of variables from a total wellness score expressed as a percentage of highest possible total, TQR- total quality recovery scale, Ln RMSSD:RR- the Ln RMSSD to R-R interval ratio, Ln RMSSD- the log transformed root mean squared sum of the consecutive R-R intervals.

DISCUSSION

It appears that several monitoring variables have poor discriminatory ability for assessing worthwhile variations in performance. However, there was a good signal-to-noise ratio for many measures including soreness, general health, wellness%, motivation, sleep, TQR, fatigue, R-R interval and the LnRMSSD: RR. As such, changes in fitness and fatigue of well-trained swimmers can be tracked with self-reported and HRV indices but these measures are poor discriminators of meaningful changes in performance.

The first part of this study assessed the test-retest reliability, week-to-week variation, and signal-to-noise ratio of commonly used monitoring tools. Many of the monitoring tools were sensitive (i.e. typical weekly changes > test-retest error) to changes in the swimmer's training programs. The magnitude of typical weekly changes of general health, soreness, wellness%, motivation, sleep, TQR, fatigue, R-R interval and the LnRMSSD:RR ratio were between 1.3-3.1 times the test-retest error. The variations in these subjective questionnaires are similar to previous studies in well-trained swimmers [18,19]. For example, over a 6 month training period Morgan, et al. [18] identified that fluctuations in mood for the 41 well-trained swimmers was associated with changes in training load. Noticeable increases in mood disturbances from the profile of mood states during peak training periods returned to baseline values throughout a taper. Similarly, during a deliberate 10-d increase in training load, self-reported general wellbeing and muscle soreness reflected individual tolerance to training demands in 12 swimmers [19]. Collectively, these findings demonstrate the ability of wellbeing measures to assess fitness and fatigue in swimmers. Moreover, applying a signal-to-noise ratio should assist practitioners to better quantify changes in fitness and fatigue measures.

The typical week-to-week variation of subjective questionnaires in the present study was noticeably lower than similar questionnaires in team sports [20,21]. The reliability CV% of subjective questionnaires over two similar training weeks ranged from 12% on game day to 32% the day immediately after the game in Australian football players [20]. Similar, larger variations (7.1 CV%) and poor sensitivity of wellness questionnaires was reported in rugby league players [15]. However, sensitivity was determined from the between-day reliability as a CV% x 0.2 to calculate the SMC without training between tests. The larger variations compared to the results in the present study (4.9% week-to-week and 2.5% test-retest) could be attributed to the differences in methodology calculating typical error and also reflect the differences in the training and match demands of team sport athletes compared to swimmers. Swimming training and competition is highly controlled, whereas team sport athletes have other external factors including weekly fixtures, tactical changes and collisions that may further affect the variability in athlete's subjective responses.

Similar to the wellness questionnaires, the signal (i.e. training induced changes) was greater than the test-retest noise for both the R-R interval and LnRMSSD:RR. Notably both the reliability and weekly CV% of HRV from this study were also lower than previous reports. For example this study reported CV% for R-R interval and LnRMSSD (3.5% and 6.3%) were lower than between-day CV% in team sport athletes (11.1 and 12.3% respectively) [10]. Accounting for methodological differences, this variance may be explained from comparing moderately-trained (5-6 h/week) to the highly-trained participants (18-22 h/week) in this study. The high sensitivity of HRV in the present investigation provides evidence that in swimmers, R-R interval and LnRMSSD: RR may be useful to guide decision-making around training prescription. Several studies have shown that endurance training outcomes can be improved through modifying training prescription based on daily changes of HRV in recreational athletes [22-24]. Surprisingly however, no studies have described the typical daily variability in these measures compared to the same day test-retest in highly-trained athletes. Taken collectively, HRV and subjective measures are sensitive to training induced changes in fitness and fatigue.

The poor diagnostic characteristics of monitoring variables raises questions of their appropriateness to identify performance change. Only general health (AUC= 0.70, CI, 0.61-0.80) in the Self-report group fit the benchmark criteria of AUC >0.70 and lower CI >0.50 to be classified as a "good" discriminatory variable for decreased performance. These findings are similar to Saw, et al. [5] whose systematic review indicated that subjective questionnaires are responsive to training load but were unable to discriminate performance change in a variety of athletes. However, fatigue could explain up to 53% of the variance in performance of elite swimmers and by combining sleep, stress, fatigue and muscle soreness this explanation has been increased up to 72% [25]. Whilst selected monitoring measures can assess performance following a taper, the accuracy of a single measure to predict performance change throughout a season with a larger sample size is not as strong.

The Youden index assesses the balance between sensitivity and specificity to quantify cut-off values identifying if an outcome is likely to occur. The poor discriminatory function of the monitoring variables is highlighted with the highest value for improved performance being TQR_{7d} (Youden index=0.35, Z-score >0.9, sensitivity= 60%, specificity=75%) and decreased performance from general health (Youden index=0.34, Z-score <0.2, sensitivity=62%, specificity=73%). However, as the present study is the first to use the Youden index to assess athlete monitoring tools, an acceptable threshold and interpretation of sensitivity and specificity to accurately identify changes in athletic performance is still relatively unknown. Indeed, little evidence is currently available to support how specific "cut-off" values are implemented. Reports from high performance sports on athlete monitoring suggest there is a strong reliance on the visual analysis of trends for when to modify training [7]. While the Youden index in the present investigation showed a weak association to changes in performance, future use of this data analysis technique may help provide meaningful cut-off values to enhance the ability of monitoring tools to assess performance change.

Assessing performance accurately can be problematic when monitoring variables are examined in isolation. An individual's capacity to perform on a given day is dependent on a multitude of factors ranging from physiological, nutritional and/or psychological. Whilst subjective measures may be able to detect fatigue, they provided little understanding of an athlete's performance capacity throughout a season. It is also difficult to classify an improvement or decrement in the performance of elite swimmers. In this investigation, SMC was used without consideration of the TE of race performance. This was due to the difficulty in assessing a true TE from two maximal race performances. Nonetheless, it should be acknowledged that this may influence the number of calculated improvements and decrements in performance, in turn affecting the ROC analysis and results. Moreover, the use of Z-scores to normalize data in this study may have weakened the intra-individual diagnostic accuracy. Furthermore, a multi-dimensional psychobiological approach to monitoring may provide more useful information to coaches. Through the longitudinal analysis of the two separate training groups, the multitude of variables assessed could assist sport scientists in the selection of useful monitoring tools for a more holistic and effective assessment of an athlete's fitness and fatigue.

PRACTICAL APPLICATIONS

Monitoring the general health of athletes was the only variable that met the criteria to assess decrements in performance. We recommend from the results of both the AUC and the Youden index that caution be taken with the interpretation of any single monitoring tool to assess performance change. Further, it is appropriate that monitoring tools are validated with each sport. The smaller CV% in swimmers compared to team sports, suggest even subtle variations in subjective and HRV measures may be important in these athletes.

CONCLUSION

The lack of discriminatory ability of any single monitoring variable brings into question the utility of this approach to accurately assess performance change. The "good" signal-to-noise ratio of the numerous monitoring tools assessed shows the variables potential to monitor athlete's fitness and fatigue. However, both the type of athlete and sport should be considered in establishing a monitoring system. A multi-factorial monitoring system to account for variations in fatigue and an athlete's performance capacity should therefore be considered.

REFERENCES

1. Kiely J. Periodization paradigms in the 21st century: evidence-led or tradition-driven. *Int J Sports Physiol Perform.* 2012;7(3):242-250.
2. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, Raglin J, Rietjens G, Steinacker J, Urhausen A. Prevention, diagnosis and treatment of the overtraining syndrome: Joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). *Eur J Sport Sci.* 2013;13(1):1-24.
3. Raysmith BP, Drew MK. Performance success or failure is influenced by weeks lost to injury and illness in elite Australian track and field athletes: a 5-year prospective study. *J Sci Med Sport.* 2016;19(10):778-783.
4. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Front Physiol.* 2014;5(73).
5. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
6. Fawcett T. An introduction to ROC analysis. *Pattern Recognit Lett.* 2006;27(8):861-874.
7. Taylor K, Chapman DW, Cronin JB, Newton MJ, Gill N. Fatigue monitoring in high performance sport: A survey of current trends. *J Aus Strength Cond.* 2012;20(1):12-23.
8. Bellenger CR, Fuller JT, Thomson RL, Davison K, Robertson EY, Buckley JD. Monitoring athletic training status through autonomic heart rate regulation: A systematic review and meta-analysis. *Sports Med.* 2016:1-26.
9. Hooper SL, MacKinnon LT. Monitoring overtraining in athletes. Recommendations. *Sports Med.* 1995;20(5):321-327.
10. Al Haddad H, Laursen PB, Chollet D, Ahmaidi S, Buchheit M. Reliability of resting and post exercise heart rate measures. *J Sports Med.* 2011;32(8):598-605.
11. Plews DJ, Laursen PB, Le Meur Y, Hausswirth C, Kilding AE, Buchheit M. Monitoring training with heart rate variability: How much compliance is needed for valid assessment? *Int J Sports Physiol Perform.* 2013;9(5):783-790.
12. Hopkins WG, Hawley JA, Burke LM. Design and analysis of research on sport performance enhancement. *Med Sci Sports Exerc.* 1999;31(3):472-485.
13. Hopkins WG. Analysis of reliability with a spreadsheet. *New View of Statistics, Internet Society for Sport Science.* 2010.
14. Seiler S, Kjerland Ø. Quantifying training intensity distribution in elite endurance athletes: is there evidence for an “optimal” distribution? *Scand J Med Sci Sports.* 2006;16(1):49-56.
15. Roe G, Darrall-Jones J, Till K, Phibbs P, Read D, Weakley J, Jones B. Between-day reliability and sensitivity of common fatigue measures in rugby players. *Int J Sports Physiol Perform.* 2015;11(5):581-586.
16. Menaspa P, Sassi A, Impellizzeri FM. Aerobic fitness variables do not predict the professional career of young cyclists. *Med Sci Sports Exerc.* 2010;42(4):805-812.
17. Schisterman EF, Perkins NJ, Liu A, Bondell H. Optimal cut-point and its corresponding Youden Index to discriminate individuals using pooled blood samples. *Epidemiol.* 2005;16(1):73-81.
18. Morgan WP, Brown DR, Raglin JS, O'connor PJ, Ellickson KA. Psychological monitoring of overtraining and staleness. *Br J Sports Med.* 1987;21(3):107-114.
19. Morgan WP, Costill DL, Flynn MG, Raglin JS, O'Connor PJ. Mood disturbance following increased training in swimmers. *Med Sci Sports Exerc.* 1988;20(4):408-414.
20. Gastin PB, Meyer D, Robinson D. Perceptions of wellness to monitor adaptive responses to training and competition in elite Australian football. *J Strength Cond Res.* 2013;27(9):2518-2526.

21. Montgomery PG, Hopkins W. The effects of game and training loads on perceptual responses of muscle soreness in Australian football. *Int J Sports Physiol Perform.* 2013;8(3):312-318.
22. Vesterinen V, Nummela A, Heikura I, Laine T, Hynynen E, Botella J, Häkkinen K. Individual endurance training prescription with heart rate variability. *Med Sci Sports Exerc.* 2016;48(7):1347–1354.
23. Kiviniemi AM, Hautala AJ, Kinnunen H, Nissilä J, Virtanen P, Karjalainen J, Tulppo M. Daily exercise prescription on the basis of HR variability among men and women. *Med Sci Sports Exerc.* 2010;42(7):1355-1363.
24. Kiviniemi AM, Hautala AJ, Kinnunen H, Tulppo MP. Endurance training guided individually by daily heart rate variability measurements. *Eur J Appl Physiol.* 2007;101(6):743-751.
25. Hooper SL, Mackinnon LT, Howard A, Gordon RD, Bachmann AW. Markers for monitoring overtraining and recovery. *Med Sci Sports Exerc.* 1995;27(1):106-112.

Chapter 4

Study 2

Can a multi-factorial athlete monitoring system identify performance changes in swimmers?

Crowcroft, S., Slattery, K., McCleave, E. and Coutts, A. J. *(Under review).* Can a multi-factorial athlete monitoring system identify performance changes in swimmers? *International Journal of Sports Physiology and Performance.*

ABSTRACT

Purpose: To assess the accuracy of a multi-factorial monitoring system to identify performance changes in highly trained swimmers.

Methods: Nine highly trained swimmers (7 males, 2 females, age: 21.6 ± 2.0 y) recorded perceived fatigue, total quality recovery (TQR) and heart rate variability (HRV: R-R interval and log transformed root mean squared difference between the consecutive R-R interval (Ln rMSSD)) and training measures (distance swum and training load) over a 16-month period. All monitoring values were analysed as a 7-d rolling average aligned with race results and converted to a Z-score (subjective questionnaires) or a standardised difference score (HRV measure) from both the athletes first race of the season and their previous race result in separate analysis. All race results (n= 124) were classified as a dichotomous outcome (0= no change, 1= performance decrement or improvement) and analysed using a generalised estimating equation (GEE). The mean probability of combining variables from GEE models were then analysed using receiver operating characteristic curves to assess the model's accuracy.

Results: The model that combined TQR while accounting for the repeated measures of the athlete had the highest diagnostic accuracy (AUC:0.80, 95% CI, 0.70-0.89) to identify improvements from baseline performances.

Conclusion: There was stronger diagnostic accuracy of a longitudinal multi-factorial athlete monitoring system compared to short term performance change models. Combining physiological responses with psychological state or training volume assisted to explain decrements in performance. Combining these variables into a single model builds on previous findings that have observed aligning HR responses with subjective questionnaires and training phase. These results support the conceptual approach of a multi-factorial monitoring system yet highlight the lower diagnostic accuracy when assessing short term performance changes.

Key words: Heart rate variability, subjective questionnaires, modelling performance

INTRODUCTION

Training prescription is often based upon the assumption that biological adaptations from a training dose elicit a predictable outcome [1]. However, an athlete's response to training is not only dependent on the nature of the session completed, but also on the interaction between other factors such as training history, life stressors and psychological state [2]. Therefore, in an attempt to support coaches in developing training plans and understanding how athletes tolerate training demands, numerous non-invasive athlete monitoring tools (i.e. heart rate (HR) derived indices, neuromuscular function tests and subjective questionnaires) have been developed [3,4]. Whilst it is generally considered that these tools aid in decision-making for training prescription, no research has assessed whether combining objective and subjective monitoring tools can be applied to predict athletic performance [3,5].

Calvert et al., [6] originally proposed that athletic performance was the result of the complex interactions of various individual capacities such as sport specific endurance, strength, skill and psychological state. In an attempt to simplify this complex model, these factors were incorporated into the "fitness – fatigue" model which estimated athletic performance outcomes from mathematically modelled 'fitness' and 'fatigue' responses to training doses [6]. Whilst attractive in its simplicity, this model may be limited as it fails to account for the large inter-individual responses to training [7] and the many factors that can influence an athletic performance (e.g. training history, sleep, stress and nutritional status) [2]. Instead, a multi-factorial approach to identifying likelihood of performance change in athletes may be warranted [8]. Indeed, previous research has demonstrated that a multi-factorial approach that contextualises changes in both physiological and perceptual measures to the athletes training loads provides more detailed insight into likely performance changes [9-11]. For example, Bellenger et al., [10] observed a moderate effect size change in time domain heart rate variability (HRV) indices, a reduced rating of training tolerance and reduced physical performance followed two weeks of intensified training in endurance runners. However, following a 10-d taper, HRV indices remained elevated yet both training tolerance ratings and physical performance improved. These findings show that interpreting changes in athlete monitoring variables should be made in the context of the nature and goal of the training program.

While many athlete monitoring tools are available to quantify an athletes training responses [4], no study has assessed how this data may assist coaches or sport scientists to identify how their athlete is likely to perform in training or competition [3]. When forecasting a binary outcome such as a performance change (i.e. Did performance change? Yes or No) from multiple monitoring variables, logistic regression analysis may be useful to inform training prescription. From this analysis a single outcome is calculated from multiple variables and converted to a probability of an outcome [12]. Although to date, no examples are available of how to combine multiple variables into a single outcome to assess athlete performance changes. Therefore, the purpose of this study was to assess the accuracy of a multi-factorial athlete monitoring system to identify improvements and decrements in performance of highly trained swimmers.

METHODS

Participants

Nine (n=9) nationally competitive swimmers (7 males, 2 females, age: 21.6 ± 2.0 y, best time in main event as a percentage of world record: 92.9 ± 1.7%, mean ± SD), were monitored daily for 16-months. Of the 9 who commenced the study one withdrew from the study due to external commitments. Each swimmer was provided a verbal and written explanation of the investigation before giving informed consent to release their data for this research. This study was approved by the Human Research Ethics Committee of University of Technology Sydney (REF NO. 2014000842).

Study Design

This longitudinal observational study monitored morning resting HR measures, subjective self-report questions and a log of all training sessions. Athletes were asked to complete all monitoring measures daily upon waking in the morning. All training and racing sessions (session rating of perceived exertion (sRPE), duration (minutes) and distance swum (km)) were logged within 30 minutes of completion. Part one of the analysis assessed a generalised estimating equation from athlete monitoring variables to explain probability of performance change. Part two assessed the true predictive ability of the probability models from Receiver Operating Characteristic (ROC) curve analysis as a marker of the model's accuracy [13].

Athlete Monitoring Variables

Subjective self-report measures recorded in this study included fatigue rating (1 = Much worse than normal, 2 = worse than normal, 3= normal, 4 = better than normal, 5 = Much better than normal) [5] and the total quality recovery scale (TQR; 6-20 scale) [14]. Athletes reported all measures based on 'how do you feel today?' on their personal smart phone, where entries were stored in a cloud-based data management system (Google Forms, Google, CA, USA). Upon waking HRV was recorded for all athletes from a 6-min supine position via R-R series using the Polar Team 2 system (1.3.0.3. Polar Electro Oy, Kempele, Finland). Athletes were asked to leave HR monitors bedside of an evening to minimise disturbance upon waking. Following recording, HR files were downloaded and analysed using Kubios HRV analysis software (The Biomedical Signal Analysis Group, University of Kuopio, Kuopio, Finland). Time domain indices selected for analysis as indicators of responsiveness to training included R-R interval, Ln rMSSD and the Ln rMSSD to R-R interval ratio. If at least 3 data points from the previous 7-days for both HRV and subjective measures were recorded, the 7-day rolling average through to the day of performance in these measures were analysed [15]. Following all training and racing, athletes were asked to record total distance swum in the training session to the nearest 50 m, report session duration in minutes and then subjectively rate the intensity of the entire session using a rating of perceived exertion 6–20 scale [16]. Training load was then quantified through the session rating of perceived exertion method (sRPE x duration) [17].

Performance Measures

All race results were recorded from electronically timed sanctioned events in standard international 50-m pools. Prior to racing, swimmers completed a full race preparation warm up. The performance of each swimmer was tracked in their designated events ranging from 50 to 400-m in freestyle, breaststroke, backstroke, butterfly or individual medley. If multiple races of the same event and day were completed (e.g. heat and final), the fastest time was recorded. For inclusion in analysis, each swimmer must have recorded a minimum of five races of the same event throughout the study period. Times for each athlete's individual events were assessed for the typical within-swimmer and event co-efficient of variation (CV%) before conversion to a dichotomous outcome [18].

Data Normalisation

To identify performance change, data was normalised using two different methods. The first approach, examined changes from baseline races (first race for each athlete in each event for the season) and identified as positive or negative longitudinal change. The second approach assessed the change in performance from the previous same event and labelled as positive and negative from previous performance models respectively. Race results were then converted to a dichotomous outcome (0 = no change, 1 = performance decrement or improvement (change in time > or < +/- 0.3 x CV% [18])) and aligned with monitoring variables and the respective athletes code (1-8).

Monitoring Variables

For both longitudinal models and changes from previous race results, subjective questionnaires were converted to 7-day average then a Z-score (7-day average – mean/ within swimmer standard deviation (SD)) and aligned with dichotomous performance outcomes. Measures of HRV and performance were calculated two separate ways (longitudinal change and change from previous race results).

Longitudinal Changes

Measures of HRV (Ln rMSSD and R-R interval) were analysed as a 7-day rolling average before conversion to a standardised difference score from baseline (7-day rolling average – 7-day rolling average from baseline)/within swimmer SD) [19]. A change in performance was calculated from each athlete's change in time from their first race of the season, where the inter-individual smallest meaningful change (SMC) was used. Each athlete's SMC for their respective event was calculated using 0.30 x CV% [18]. Prior to analysis, times were then coded as a dichotomous outcome variable (0= no change, 1= change), to show both an improvement (change < baseline time - SMC) or decrement (change > baseline time + SMC) in performance. Dichotomous outcomes were then aligned with monitoring variables.

Short Term Change

The short-term change was classified as a change in HRV and performance measures from the athlete's previous race result. HRV measures were expressed as a 7-day rolling average and aligned with race results and converted to standardised difference score from previous races values (7-day rolling average – previous races 7-day average/ within swimmer SD). Performance change was expressed as change in previous race results, where the inter-individual SMC (0.30 x CV%) was used to demonstrate a meaningful change in times. Times were then coded as a dichotomous outcome variable (0= no change, 1= change) to assess both improvement (change < previous time - SMC) and decrements (change > previous time + SMC) in performance.

Statistical Analysis

Generalised Estimating Equation

Generalised Estimating Equations (GEE) were constructed to explain the relationship of the binary performance outcomes (change or no change) and aligning monitoring variables for four separate models. All GEE models used a binary logistic distribution for the response variable with an independent correlation structure. All models included a random effect (factor) to account for the repeat measure design in this analysis [12]. Firstly, between athlete variance (Athlete 1-8) was included in the model. If this was to complex with complete separation of data, differences in race results were classified as either "sprint" for 50-100 m events or "middle distance" or 200-400 m events. An inclusion of an additional variable was based on the evaluation of model fit, where an additional variable was only included in the model if the Wald Chi Squared was significant and the Quasi Likelihood under Independence Model Criterion (QIC) decreased from visual inspection [20]. Pearson's correlation co-efficient was checked for co-linearity of variables. Variables were not included in the same model if Pearsons correlation coefficient > = (±) 0.60 with another variable. To build a multi-factorial model and avoid co-linearity, models included a maximum of 1 subjective questionnaire (Fatigue or TQR), 1 physiological measures (R-R interval or Ln rMSSD) and 1 training measure (KM or training load). The predictive probability value of the mean response was calculated automatically in SPSS from the strongest models to assess probability of both improvements and decrements in longitudinal and previous race results (SPSS, Version 23. IBM Company, New York, USA).

Receiver Operating Characteristic Curves

A receiver operating characteristic (ROC) curve was used to compare accuracy of the four models to identify probability of an improvement or decrease in performance (change > or < SMC) through producing an area under the curve (AUC) using sensitivity (true positive rate) and specificity (true negative rate). An AUC of 1.00 (100%) represents perfect discriminatory power, where 0.50 (50%) would represent no discriminatory power [21]. An AUC was classified as a "good" benchmark if an AUC was >0.70 with a lower CI >0.50 [22]. All ROC curve results were presented as AUC ± 95% CI [13] with analysis performed using SPSS (Version 23. IBM Company, New York, USA).

RESULTS

Race Results

One hundred and twenty-four race results were included in this analysis (16 ± 5 races per athlete). When assessing previous race results, there were 59 improvements and 43 decrements in performance. Changes from baseline had 78 improvements and 32 decrements in performance.

Generalised Estimating Equations

All GEE results are reported in Table 4:1. Of the four models assessed, both improvements and decrements from baseline had a lower QIC (129.95 and 125.38) than the equivalent previous race results models. Decrements in performance from baseline had complete separation of data with the inclusion of a random effect (Athlete), therefore a simplified model of different events (sprint and middle distance) as random intercepts combined with monitoring variables was assessed.

Receiver Operating Characteristic curves

Figure 4:1 shows the AUC and ROC curve for both improvements and decrements in performance. Both longitudinal improvements and decrement models met the criteria as a good measure to identify performance change (Positive change from baseline AUC: 0.80, 95% CI, 0.72 – 0.88 and Negative change from baseline AUC: 0.79, 95% CI, 0.71 – 0.87). Neither improvements nor decrements from previous race results met the criteria of a “good” benchmark to identify performance change (positive change from previous AUC: 0.63, 95% CI, 0.53 – 0.72, negative change from previous AUC: 0.69, 95%CI, 0.60 – 0.79).

Table 4:1 Generalised Estimating Equation to assess changes in performance from both baseline and previous race results.

Model	Parameter	*B*	S.E.	Exp.(*B*) *(± 95% CI)*	QIC
Decrement from previous	Intercept	-0.61	0.02	0.55 *(0.52 – 0.57)*	150.23
	Athlete 1	0.38	0.15	1.46 *(1.10 – 1.95)*	
	Athlete 2	0.47	0.09	1.59 *(1.33 – 1.90)*	
	Athlete 3	0.19	0.04	1.21 *(1.11 – 1.32)*	
	Athlete 4	0.59	0.14	1.81 *(1.36 – 2.40)*	
	Athlete 5	-0.38	0.06	0.68 *(0.61 – 0.77)*	
	Athlete 6	-0.24	0.08	0.79 *(0.68 – 0.91)*	
	Athlete 7	0.38	0.02	1.47 *(1.41 – 1.53)*	
	Athlete 8	0.00		1.00	
	Fatigue	-0.47	0.18	0.62 *(0.44 – 0.88)*	
	R-R Interval	0.30	0.14	1.36 *(1.03 – 1.79)*	
Improvement from previous	Intercept	-0.14	0.05	0.87 (0.79 – 0.95)	164.97
	Athlete 1	-0.34	0.17	0.71 *(0.51 – 1.00)*	
	Athlete 2	-0.43	0.08	0.65 *(0.56 – 0.76)*	
	Athlete 3	-0.42	0.06	0.66 *(0.58 – 0.75)*	
	Athlete 4	-0.24	0.17	0.79 *(0.56 – 1.10)*	
	Athlete 5	-0.16	0.00	0.85 *(0.85 – 0.86)*	
	Athlete 6	-0.63	0.06	0.53 *(0.48 – 0.60)*	
	Athlete 7	0.23	0.02	1.26 *(1.21 – 1.31)*	
	Athlete 8	0.00		1.00	
	TQR	0.50	0.18	1.64 *(1.16 – 2.32)*	
Decrement from baseline	Intercept	-3.30	0.96	0.04 *(0.01 - 0.24)*	125.38
	Sprint	-1.33	0.47	0.26 *(0.11 - 0.66)*	
	Middle Distance	0.00			
	7d KM	0.07	0.02	1.07 *(1.03 - 1.11)*	
	Ln rMSSD	-0.39	0.19	0.68 *(0.47 - 0.98)*	
Improvement from baseline	Intercept	-0.64	0.05	0.53 *(0.48 – 0.58)*	129.95
	Athlete 1	1.70	0.08	5.46 *(4.66 – 6.39)*	
	Athlete 2	1.52	0.04	4.57 *(4.25 – 4.90)*	
	Athlete 3	-0.60	0.07	0.55 *(0.48 – 0.63)*	
	Athlete 4	1.42	0.10	4.15 *(3.43 – 5.03)*	
	Athlete 5	1.38	0.05	3.98 *(3.58 – 4.42)*	
	Athlete 6	2.48	0.06	11.99 *(10.65 – 13.51)*	
	Athlete 7	0.11	0.01	1.11 *(1.09 – 1.14)*	
	Athlete 8	0.00		1.00	
	TQR	0.60	0.15	1.82 *(1.36 – 2.43)*	

β- Unstandardised beta co-efficients, S.E.- Standard error, Exp.(B) (± 95% C.I.)- Exponential of unstandardised beta co-efficient with 95% Wald Confidence intervals, QIC- Quasi Likelihood under Independence Model Criterion, TQR- Total quality recovery scale, 7d KM- Kilometres swum in previous 7d days,Ln rMSSD – Log transformed root mean squared sum of differences between the consecutive R-R interval, S.E.- Standard error.

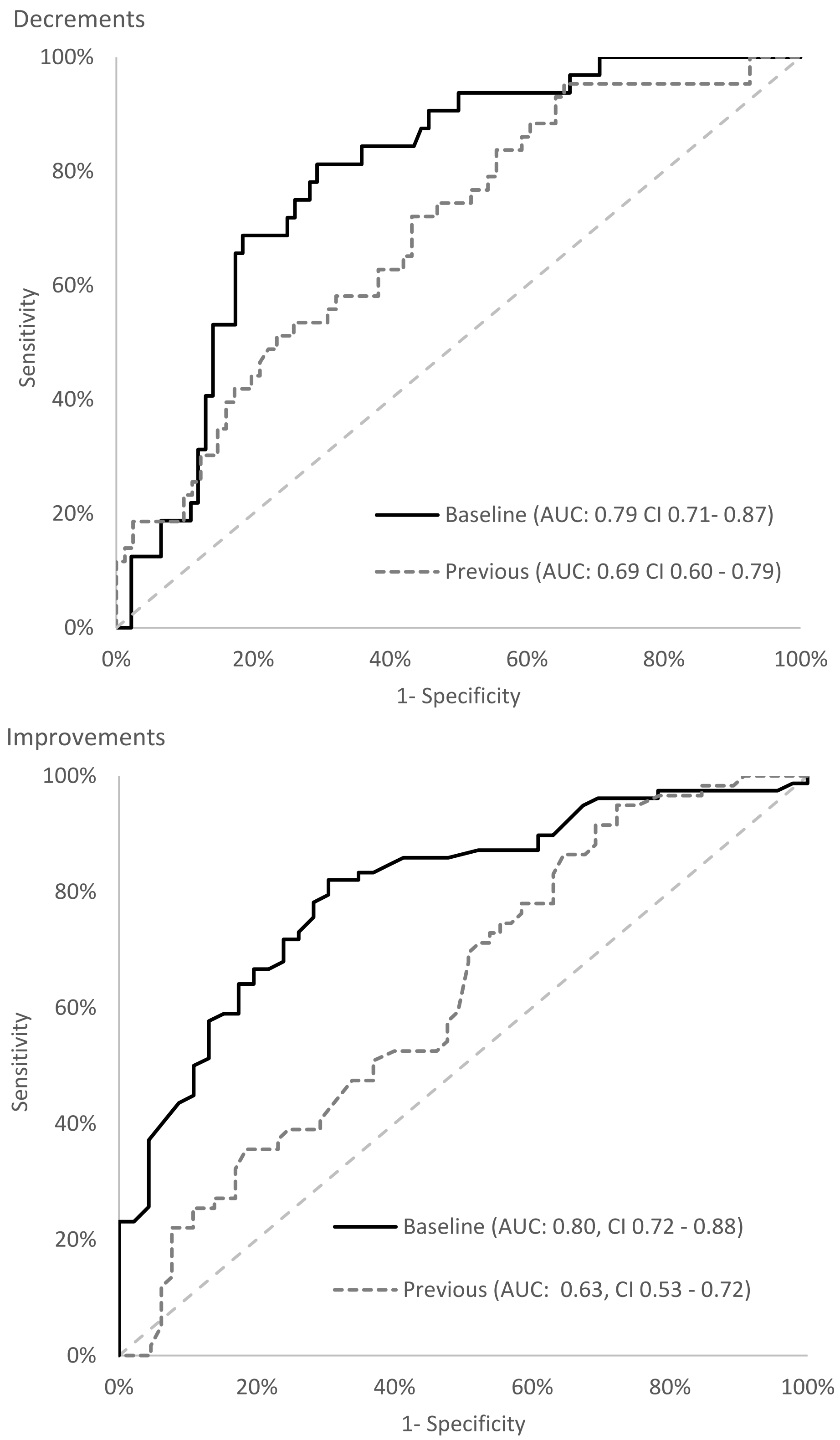

Figure 4:1 Receiver Operator Characteristic Curves of decrements and improvements in performance. Decrements- Decrease in performance models, Improvements- Improvement in performance models, AUC- Area Under the Curve. Sensitivity- True positive rate, 1- Specificity- 1-True negative rate.

DISCUSSION

The purpose of this study was to assess the accuracy on a multi-factorial athlete monitoring system to identify both improvements and decrements in performance of highly trained swimmers. From the variables collected, after accounting for the individual athlete, TQR could assist to explain improvements in performance. Further, the combining of a physiological measure of HR (R-R interval or Ln rMSSD) combined with either a rating perceived fatigue or training volume could assist to identify a likely decrement in performance. These findings build upon previous overreaching studies suggesting the use of a multi-factorial monitoring approach to identify performance changes [9,10,23].

The present study demonstrated improved diagnostic accuracy of a predictive multi-factorial model improves when accounting for individual differences compared to any single variable in isolation [5]. For example, the observed AUC was significantly greater than previous analysis on the same cohort of athletes, where the strongest marker of performance change in highly trained swimmers was a perceptual rating of general health (AUC = 0.70, CI 0.61–0.80, Youden index= 0.34) [5]. As such, the diagnostic accuracy of identifying a likely improvement in performance increase when combining psychological state of recovery (TQR) with accounting for the individual athlete in a single model. Furthermore, decrements in performance, improved prediction accuracy compared to previous findings through combining a physiological change with psychological state (perceived fatigue) or training completed. Indeed, initial research into modelling athletic performance proposed a theoretical multi-factorial model to predict performance outcomes applicable across sports through measures of endurance, strength, skill and psychological state [6]. However, when this conceptual model was first proposed, there were numerous challenges inhibiting sport scientists to quantify these factors. However, with recent advancements in technology ease of data collection in high performance sport, these limitations have been addressed. Our study has extended the initial conceptual approach to interpret multiple athlete monitoring variables into a single probability model for assessing the likelihood of performance change [13]. These findings provide support for the integration of accounting for individual athlete differences and integrating a multi-factorial approach to improve the diagnostic accuracy of performance change beyond that of any single monitoring tool in isolation.

When assessing both longitudinal and short-term improvements in performance, an increase in TQR Z-score and accounting for individual athlete differences increased the likelihood of identifying performance changes. While highly trained athletes often complete periods of increased training to elicit a supercompensation, recent studies have shown that only athletes that either tolerate or continue to adapt to this overload will gain larger performance improvements [23]. Therefore, a common approach that is used to assess how athletes are tolerating intensified training periods is through the use of subjective or self-report questionnaires [24]. These present findings show that changes in TQR measures can be used to identify if an athlete is tolerating training demands, in turn, identify a likely change in performance. Although subjective questionnaires are sensitive to changes in training load, few studies have related these measures to performance outcomes [24]. For example, Buchheit [25] identified the low sensitivity (true positive rate) of subjective questionnaires to assess changes in physical performance measures in adolescent handball players. Furthermore, measures from wellness questionnaires have been used to assess “staleness” following a taper to identify either no change or a decrement in performance of highly trained swimmers. Surprisingly, despite the widespread use of subjective questionnaires in high performance sport, there is limited evidence to support the use of subjective questionnaires to assess athlete’s performance changes [3]. As such, these findings provide evidence for the use of TQR to identify both longitudinal and performance changes from previous race results.

While only select physiological variables were assessed in this study, no HR measures improved the accuracy of the models developed to identify a longitudinal or short-term improvement in performance. These findings demonstrate the poor predictive ability of HR measures for assessing improvements in performance outcomes. These findings have provided similar results to previous analysis reporting the lack of sensitivity of HR measures to changes in physical performances in handball players [25]. This finding may be due to the linear analysis used as HR indices were converted to a standardised difference score. This analysis was done to align with similar previous studies that have support contextualising change in HR indices relevant to both psychological state and training phase [9,10]. However, a positive directional change in HRV is dependent upon an athlete's training phase (e.g. early season aerobic training or taper phase) and needs to be contextualised relevant to psychological state [23,26]. Therefore, in this analysis subjective questionnaires may explain improvements in performance, whereas both increases or decrements in HRV may reflect positive adaptations dependent on training phase.

For a longitudinal decrement in performance, a reduction in Ln rMSSD from baseline combined with an acute increase in training volume, improved the likelihood to identify a performance decrement. Previous theoretical mathematical modelling and observational training studies have shown that an increase in training load prior to a taper is an optimal training strategy to enhance endurance performance [27]. However, recent findings suggest that these outcomes may only be beneficial when athletes are in an adaptive state and functional overreaching is not present [23]. In a comparative 8-week study of 28 triathletes, a greater improvement in maximal aerobic performance was observed from those who continued to improve throughout a three-week intensified training block (i.e. 30% increase in total training completed) compared to those who either had no change or a performance decrement [23]. The findings from the present study further highlight that greater performance changes occur in athletes who continue to show positive training adaptations combined with a reduction in training volume prior to competition.

It is now well established with endurance training, that HRV fluctuates in accordance to changes in training load [11]. Indeed, an increased parasympathetic modulation is likely to occur during the extensive aerobic or early season endurance training driven through an increased volume load on the heart. This leads to an increase in left ventricular size, wall thickness and end-diastolic volume resulting in a greater stroke volume and reduced HR to maintain cardiac output [28]. Previous research has also reported positive aerobic training adaptations such as improved cardiac efficiency and changes in blood volume are reflected through the modulation of Ln rMSSD measures [11]. As such, monitoring HRV relevant to training volume may signify the chronic positive or negative longitudinal physiological responses that occur throughout a season and highlight the likelihood of a performance decrement in highly trained swimmers.

The present findings provide support for combining a short-term increase in the R-R interval with a rating of perceived fatigue to identify the likelihood of a short-term performance decrement. These results support previous evidence that has shown parasympathetic hyperactivity combined with changes in psychological state during periods of overload may identify a decrement in performance or functional overreaching [9,29]. Alternatively, a positive physiological response would identify as a reduction in HRV (Ln rMSSD) or R-R interval prior to competition to identify an improved performance [30]. Indeed, a reduced parasympathetic modulation toward a sympathetic predominance has previously been reported during periods of intensified training or in preparation for competition of endurance athletes [11]. For example, this response has been reported in highly trained rowers as the cardiovascular system responds to the sudden increases and variations in HR during race specific training or around the time of competition [30,31]. These findings may be due to pre-competition anxiety or adaptations to enhance cardio-acceleration such as an increase in muscle perfusion, acute shifts in blood or plasma volume and changes in cardiac output [31]. Therefore, the present findings provide further evidence showing value in contextualising changes in HRV-derived indices (Ln rMSSD and R-R

Interval) relevant to either training completed or psychological state to identify decrements in performance.

The present study provides conceptual support for the use of an integrated probability model to assess performance changes in highly trained swimmers. However, there is relatively weak diagnostic accuracy when assessing performance change from previous race results. While both longitudinal improvements and decrements had good diagnostic accuracy, there is limited practicality of these models when looking to inform training prescription or assess an athlete's readiness to perform. As such it should be recognised that the efficacy of these models lacks strong evidence for their usefulness to inform sport scientists to assess how an athlete will perform compared to previous race results. Furthermore, the information collected from this case study has only been assessed from one training squad. It is still unknown if these models can be transferred to similar athletes from separate training backgrounds or an out of sample population.

A limitation of this study was the simplified approach used to assess longitudinal decrements in performance. Indeed, the type of event (sprint or middle distance) was used to account for repeated measures and not between athlete differences in performance. This was due the complete separation of data when accounting for repeat measures on the same athletes in a small data set in a GEE model. Furthermore, the SMC was used as an arbitrary cut off value to determine a performance decrement or increase, without consideration of the technical error of maximal swimming performance. This was implemented to have consistency with previous findings assessing the diagnostic accuracy of a single monitoring tool to identify performance change of highly trained swimmers [5]. While it is recognised that there are limitations of using arbitrary cut-off values, this approach may provide a simple model that can be used to compare performance changes relevant to set times as done in this study. Although the present findings show the improved accuracy of a multi-factorial approach, all race results from 50-400 m events were pooled for a generic model in this study. Future research may further improve these findings with specific algorithms with different weighting of each variable relevant for each distance or specific event.

PRACTICAL APPLICATIONS

Based on the present findings, the use of a multi-factorial monitoring system may assist to identify longitudinal changes in performance. However, caution should be taken when interpreting this data compared to previous race results. These findings support the use of TQR to identify both longitudinal and short-term improvements in an athlete's performance. Furthermore, combining HR indices with either a psychological or a training measure could be implemented into regular monitoring to assist identify decrements in performance.

CONCLUSION

The findings from this study show that a single probability model from multiple predictor variables was able to assess changes in performance. These findings support the integrated approach that combining changes in physiological measures (i.e. HR indices) relevant to training completed or psychological state while accounting for the individual athlete can improve accuracy for assessing decrements in performance. Furthermore, this study provides evidence of the use of monitoring TQR and accounting for the individual athlete to identify likely improvements in performance. However, this study also identified that these models could more accurately assess longitudinal performance change compared to the assessment of previous race results.

REFERENCES

1. Kiely J. Periodization paradigms in the 21st century: evidence-led or tradition-driven. *Int J Sports Physiol Perform.* 2012;7(3):242-250.
2. Mann TN, Lamberts RP, Lambert MI. High responders and low responders: Factors associated with individual variation in response to standardized training. *Sports Med.* 2014;44(8):1113-1124.
3. Taylor K, Chapman DW, Cronin JB, Newton MJ, Gill N. Fatigue monitoring in high performance sport: A survey of current trends. *J Aus Strength Cond.* 2012;20(1):12-23.
4. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med.* 2014;44(2):139-147.
5. Crowcroft S, McCleave E, Slattery K, Coutts AJ. Assessing the measurement sensitivity and diagnostic characteristics of athlete-monitoring tools in national swimmers. *Int J Sports Physiol Perform.* 2017;12(2):S2-95.
6. Calvert TW, Banister EW, Savage MV, Bach T. A systems model of the effects of training on physical performance. *IEEE Trans Syst Man Cybern Syst.* 1976;2:94-102.
7. Hellard P, Avalos M, Lacoste L, Barale F, Chatard JC, Millet GP. Assessing the limitations of the Banister model in monitoring training. *J Sports Sci.* 2006;24(5):509-520.
8. Borresen J, Lambert MI. The quantification of training load, the training response and the effect on performance. *Sports Med.* 2009;9:779-795.
9. Aubry A, Hausswirth C, Louis J, Coutts AJ, Buchheit M, Le Meur Y. The development of functional overreaching is associated with a faster heart rate recovery in endurance athletes. *PloS one.* 2015;10(10):e0139754.
10. Bellenger CR, Karavirta L, Thomson RL, Robertson EY, Davison K, Buckley JD. Contextualising parasympathetic hyperactivity in functionally overreached athletes with perceptions of training tolerance. *Int J Sports Physiol Perform.* 2016;11(5):685-692.
11. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Front Physiol.* 2014;5(73).
12. Zeger SL, Liang K, Albert PS. Models for longitudinal data: a generalized estimating equation approach. *Biometrics.* 1988:1049-1060.
13. Fawcett T. An introduction to ROC analysis. *Pattern Recognit Lett.* 2006;27(8):861-874.
14. Kenttä G, Hassmén P. Overtraining and recovery: A conceptual model. *Sports Med.* 1998;26(1):1-16.
15. Plews DJ, Laursen PB, Le Meur Y, Hausswirth C, Kilding AE, Buchheit M. Monitoring training with heart rate variability: How much compliance is needed for valid assessment? *Int J Sports Physiol Perform.* 2013;9(5):783-790.
16. Wallace LK, Slattery KM, Coutts AJ. Establishing the criterion validity and reliability of common methods for quantifying training load in athlete's. *J Strength Cond Res.* 2014;28(8):2330-2337.
17. Foster C, Daines E, Hector L, Snyder AC, Welsh R. Athletic performance in relation to training load. *Wis Med J.* 1996;95(6):370-374.
18. Hopkins WG, Hawley JA, Burke LM. Design and analysis of research on sport performance enhancement. *Med Sci Sports Exerc.* 1999;31(3):472-485.
19. Pettitt RW. The standard difference score: A new statistic for evaluating strength and conditioning programs. *J Strength Cond Res.* 2010;24(1):287-291.
20. Pan WK. Akaike's information criterion in generalized estimating equations. *Biometrics.* 2001;57(1):120-125.
21. Schisterman EF, Perkins NJ, Liu A, Bondell H. Optimal cut-point and its corresponding Youden Index to discriminate individuals using pooled blood samples. *Epidemiol.* 2005;16(1):73-81.

22. Menaspa P, Sassi A, Impellizzeri FM. Aerobic fitness variables do not predict the professional career of young cyclists. *Med Sci Sports Exerc.* 2010;42(4):805-812.
23. Aubry A, Hausswirth C, Louis J, Coutts AJ, Le Meur Y. Functional overreaching: the key to peak performance during the taper? *Med Sci Sports Exerc.* 2014;46(9):1769-1777.
24. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
25. Buchheit M. Sensitivity of monthly heart rate and psychometric measures for monitoring physical performance in highly trained young handball players. *J Sports Med.* 2015;36(5):351-356.
26. Plews DJ, Laursen PB, Kilding AE, Buchheit M. Heart rate variability and training intensity distribution in elite rowers. *Int J Sports Physiol Perform.* 2014;9(6):1026-1032.
27. Thomas LC, Busso T. A theoretical study of taper characteristics to optimize performance. *Med Sci Sports Exerc.* 2005;37(9):1615-1621.
28. Bellenger CR, Fuller JT, Thomson RL, Davison K, Robertson EY, Buckley JD. Monitoring athletic training status through autonomic heart rate regulation: A systematic review and meta-analysis. *Sports Med.* 2016:1-26.
29. Le Meur Y, Pichon A, Schaal K, Schmitt L, Louis J, Gueneron J, Vidal P, Hausswirth C. Evidence of parasympathetic hyperactivity in functionally overreached athletes. *Med Sci Sports Exerc.* 2013;45(11):2061-2071.
30. Iellamo F, Legramante JM, Pigozzi F, Spataro A, Norbiato G, Lucini D, Pagani M. Conversion from vagal to sympathetic predominance with strenuous training in high-performance world class athletes. *Circulation.* 2002;105(23):2719-2724.
31. Plews DJ, Laursen PB, Stanley J, Kilding AE, Buchheit M. Training adaptation and heart rate variability in elite endurance athletes: opening the door to effective monitoring. *Sports Med.* 2013;43(9):773-781.

Chapter 5

Study 3

Man vs. Monitoring: Assessing a coach's expectations of athletic performance, training intensity, perceived fatigue and recovery

Crowcroft, S., Slattery, K., McCleave, E. and. Coutts, A. J. *(Under review).* Man vs. Monitoring: Assessing a coach's expectations of athletic performance, training intensity, perceived fatigue and recovery. *International Journal of Sports Physiology and Performance.*

ABSTRACT

Purpose: This study assessed coach predicted to actual athlete race results and the association of coach expected to athlete reported subjective questionnaires. Secondly, this study examined if subjective questionnaires could identify a likely difference between coach planned to athlete reported session rating of perceived exertion (sRPE).

Methods: Nine highly trained swimmers (male: n=7, female: n=2, age: 21.6±2 y) were monitored daily over a 10-week period. Athletes recorded daily subjective measures of total quality recovery (TQR) and perceived fatigue and sRPE following training. Prior to training the experienced swim coach reported these expected measures. Before races, the coach predicted each athlete's swim times. Results were correlated to coach expected outcomes. Generalised estimating equations and receiver operating characteristic curves assessed if subjective measures could identify the difference in sRPE.

Results: There was a very large-to-almost perfect relationship (r= 0.92, 90%CL 0.88 – 0.95) of coach expected to athlete race results. Individual results of coach planned to athlete reported results showed a moderate-to-very large relationship for sRPE (r= 0.38 to 0.75), and an unclear-to-moderate relationship to TQR (r= -0.07 to 0.45) and perceived fatigue (r= 0.16 to 0.48). Both the coach higher (AUC: 0.64 95% CI, 0.60 – 0.68) or athlete higher (AUC: 0.64 95% CI, 0.60 – 0.68) models had poor accuracy to identify a difference in sRPE.

Conclusion: These findings showed an experienced swim coach has a strong understanding of how their athlete's will perform. Although there is discrepancy and large heterogeneity of expected to actual sRPE, TQR and perceived fatigue. Furthermore, TQR or perceived fatigue could not identify a difference between coach to athlete sRPE.

Keywords: Subjective questionnaires, coach prediction, coaching, session rating of perceived exertion

INTRODUCTION

The planning and organisation of athletic training is critical to achieve optimal performance [1]. Historically, training periodization (i.e. optimal frequency and timing of both volume and intensity) in preparation for competition has been guided through coaching experience and intuition [2]. However, when this approach becomes successful and left unchallenged, coaching expertise and intuition may become biased resulting in sub-optimal training programs [3]. Whilst the planning processes can be inherently complex [1], coaches can refine their professional judgement and improve their subjective decision-making through experience and reflective practice [3]. To assist coaches with decisions on training prescription, athlete monitoring systems are implemented in high performance sport [4]. Athlete monitoring systems aim to quantify training dose, fitness and fatigue responses and are believed to assist both coaches and sport scientists determine how athletes are responding to training or assess readiness to perform [5]. However, despite their ubiquitousness in high performance sport, no research has determined what further meaningful information is added using athlete monitoring tools beyond experienced coaches' professional judgement or subjective assessment of their athletes.

Early athlete monitoring studies proposed a multi-factorial approach integrating physical parameters (specifically cardiovascular state and strength training), execution of sport specific skills and a current psychological state to explain performance change through mathematical modelling [6]. Following this, a two-component systems model ("fitness – fatigue" model) was developed to overcome issues quantifying several of these measures. This model was based on the assumption that performance outcomes could be estimated from modelled positive fitness and negative fatigue responses from a set training dose [6]. Although these models have since been refined, there is large inter-individual variability in modelling performance in highly trained athlete's [5,7]. This variability, may be explained from the individual response of a set training dose and the numerous components that can influence an elite athletes performance not accounted for with the simplified two component systems approach [8,9]. An alternative to assess an athletes training response is through an integrated approach including observation of objective and subjective athlete monitoring tools, analysis of available data combined with coaching experience and intuition to inform both training prescription and assess performance changes [10-12]. However, the efficacy of athlete monitoring tools to improve performance or the training process, beyond an intuitive coach led training program has yet to be empirically assessed.

The discrepancy of coach planned to athlete reported training intensity (session rating of perceived exertion (sRPE)) has previously been well documented [13-15]. For example, in well-trained swimmers a higher athlete sRPE was reported for low intensity coach planned sessions and a lower athlete reported sRPE for high intensity coach planned sessions [13]. Indeed, this mismatch between coach prescribed and athlete reported training intensity may demonstrate poor understanding of an athlete's physical capacity, or inappropriate implementation of the prescribed training session. Due to this, there may be a difference in coach expected training response (i.e. changes in fitness and fatigue) from the initial planned training. Previously, Doeven, et al. [16] identified a discrepancy between coach expected to athlete reported total quality recovery in elite basketballers. In turn, these consistent differences may lead to poor training control resulting in unexpected training induced fatigue, non-functional overreaching or poor performance [17]. Interestingly, the use of pre-training subjective questionnaires has explained variation in internal and external training loads (TL) from set training sessions in team sport athletes [18]. However, to date no studies have attempted to assess if the discrepancy of coach planned training intensity to athlete recorded could be explained through reporting of athlete monitoring tools. Therefore, the purpose of this study was to firstly compare an experienced coach's perception of athlete reported perceived fatigue, recovery and performance to those reported by well-trained swimmers in an ecological training and competition environment. Secondly to assess the efficacy of coach expected and athlete reported subjective monitoring tools could identify a likely difference in coach expected to athlete reported training intensity.

METHODS

Participants

Nine (n=9) highly trained swimmers (male: n=7, female: n=2, age: 21.6 ± 2 y, personal best as a percentage of world record: 92.9 ± 1.7%), training between 18-22 hours per week and the athlete's swim coach (n=1) (13 years national and international coaching experience, Australian Swim Coaches Teaching Association (ASCTA) gold license) were monitored daily over a 10-week period leading into their major national competition. All athletes had been training with the same coach between 12 to 24 months prior to the commencement of this study. All participants were provided a verbal and written explanation of the investigation before giving informed consent to release their data for this research. This study was approved by the Human Research Ethics Committee of University of Technology Sydney (REF NO. 2014000842).

Study Design

The swimmers recorded their total quality recovery (TQR) and perceived fatigue daily over a 10-week period [19,20]. The swimmers' coach (n=1) reported expected TQR and perceived fatigue for each athlete as the swimmers commenced their warm up for the first session of the day. At the beginning of each session, the coach recorded the planned sRPE for each athlete for each swim session with no additional information given to the coach. Following each training session, athlete's reported their sRPE within 30 mins of completion. Prior to each planned race, the coach was presented with previous race results for the main two events of each athlete and asked to predict times.

Part one of the analysis investigated the association of coach expected to athlete reported TQR, perceived fatigue and sRPE where each athlete reported to coach expected measures were correlated separately. A within individual correlation for each athlete's race times to coach predicted times was completed (69 races). Part two of the analysis assessed if the use of athlete reported TQR and perceived fatigue could identify any difference in coach planned to athlete reported sRPE using a binomial Generalised Estimating Equation (GEE). Receiver Operating Characteristics (ROC) curves and Area Under the Curve (AUC) were used to assess the likelihood of either a higher coach expected, or higher athlete reported sRPE.

Monitoring Variables

Each morning prior to the first training session of the day, or on days of no training upon waking, athlete's completed a perceived fatigue rating (1=Much worse than normal, 3=Normal, 5=Much better than normal) and the total quality recovery scale (TQR; 6-20 scale) [19,20]. Athletes were asked to report measures with 'how you feel today'. Within the first 15 minutes of training, the coach was then asked to complete the same perceived fatigue and TQR scales for how they expected each athlete would report these measures. The coach was able to observe the athletes complete their usual warm up routine with no changed to their normal pre-training interactions. However, both athletes and coach were informed not to discuss monitoring values with one another. Prior to familiarisation, no athletes or the coach had been using subjective questionnaires to inform training prescription. At the commencement of each training session, the coach was asked to complete an expected sRPE for each athlete using a rating of perceived exertion 6–20 scale [21]. This scale was selected as both the athletes and coach had previous familiarisation with this monitoring tool. Following all training and racing, athletes were then asked to record their perceived training intensity of the entire session from the same scale [21]. No discussion or reporting of results was provided back to the coach or the athletes throughout the study period. All information was recorded on the athlete's personal smart phone and all coach information was recorded on a dedicated coach tablet. All information was stored to a cloud-based data management system (Google Docs, USA).

Performance Measures

Race performances included in the analysis were electronically timed by official swimming governing bodies (Swimming Australia or FINA) at sanctioned events in standard international 50 m pools. Prior to racing, swimmers completed a full race preparation warm up. The performance of each swimmer was tracked in their designated events ranging from 100 to 400 m in freestyle, breaststroke, backstroke, butterfly and individual medley. If multiple races of the same event (e.g. heat and final) were recorded on the same day, the fastest time from that day was recorded for analysis. Coach expected race results were recorded within 24 h of competition and at least 1 h prior to each event. At this time the coach was presented with each athlete's two main events and times relating to a -6% decrement to a 6% improvement in performance from each athlete's previous race results. The coach was then asked to record the fastest race time they expect the athlete to complete to the nearest tenth of a second in a customised excel spreadsheet.

Statistical Analysis

Prior to analysis, coach expected race times and actual athlete race results were converted to a change in time (seconds) from the most recent previous race of the same event for that athlete. All data in the text and figures are presented as a mean value with ±90% confidence limits. The relationships between individual athletes reported perceived fatigue, TQR and sRPE and coach expected outcomes were analysed separately to provide an individual correlation for each athlete. Due to the lower total number of performances completed in this period (69 races), all athlete race results were combined and compared against coach predicted results. The following criteria were adopted for the interpretation of the magnitude of correlations (r) between measures: ≤0.1 trivial, >0.1 – 0.3 small, >0.3 – 0.5 moderate, >0.5 – 0.7 large, >0.7 – 0.9 very large, >0.9 – 1.0 almost perfect. If the 90% confidence intervals overlapped small positive and negative values the magnitude was deemed unclear [22].

For the second part of the analysis, both athlete reported, and coach expected TQR and perceived fatigue Z-scores were calculated (daily subjective measures subtracted from individual athlete mean value over the study period and divided by the individual athlete standard deviation) to standardise values for all athletes. Following this, any difference in athlete reported to coach planned sRPE was calculated and then converted to a dichotomous outcome (0= No difference, 1= Difference) in two separate analysis. The first analysis classified a difference as when the coach expected was higher than an athlete reported sRPE. The second analysis classified a difference when athlete reported sRPE was higher than coach expected. Z-scores of athlete reported TQR and perceived fatigue were aligned with the binary outcomes (sRPE difference) from the same day's training and assessed using a GEE with a binary logistic distribution for the response variable with an independent correlation structure [23]. Results from these models included unstandardized βeta co-efficient, exponential βeta-coefficient (95% Confidence intervals (C.I.)) Wald Chi Squared values and the Quasi Likelihood under Independence Model Criterion (QIC) [24]. The addition of further variables into a model was terminated if the Wald Chi Squared was not significant or there was no reduction in the QIC. Probability of a likely difference in sRPE then was calculated automatically in SPSS (Version 23. IBM Company, New York, USA).

The probability produced was then assessed to determine the diagnostic accuracy of identifying a difference between coach planned and athlete reported sRPE. A ROC curve was used to compare the accuracy of the two models to identify a difference in sRPE through producing an

AUC using sensitivity (true positive rate) and specificity (true negative rate). An AUC of 1.00 (100%) represents perfect discriminatory power, where 0.50 (50%) would represent no discriminatory power [25]. An AUC was classified as a "good" benchmark if an AUC was >0.70 with a lower CI >0.50 [26]. All ROC curve results were presented as AUC ± 95% CI [27]. All analysis was performed using SPSS (Version 23. IBM Company, New York, USA).

RESULTS

A total of 69 athlete race results were correlated with coach predicted times with a very large-to-almost-perfect relationship (r= 0.92 90%CL 0.88 – 0.95). Individual correlations between coach expected and athlete reported perceived fatigue and TQR were based on 70.0 ± 0.3 measures per athlete and sRPE correlated from 82 ± 3 responses per athlete. Combined correlations of coach expected to athlete reported measures are presented in Figure 5:1. The relationship between individual athlete reported to coach expected perceptual measures are shown in Table 5:1. Individual athlete results showed there was an unclear-to-moderate relationship to TQR (r= -0.07 to 0.45) and perceived fatigue (r= 0.16 to 0.48) and a moderate-to-very large relationship for sRPE (r= 0.38 to 0.75). Both GEE and ROC results are reported in Table 5:2. Of the two models assessed, both coach higher sRPE and athlete higher sRPE models only included perceived fatigue. Neither the coach higher (AUC: 0.64; 95% CI, 0.60 – 0.68) or athlete higher sRPE (AUC: 0.64; 95% CI, 0.60 – 0.68) model met the criteria as a "good" diagnostic classifier to identify a difference in sRPE.

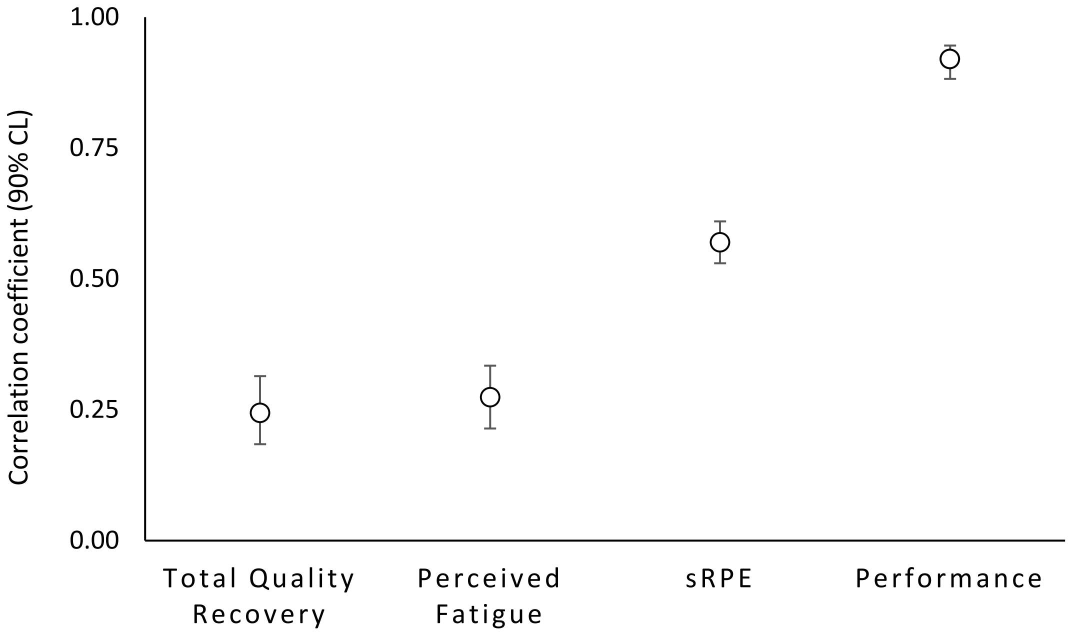

Figure 5:1 Combined correlation coefficient between coach and athlete ratings of total quality recovery, perceived fatigue, session rating of perceived exertion (sRPE) and the correlation of coach predicted to actual athlete performance.

Table 5:1 Individual correlations of the coach expected to athlete reported total quality recovery scale, perceived fatigue and session rating of perceived exertion.

Swimmer	Total Quality Recovery *(90% CL)*		Perceived Fatigue *(90% CL)*		sRPE *(90% CL)*	
1	**0.45**	*(0.28 - 0.60)*	**0.48**	*(0.31 - 0.62)*	**0.65**	*(0.52 - 0.74)*
2	**-0.07**	*(-0.26 - 0.13)*	**0.23**	*(0.04 - 0.41)*	**0.65**	*(0.53 - 0.75)*
3	**0.22**	*(0.02 - 0.40)*	**0.21**	*(0.01 - 0.39)*	**0.75**	*(0.66 - 0.82)*
4	**0.30**	*(0.11 - 0.47)*	**0.39**	*(0.21 - 0.55)*	**0.54**	*(0.40 - 0.66)*
5	**0.39**	*(0.20 - 0.55)*	**0.44**	*(0.27 - 0.59)*	**0.52**	*(0.37 - 0.65)*
6	**0.40**	*(0.22 - 0.56)*	**0.18**	*(-0.02 - 0.37)*	**0.38**	*(0.20 - 0.54)*
7	**0.24**	*(0.05 - 0.42)*	**0.11**	*(-0.10 - 0.30)*	**0.63**	*(0.49 - 0.73)*
8	**0.39**	*(0.21 - 0.54)*	**0.16**	*(-0.04 - 0.35)*	**0.58**	*(0.44 - 0.69)*
9	**0.17**	*(-0.03 - 0.36)*	**0.35**	*(0.16 - 0.51)*	**0.54**	*(0.39 - 0.67)*
Combined	**0.24**	*(0.18 - 0.31)*	**0.27**	*(0.21 - 0.33)*	**0.57**	*(0.53 - 0.61)*

sRPE: Session rating of perceived exertion, CL: Confidence limit.

Table 5:2 Generalised estimating equation regression models to identify the difference between coach planned and athlete reported sRPE.

	Parameter	*β*	S.E.	Wald Chi-Squared	Exp.(*β*) (95% CI)	QIC	AUC (95% CI)
Athlete Higher	Intercept	0.05	0.00	29940.01	1.05 *(1.05 - 1.05)*	957.23	0.64 *(0.60 - 0.68)*
	Athlete 1	0.31	0.00	11228.96	1.36 *(1.35 - 1.37)*		
	Athlete 2	-0.83	0.01	21241.36	0.44 *(0.43 - 0.44)*		
	Athlete 3	-0.87	0.01	21342.81	0.42 *(0.42 - 0.43)*		
	Athlete 4	0.14	0.00	7128.27	1.15 *(1.15 - 1.16)*		
	Athlete 5	-0.15	0.00	171419.90	0.86 *(0.86 - 0.86)*		
	Athlete 6	-1.03	0.01	20376.29	0.36 *(0.35 - 0.36)*		
	Athlete 7	-0.32	0.00	14266.72	0.73 *(0.72 - 0.73)*		
	Athlete 8	-0.66	0.00	22861.31	0.51 *(0.51 - 0.52)*		
	Athlete 9	0.00					
	Perceived Fatigue	-0.22	0.08	8.51	0.80 *(0.69 - 0.93)*		
Coach Higher	Intercept	-0.89	0.01	13550.57	0.41 *(0.41 - 0.42)*	952.34	0.64 *(0.60 - 0.68)*
	Athlete 1	0.11	0.00	20109.88	1.11 *(1.11 - 1.12)*		
	Athlete 2	0.84	0.01	15073.21	2.31 *(2.31 - 2.34)*		
	Athlete 3	0.96	0.01	13297.20	2.62 *(2.62 - 2.66)*		
	Athlete 4	0.24	0.00	21645.29	1.27 *(1.27 - 1.27)*		
	Athlete 5	0.27	0.00	53833.45	1.31 *(1.31 - 1.31)*		
	Athlete 6	1.41	0.01	11804.13	4.08 *(4.08 - 4.19)*		
	Athlete 7	0.34	0.00	9048.09	1.40 *(1.40 - 1.41)*		
	Athlete 8	0.52	0.00	16793.11	1.69 *(1.69 - 1.70)*		
	Athlete 9	0.00					
	Perceived Fatigue	0.27	0.08	12.54	1.31 *(1.31 - 1.52)*		

sRPE- Session rating of perceived exertion, β- Unstandardised beta co-efficient, Sig- Significance, Exp.(B) (± 95% CI)- Exponential of unstandardised beta co-efficient with 95% Confidence intervals. S.E – Standard error, QIC - Quasi Likelihood under Independence Model Criterion.

DISCUSSION

The purpose of this study was to assess an experienced coach's expected perceived fatigue, recovery and performance to actual responses of well-trained swimmers in an ecological training and competition environment. Secondly, to assess the efficacy of coach expected and athlete reported subjective monitoring tools to improve the relationship of coach planned to athlete reported training intensity. The very large-to-almost perfect relationship of coach predicted to actual athlete performances supports a coach assessment of their athlete's readiness to perform. However, the trivial-to-small relationship of coach expected to athlete reported perceived fatigue and recovery suggests a coach may not understand the acute changes in these measures. Furthermore, the poor diagnostic accuracy of subjective measures in isolation identify the limited ability of these tools to explain a discrepancy between coach expected to athlete reported sRPE.

To inform decision-making, coaching expertise requires a nested approach of both skilled intuitive based decisions and thoughtful well-considered problem solving [3]. These results showed that the experienced coach's race predictions had a very strong relationship to the actual athlete race results. This was likely due to the coach's professional judgement rather than coaching intuition as predicted race results were well considered, were compared to previous race times and had limited time pressures [3,28]. For example in the development of training plans for elite athletes, there are numerous components including physiological, biomechanical, psychological and lifestyle that contribute to a performance outcome [9]. However, performance changes may occur from the progression or degradation of any of these contributing factors during training, likely with the coach present. In the current study the coach spent 18-22 hours per week co-ordinating training sessions. These opportunities may provide the coach adequate time to observe and reflect on how the athletes are likely to perform prior to predicting a race result [29]. As such this study provides supports for an experienced coach's professional judgement and subjective assessment of an athletes' race results, provided there is appropriate time to observe the athlete's progression in training.

The consistent discrepancy between coach planned to athlete reported training intensity may demonstrate a coach's poor understanding of an athlete physical capacity, or an athlete's inappropriate implementation of the prescribed training session. The observed difference between athlete reported and coach planned sRPE in this study supports the existing evidence for a mismatch between coach expected and athlete reported sRPE in swimmers [13-15]. In a comparison between coach planned and athlete reported training intensity, there has been a consistent discrepancy of sRPE from a small relationship of 11-12 year old's (r = 0.31), moderate to high within 15-16 year old's (r = 0.74) and very strong with highly trained swimmers (r = 0.84) [13-15]. A novel finding in this study identified large variation in coach to individual athlete sRPE from a homogenous group of highly trained swimmers. It is common within swimming to prescribe training based on external measures such as distance or a time cycle (velocity) [13]. However, this approach does not account for the physiological demands required to complete the prescribed training dose. As no feedback of sRPE was provided to the coach throughout the study, this may have influenced the coach's understanding of the relative intensity of the completed training sessions causing a continued mismatch in sRPE and how the athlete presents and performs in subsequent training sessions. Therefore, the collection and then reporting of coach planned to athlete reported sRPE may provide information highlighting the incorrect implementation of the prescribed training session from the athlete, or inappropriate prescription from the coach based on the athlete's physical capabilities.

Overall, there was a trivial-to-poor relationship between coach expected to athlete reported perceived fatigue and TQR. Indeed, training prescription is often based upon the assumption that training adaptations, acute fatigue and recovery responses each elicit a predictable outcome [12]. However, previous studies have shown when coaches design sessions of planned high intensity these are commonly perceived as easier, and planned low intensity sessions are perceived by athletes to be harder [13]. As such, high intensity efforts planned by the coach may not be reached during training contributing to the discrepancy between coach expected to athlete reported fatigue and recovery. Similar results have previously been discussed in elite basketball players, with an overestimation of coach expected TQR [16]. These results show the training response is dependent not only on the session completed, but also on the interaction between numerous factors that may influence recovery (e.g. sleep, psychological state, life stressors or training history) [8,16]. However, the large discrepancy of athlete reported to coach expected perceived fatigue and TQR, may highlight unexpected responses from set training sessions. Although, with the very strong coach understanding of athlete performance, there may be numerous other components to inform a coach when assessing how an athlete is likely to perform.

The subjective questionnaires used in this study could not independently identify a difference between the coach planned to athlete reported sRPE. However, the findings from the binomial GEE model highlight a change in perceived fatigue may increase the likelihood of a difference in both coach higher or athlete higher sRPE. Previous studies have shown the use of subjective pre-training wellness questionnaires in Australian rules football players may precede an associated change in total training completed in the subsequent training session [30]. Furthermore, subjective ratings of perceived muscle soreness have been related to an athletes TL in American college football players and a determinant of how players will cope in response to a standardised training stimulus [18]. However, limited evidence is available to show how subjective questionnaires may be utilised in individual sports where training intensity can be well controlled to that of team sports [31]. In comparison to a coach's prediction of the athlete's performances, there was a poor relationship of coach expected to athlete reported acute subjective recovery and fatigue prior to training. As there can be large inter-individual differences to a specific training session, it is often not known how an athlete may respond to a set training dose [8]. Therefore identifying a discrepancy of coach planned to athlete reported measures may provide insight to emphasize the importance of reviewing subjective questionnaires (and other information) for a coach to better understand the acute individual athlete response [29]. Accordingly, these findings provide some explanation for the difference between coach planned to athlete reported sRPE from subjective questionnaires. However, in isolation subjective questionnaires may be insufficient to provide meaningful information to inform the discrepancy of coach planned to athlete reported sRPE.

While the findings from this study provide insight into a coach's understanding of their athlete's performance, sRPE, TQR and perceived fatigue, there are limitations that should be acknowledged. As this is a case study of a swimming squad and one experienced coach, caution should be taken to draw definitive conclusions from these results. Secondly, no feedback of sRPE was provided to the coach, which in turn may have been a confounding factor for the poor relationship of coach expected to athlete reported perceived fatigue and TQR. Future research may investigate coaches with different backgrounds or experiences to explore what contributes to coach's professional judgements and the subjective assessment of athletic performance. These findings provide an opportunity for future research to assess how athlete monitoring tools and coach predictions may be combined to improve coach predictive ability. Future research may assess the underlying mechanism as to why there is a poor association between athlete reported and coach expected perceived fatigue and recovery. For example, it is not known the common findings of a discrepancy in sRPE between coach planned and athlete reported is from a coach's poor understanding of their athlete's capability, or the inappropriate implementation of prescribed training. Further the findings from this study highlight the poor association of coach expected to athlete reported perceived fatigue and TQR. However perceived fatigue only explained a small amount of potential variation in the coach planned to athlete reported sRPE.

PRACTICAL APPLICATIONS

Coach predictions are an effective approach to assess an athlete's performance change. Furthermore, the reporting of sRPE, perceived fatigue and TQR may improve coaches' understanding of an athlete's training response. However perceived fatigue could only explain a small amount of variation between coach planned to athlete reported sRPE.

CONCLUSION

The findings from this study support a very strong relationship of coach expected to athlete reported performances. These findings provide initial support for a coach's strong subjective assessment and professional judgement to assess athletic performance. However, there was a large discrepancy between coach expected to athlete report perceived fatigue, TQR and SRPE. Although, perceived fatigue in isolation had a weak contribution to identify a likely difference in coach planned to athlete reported sRPE.

REFERENCES

1. Mujika I, Halson S, Burke LM, Balagué G, Farrow D. An integrated, multifactorial approach to periodization for optimal performance in individual and team sports. *Int J Sports Physiol Perform.* 2018;13(5):538-561.
2. Kiely J. Periodization theory: confronting an inconvenient truth. *Sports Med.* 2018;48(4):753-764.
3. Abraham A, Collins D. Taking the next step: Ways forward for coaching science. *Quest.* 2011;63(4):366-384.
4. Robertson S, Bartlett JD, Gastin PB. Red, Amber or Green? Athlete monitoring in team sport: the need for decision support systems. *Int J Sports Physiol Perform.* 2017;12(2):S2-73.
5. Borresen J, Lambert MI. The quantification of training load, the training response and the effect on performance. *Sports Med.* 2009;9:779-795.
6. Calvert TW, Banister EW, Savage MV, Bach T. A systems model of the effects of training on physical performance. *IEEE Trans Syst Man Cybern Syst.* 1976;2:94-102.
7. Hellard P, Avalos M, Lacoste L, Barale F, Chatard JC, Millet GP. Assessing the limitations of the Banister model in monitoring training. *J Sports Sci.* 2006;24(5):509-520.
8. Mann TN, Lamberts RP, Lambert MI. High responders and low responders: Factors associated with individual variation in response to standardized training. *Sports Med.* 2014;44(8):1113-1124.
9. Smith DJ. A framework for understanding the training process leading to elite performance. *Sports Med.* 2003;33(15):1103-1126.
10. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med.* 2014;44(2):139-147.
11. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
12. Kiely J. Periodization paradigms in the 21st century: evidence-led or tradition-driven. *Int J Sports Physiol Perform.* 2012;7(3):242-250.
13. Wallace LK, Slattery KM, Coutts AJ. The ecological validity and application of the session-RPE method for quantifying training loads in swimming. *J Strength Cond Res.* 2009;23(1):33-38.
14. Barroso R, Cardoso RK, do Carmo EC, Tricoli V. Perceived exertion in coaches and young swimmers with different training experience. *Int J Sports Physiol Perform.* 2014;9:212-216.
15. Brink MS, Frencken WGP, Jordet G, Lemmink KAPM. Coaches' and players' perceptions of training dose: Not a perfect match. *Int J Sports Physiol Perform.* 2014;9(3):497-502.
16. Doeven SH, Brink MS, Frencken WG, Lemmink KA. Impaired player–coach perceptions of exertion and recovery during match congestion. *Int J Sports Physiol Perform.* 2017;12(9):1151-1156.
17. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, Raglin J, Rietjens G, Steinacker J, Urhausen A. Prevention, diagnosis and treatment of the overtraining syndrome: Joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). *Eur J Sport Sci.* 2013;13(1):1-24.
18. Govus AD, Coutts A, Duffield R, Murray A, Fullagar H. Relationship between pretraining subjective wellness measures, player load, and rating-of-perceived-exertion training load in American college football. *Int J Sports Physiol Perform.* 2018;13(1):95-101.
19. Crowcroft S, McCleave E, Slattery K, Coutts AJ. Assessing the measurement sensitivity and diagnostic characteristics of athlete-monitoring tools in national swimmers. *Int J Sports Physiol Perform.* 2017;12(2):S2-95.

20. Kenttä G, Hassmén P. Overtraining and recovery: A conceptual model. *Sports Med.* 1998;26(1):1-16.
21. Wallace LK, Slattery KM, Coutts AJ. Establishing the criterion validity and reliability of common methods for quantifying training load in athlete's. *J Strength Cond Res.* 2014;28(8):2330-2337.
22. Hopkins W, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. *Med Sci Sports Exerc.* 2009;41(1):3.
23. Zeger SL, Liang K, Albert PS. Models for longitudinal data: a generalized estimating equation approach. *Biometrics.* 1988:1049-1060.
24. Pan WK. Akaike's information criterion in generalized estimating equations. *Biometrics.* 2001;57(1):120-125.
25. Schisterman EF, Perkins NJ, Liu A, Bondell H. Optimal cut-point and its corresponding Youden Index to discriminate individuals using pooled blood samples. *Epidemiol.* 2005;16(1):73-81.
26. Menaspa P, Sassi A, Impellizzeri FM. Aerobic fitness variables do not predict the professional career of young cyclists. *Med Sci Sports Exerc.* 2010;42(4):805-812.
27. Fawcett T. An introduction to ROC analysis. *Pattern Recognit Lett.* 2006;27(8):861-874.
28. Collins L, Collins D. Integration of professional judgement and decision-making in high-level adventure sports coaching practice. *J Sports Sci.* 2015;33(6):622-633.
29. Collins D, Collins L, Carson HJ. "If it feels right, do it”: Intuitive decision making in a sample of high-level sport coaches. *Front Psychol.* 2016;7(504).
30. Gallo TF, Cormack SJ, Gabbett TJ, Lorenzen CH. Pre-training perceived wellness impacts training output in Australian football players. *J Sports Sci.* 2016;34(15):1445-1451.
31. Hill-Haas SV, Dawson B, Impellizzeri FM, Coutts AJ. Physiology of small-sided games training in football. *Sports Med.* 2011;41(3):199-220.

Chapter 6

Study 4

Do athlete monitoring tools improve a coach's understanding of performance change?

Crowcroft, S., Slattery, K., McCleave, E. and Coutts, A. J. (Under review). Do athlete monitoring tools improve a coach's understanding of performance change? *International Journal of Sports Physiology and Performance.*

ABSTRACT

Purpose: To assess a coach's subjective assessment of their athlete's performances. Secondly, to assess if the use of athlete monitoring tools could improve on a coach's prediction to identify performance changes.

Methods: Nine highly trained swimmers (7 males, 2 females, age: 21.6 ± 2.0 y) recorded perceived fatigue, total quality recovery and heart rate variability (HRV) over a 9-month period. Prior to each race of the swimmer's main two events, the coach (n=1) was presented with their previous race results and asked to predict a time of how the athlete would perform. HRV and the coach prediction were converted to a standardised difference score from previous race result. All race results (n=93) with aligning coach predictions were recorded then classified as a dichotomous outcome (0= no change, 1= performance decrement or improvement (change +/- > or < smallest meaningful change). A Generalised Estimating Equation (GEE) with binomial outcomes was used to assess the prediction accuracy of a coach and to determine whether combining monitoring variables to the analysis could improve upon the coach predictions. The probability from GEE models were analysed using Receiver Operating Characteristic curves to assess the model's accuracy.

Results: Coach predictions had the highest diagnostic accuracy to identify both decrements (AUC: 0.93, 95%CI, 0.88 – 0.99) and improvements (AUC: 0.89, 95%CI, 0.83 – 0.95) in performance.

Conclusion: These findings highlight the high accuracy of a coach's subjective assessment of performance. Considering, no monitoring tool assisted to improve a coach prediction, these results provide a future benchmark for athlete monitoring systems to be able to improve upon a coach's existing understanding of swimming performance.

Key words: Heart rate variability, subjective questionnaires, modelling performance, coaching

INTRODUCTION

In high performance sport, coaches aim to optimise athletic performance through individualised training programs. However, these training plans are often based upon a coach's prior experiences and intuition [1]. As such, if coaches have success with these methodologies, it may lead to inherit biases in their coaching philosophy [2]. This approach may lead to generic or repetitive training programs and sub-optimal performance. However, professional judgement and coach subjective decision-making is a crucial component of high performance sport. A commonality of expert coaches is their ability to recognise relevant cues (e.g. athlete behaviour or body language) and provide an appropriate course of action based on prior experiences and skilled intuition [2-4]. While, expert coaches decision making is often perceived as fast paced and intuitive, coaches may engage in an approach known as "nested thinking" [2,4]. This approach identifies that skilled intuitive decision making (e.g. training prescription or manipulating training sessions) is closely linked to overall planning and long-term athlete progression [2,4]. Whilst a coaches professional judgement and skilled intuition may be a parsimonious approach to guide training prescription, athlete monitoring systems are now commonly implemented in high performance sport to assist in the decision-making process [5,6]. However, no research has investigated if the use of athlete monitoring tools can improve upon experienced coaches' subjective assessment of athletic performance.

Promoting coaching intuition and the development of skilled professional judgements in training, may be detrimental unless there is a clear link back to higher order processes and a long-term athlete training plan. Indeed, if intuitive decisions are not reviewed and closely linked back to overall training plans, overconfidence can quickly develop, with poor decision-making and coaching mistakes being ignored or blamed elsewhere [2]. For example, in a meta-analysis of psychiatry and medical practice, it is common that professional judgements can be outperformed by statistical predictions. These findings may be due to a practitioner's unexplained intuition in decision-making, lack of developed expertise or an overreliance on irrelevant cues [7]. As such, a nested approach allows for coaches to respond to both relevant cues in daily training while promoting critical thinking, reflection on prior experiences and higher order processing to limit bias in coach decision-making [2]. Furthermore, athlete monitoring tools may assist coaches to have more detailed feedback and a greater understanding of the training process. However, no studies have assessed if athlete monitoring tools can assist a coach decision-making or support a coach prediction of how their athlete will perform.

Early studies investigated multi-factorial mathematical models to assess performance changes from an athlete's completed training [8]. Whilst these models have been refined, there is still large variability in these results that limit their efficacy to guide daily training and predict acute performance changes [9]. This variability, may be explained by the individual response from a standardised training dose and the numerous components that can influence an elite athlete's performance [10]. To account for this individual response, numerous observational studies support combining multiple athlete monitoring tools to identify performance changes [11,12]. For example, in highly trained runners and triathletes following an intensified training block, both changes in heart rate variability (HRV) derived indices combined with a subjective athlete report of training tolerance identified athletes who had greater performance changes [11,12]. However, while training studies support the use of monitoring tools to inform training prescription, no research has assessed the use of combining these monitoring tools with a coaches' subjective assessment or skilled intuition to identify performance change. Therefore, the purpose of this study was to firstly assess a coach's subjective assessment of their athlete's performances. Secondly, to assess if the use of athlete monitoring tools could improve a coach's prediction in identifying performance changes.

METHODS

Participants

Nine (n=9) nationally competitive swimmers (7 males, 2 females, age: 21.6 ± 2.0 y, best time in main event as a percentage of world record: 92.9 ± 1.7%, mean ± SD) training between 18-22 hours per week and the athlete's swim coach (n=1) (13 years national and international coaching experience, Australian Swim Coaches Teaching Association (ASCTA) gold license) were monitored over a 9-month period. Of the 9 who commenced the study one withdrew due to external commitments. All participants were provided a verbal and written explanation of the investigation before giving informed consent to release their data for this research. This study was approved by the Human Research Ethics Committee of University of Technology Sydney (REF NO. 2014000842).

Study Design

This observational study occurred over a 9-month period. Throughout this period, all swimmers recorded morning resting HRV derived measures and answered subjective questions regarding total quality recovery and perceived fatigue upon waking. All training and racing sessions were logged within 30 minutes of completion including session rating of perceived exertion (sRPE), duration (minutes) and distance swum (km). Prior to each planned race, the coach was presented with previous race results for each athlete's two main events and asked to predict their times. Both coach predictions and combined coach prediction with athlete monitoring were assessed for their model fit using Generalised Estimating Equations (GEE) and then for their diagnostic accuracy from Receiver Operating Characteristic (ROC) curve analysis.

Athlete Monitoring Variables

Subjective self-report measures recorded in this study included perceived fatigue rating (1 = Much worse than normal, 2 = Worse than normal, 3 = Normal, 4 = Better than normal and 5 = Much better than normal) [13] and the total quality recovery scale (TQR; 6-20 scale) [13,14]. Athletes reported all measures based on 'how do you feel today?' using their personal smart phone, where entries were stored in a cloud-based data management system (Google Forms, Google, CA, USA). Upon waking, HRV was recorded for all athletes from a 6-min supine position via R-R series using the Polar Team 2 system (1.3.0.3. Polar Electro Oy, Kempele, Finland). Athletes were asked to leave heart rate (HR) monitors on their bedside of an evening to minimise disturbance upon waking. Following recording, HR files were downloaded and analysed using Kubios HRV analysis software (The Biomedical Signal Analysis Group, University of Kuopio, Kuopio, Finland). Time domain indices selected for analysis as indicators of responsiveness to training included R-R interval, Ln rMSSD and the Ln rMSSD to R-R interval ratio. When at least 3 data points from the previous 7-days for both HRV and subjective measures were recorded, the 7-day rolling average of these measures through to the day of performance in these measures were analysed due to their improved diagnostic accuracy [13,15]. Following all training and racing, athletes were asked to record total distance swum in the training session to the nearest 50 m, report session duration in minutes and then subjectively rate the intensity of the entire session using a rating of perceived exertion 6–20 scale [16]. Training load was then quantified through the session rating of perceived exertion method (sRPE x duration) [17].

Performance Measures

Race performances included in analysis were electronically timed by official swimming governing bodies (Swimming Australia or Fédération Internationale de Natation (FINA)) at sanctioned events in standard international 50 m pools. Prior to racing, swimmers completed a full race preparation warm up. The performance of each swimmer was tracked in their main two events ranging from 100 to 400 m freestyle, breaststroke, backstroke, butterfly and individual medley. If multiple races of the same event (e.g. heat and final) were recorded on the same day, the fastest time was recorded for analysis. Each swimmer recorded a minimum of five races of the same event throughout the study period. Times for each athlete's individual events were averaged to give a mean time and the smallest meaningful change (SMC) was determined as 0.3 x within-swimmer co-efficient of variation (CV%) of race performance times [18]. Times outside of the SMC were then coded as a dichotomous outcome variable (0= No change, 1= Change) to assess both improvements (change < previous time - SMC) and decrements (change > previous time + SMC) in performance in separate analysis. Coach predicted race results were recorded within 24-h of competition and at least 1-h prior to each event. At this time the coach was presented with each athlete's two main events and times relating to a -6% decrement and to a 6% improvement in performance compared to each athlete's previous race results. The coach was then asked to record the fastest race time they expect the athlete to complete in their two main events to the nearest tenth of a second on that day in a customised excel spreadsheet.

Statistical Analysis

Prior to analysis, coach predicted performance change was expressed as standardised difference score [19] from previous race results (Predicted time – previous athlete race result)/ Inter-individual athlete CV%). All subjective questionnaires (perceived fatigue and TQR) were converted to a rolling 7-day average, then a Z-score ((7-day average – individual mean reported from all values within the study)/ within swimmer standard deviation (SD))). Heart rate variables were expressed as a 7-day rolling average and converted to a standardised difference score from previous race values (7-day rolling average – previous 7-day average of race results/ within swimmer SD) and then aligned with race results. To identify performance change, the athlete's race results were then converted to a dichotomous outcome (0 = no change, 1 = performance decrement or improvement (> or < +/- 0.3 X CV% from previous race results)) and aligned with both monitoring variables and coach predictions.

GEE models were constructed to explain the relationship of coach predictions and monitoring variables to assess both improvements and decrements in performance in separate models [20]. All GEE models used a binary logistic distribution for the response variable with an independent correlation structure. The GEE was chosen as it considers the repeated measures structure of performance data. As such all models included a random effect (factor) to identify the between athlete variance (Athlete 1-8). To build a multi-factorial model and avoid co-linearity, models included a maximum of 1 subjective questionnaire (perceived fatigue or TQR), 1 physiological measures (R-R interval or Ln rMSSD) and 1 training measure (KM or training load). Pearson's correlation co-efficient was checked for co-linearity of variables. Variables were not included in the same model if Pearson's correlation coefficient > = (±) 0.60 with another variable. The inclusion of additional monitoring variables into the model was evaluated based on the model fit, only if the Wald Chi Square was significant and the Quasi likelihood under independence model criterion (QIC) decreased [21]. The predictive probability value of the mean response was calculated automatically in SPSS from the strongest models to assess the probability of both improvements and decrements in performance from the athlete's previous race results.

The probability produced from GEE binomial models were aligned with the binary performance outcomes and assessed with a ROC curve to identify probability of an improvement or decrement in performance in separate models. This analysis produces an area under the curve (AUC) using sensitivity (true positive rate) and specificity (true negative rate). An AUC of 1.00

(100%) represents perfect discriminatory power, where 0.50 (50%) would represent no discriminatory power. An AUC was classified as a “good” benchmark if an AUC was >0.70 with a CI > 0.50. All ROC curve results were presented as AUC ± 95% CI [22]. All analysis was performed using SPSS (Version 23. IBM Company, New York, USA).

RESULTS

There was a total of 93 race results with aligning coach predictions. Of those race results, 34 were classified as a decrement and 43 as improvements from previous race result. ROC curves and GEE models can be seen in Figure 6:1 and Table 6:1 respectively. After accounting for individual athlete differences, the coach prediction was the strongest model to assess both decrements in performance (AUC: 093, 95% CI, 0.88 – 0.99) and improvements in performance (AUC: 0.89, 95% CI, 0.83 – 0.95). No athlete monitoring variables could improve the model fit to assess either improvements or decrements in performance.

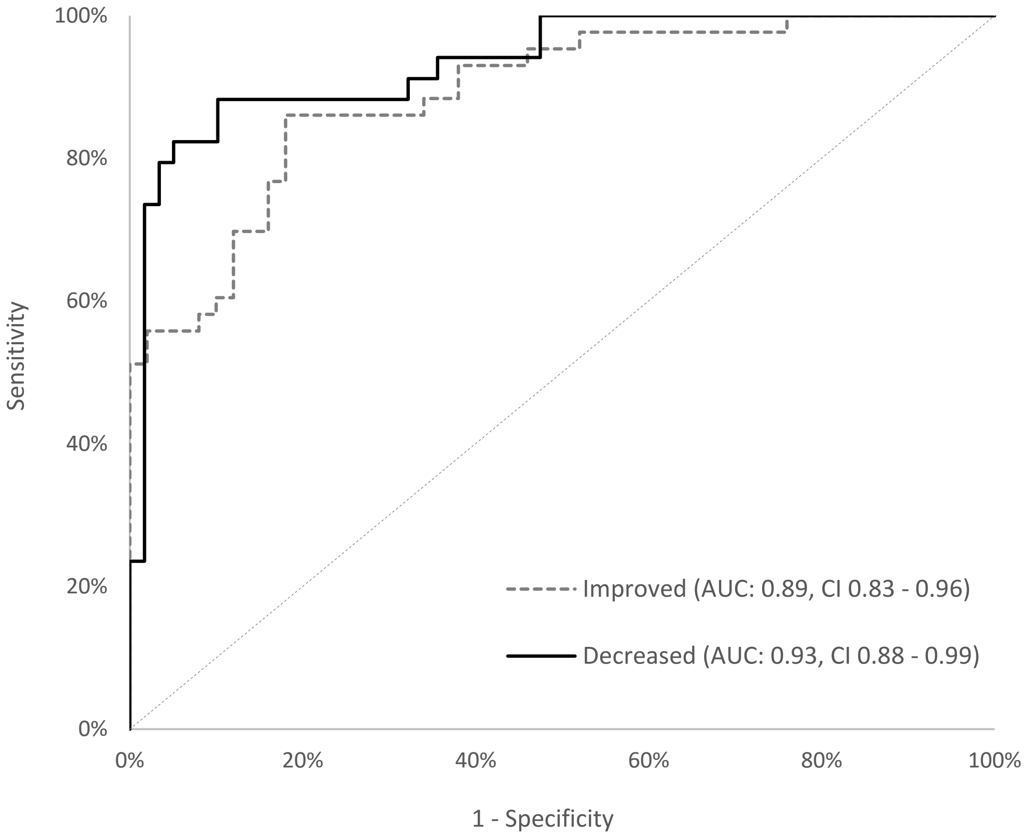

Figure 6:1 Receiver Operator Characteristic Curves of decrements and improvements in performance. *AUC- Area Under the Curve. Sensitivity- True positive rate, 1- Specificity- 1 - True negative rate, Improved- Models to assess coach predictions identifying improvements in performance from previous race results, Decreased- Models to assess coach predictions identifying decrements in performance from previous race results.*

Table 6:1 Generalised estimating equation models to assess performance changes.

Model	Parameter	*β*	S.E.	Wald Chi-Square	Exp.(*β*) *(± 95% CI)*	QIC
Improvements in Performance	Intercept	-0.54	0.18	8.73	0.58 *(0.41 - 0.83)*	75.84
	Coach Prediction	-1.56	0.45	11.96	0.21 *(0.09 - 0.51)*	
	Athlete 1	0.64	0.22	8.68	1.89 *(1.24 - 2.89)*	
	Athlete 2	0.19	0.07	8.31	1.21 *(1.06 - 1.38)*	
	Athlete 3	-1.41	0.25	32.61	0.24 *(0.15 - 0.40)*	
	Athlete 4	0.23	0.14	3.02	1.26 *(0.97 - 1.65)*	
	Athlete 5	-0.86	0.03	673.50	0.42 *(0.40 - 0.45)*	
	Athlete 6	-0.22	0.09	6.25	0.80 *(0.67 - 0.95)*	
	Athlete 7	1.39	0.37	14.15	4.01 *(1.94 - 8.27)*	
	Athlete 8	0.00			1.00	
Decrements in Performance	Intercept	1.03	0.52	3.89	2.81 *(1.01 - 7.86)*	50.85
	Coach Prediction	2.71	1.23	4.87	15.09 *(1.35 - 168.03)*	
	Athlete 1	-4.55	1.84	6.14	0.01 *(0.00 - 0.39)*	
	Athlete 2	-1.01	0.40	6.35	0.36 *(0.17 - 0.80)*	
	Athlete 3	-1.97	1.05	3.52	0.14 *(0.02 - 1.09)*	
	Athlete 4	-2.58	1.18	4.80	0.08 *(0.01 - 0.76)*	
	Athlete 5	-3.41	1.31	6.75	0.03 *(0.00 - 0.43)*	
	Athlete 6	-2.70	1.25	4.66	0.07 *(0.01 - 0.78)*	
	Athlete 7	-2.33	0.98	5.63	0.10 *(0.01 - 0.67)*	
	Athlete 8	0.00			1.00	

β- Unstandardised beta co-efficient, Sig- Significance, Exp.(B) (± 95% C.I.)- Exponential of unstandardised beta co-efficient with 95% confidence intervals, AUC (95% CI)- Area under the curve with 95% confidence intervals. S.E.- Standard error, QIC - Quasi likelihood under independence model criterion.

DISCUSSION

The first purpose of this study was to assess the prediction accuracy of a coach's subjective assessment of athlete performance. A second purpose was to assess if the use of athlete monitoring tools could improve on a coach's prediction accuracy of their athlete's race results. This was the first investigation to demonstrate the high accuracy of coach predictions when assessing performance changes. However, no athlete monitoring tools were able to improve on a coach prediction to assess an athlete's performance outcome. This study shows that coach predictions may be more effective than athlete monitoring tools to assess performance change in their athletes.

The experienced coach examined in this case study had a strong ability to assess their athlete's readiness to perform in competition. These results may be due to the coach's well established professional judgement and skilled intuition [2]. Within swimming, it is common practice for coaches to deliver most training sessions and directly observe the many factors, including an athlete's execution of sport specific skills, psychological state and progression of in training efforts that contribute to performance changes [5]. Previous studies have identified that to develop skilled intuition and expertise, the environment must provide regular and valid cues that are strongly related to a performance outcome [23]. In particular, developing expertise from subjective assessments needs an environment which has high predictability of an outcome, requires many years of experience and that the sport or work environment has good feedback of outcome measures (e.g. race results) [23]. Therefore, as individual physiological and skill-based sports such as swimming have a consistent performance environment, race results are easily quantified providing consistent feedback available to the coach through direct observations [5]. This environment can create an ideal environment to develop skilled intuition. As such this case study provides initial evidence to support a swim coach's subjective assessment of how their athletes will perform in competition.

No subjective questionnaires included in this study improved coach predictions to identify a performance change. Despite the widespread use in high performance sport, there are very few studies to show how subjective questionnaires can be used to explain changes in athletic performance [6]. While the use of subjective measures has previously been shown to explain staleness during a taper and linked to either no change or a decrement in performance in swimmers [24], subjective questionnaires are not consistently related to performance changes. For example, the Profile of Mood States has been shown to have poor accuracy to identify performance changes in athletes when regressed against the 30-15 intermittent fitness test [25]. Although, based on the present results, it may be that the coach was able to account for many of these changes in their predictive assessment through observational analysis [5]. Despite the numerous reviews supporting the usefulness of subjective monitoring tools [26,27] and their association to changes in training load [28], no studies have shown how subjective measures can improve on a coaches subjective assessment of how their athlete will perform.

Heart rate indices did not contribute to identifying performance change beyond the coach predictions. While previous studies have related changes in HRV-derived indices to positive or negative training adaptations and reflect the acute training response [29], this has not been consistently observed when assessing performance changes. Indeed, inconsistent findings have been reported for the use of HRV measures to identify an athlete's readiness to perform in training or competition [25,30,31]. For example, when modelled against actual race results, the use of HRV indices (nocturnal measurement) have shown a moderate to strong relationship to actual performance outcomes [30]. However, from less invasive measurements of HRV (10-min upon waking in the morning), there has been poor reported sensitivity to assess changes in physical performance measures in adolescent athletes [25]. As such, while the use of HRV-derived measures may assist to explain underlying physiological training responses, no studies have shown how the use of HRV can improve on a coach prediction of athletic performance.

While initial findings support the strong understanding of a coach to predict athletic performance, skill intuition and subjective assessments do have potential to be incorrect or hindered by biases [4]. These situations may arise when there is a lack of skilled intuition or when an unfamiliar situation may present. Indeed, in a meta-analysis of human health and behaviours, professional judgements (subjective decision-making from data and subjective measures) were out performed or equalled by statistical predictions [7]. The findings summarised that worse professional judgements may be due to a lack of expertise, overreliance on irrelevant cues and an unexplained intuition. It is therefore important to emphasize the current findings are reflective of the coach and swimmers examined in this study. Additionally the coach's predictive ability was not perfect, therefore recognition of these inconsistencies may allow for development and refinement of coach expertise (if reviewed) [32]. Indeed, previous studies on human judgements identified that with the same information, human judgements can often reach differing conclusions [33]. As such, information provided through objective data, could present information unbeknown to the coach to provide a more informed decision in the assessment of athletic performance. Although this study was only observational, and the coach did not receive any feedback from any of the monitoring data collected.

Although the results from this study report high coach prediction accuracy, there are some considerations that need to be addressed. It is possible the coach subjective assessment of athlete performances was improved in this study from having a reference value of the athlete's previous race result when predicting each athlete's performance times. However, no research has attempted to quantify a coach's predictions of their athlete's race results. Therefore, it is currently unknown if the high coach prediction accuracy may be attributed to the methodology in this study. Furthermore, this is a case study in one group of high trained swimmers and their coach. Future research may look to assess this approach in a larger sample size to quantify between coach differences. Finally, due to uneven distribution and multiple events per athlete, all results from 100-400 m events were pooled and converted into a dichotomous outcome. Future research may wish to assess each event independently for the potential differences in stroke and distance.

PRACTICAL APPLICATION

It is important for a coach to observe athletes in training to develop their skilled intuition and subjective assessment of athletic performance. Caution should also be taken when interpreting a coach subjective assessment of athlete performance in isolation due to the potential for inherent biases or unexplained intuitions. Therefore, the use of objective data and reflection of subjective assessments should be used to assist a coach to refine their expertise.

CONCLUSIONS

The findings from this study support a very strong coach understanding of their athlete's performances and attempted to quantify a coach's professional judgement. Furthermore, no athlete monitoring tools improved the model's accuracy to explain either improvements or decrements in performance. These findings provide a reference value for future research investigating the accuracy of athlete monitoring systems to ensure that changes in the measures can contribute or outperform a coach assessment of athletic performance.

REFERENCES

1. Kiely J. Periodization paradigms in the 21st century: evidence-led or tradition-driven. *Int J Sports Physiol Perform.* 2012;7(3):242-250.
2. Abraham A, Collins D. Taking the next step: Ways forward for coaching science. *Quest.* 2011;63(4):366-384.
3. Collins D, Collins L, Carson HJ. "If it feels right, do it": Intuitive decision making in a sample of high-level sport coaches. *Front Psychol.* 2016;7(504).
4. Kahneman D, Klein G. Conditions for intuitive expertise: a failure to disagree. *Am Psychol.* 2009;64(6):515-526.
5. Borresen J, Lambert MI. The quantification of training load, the training response and the effect on performance. *Sports Med.* 2009;9:779-795.
6. Taylor K, Chapman DW, Cronin JB, Newton MJ, Gill N. Fatigue monitoring in high performance sport: A survey of current trends. *J Aus Strength Cond.* 2012;20(1):12-23.
7. Grove WM, Zald DH, Lebow BS, Snitz BE, Nelson C. Clinical versus mechanical prediction: a meta-analysis. *Psychol Assess.* 2000;12(1):19-30.
8. Calvert TW, Banister EW, Savage MV, Bach T. A systems model of the effects of training on physical performance. *IEEE Trans Syst Man Cybern Syst.* 1976;2:94-102.
9. Hellard P, Avalos M, Lacoste L, Barale F, Chatard JC, Millet GP. Assessing the limitations of the Banister model in monitoring training. *J Sports Sci.* 2006;24(5):509-520.
10. Mann TN, Lamberts RP, Lambert MI. High responders and low responders: Factors associated with individual variation in response to standardized training. *Sports Med.* 2014;44(8):1113-1124.
11. Bellenger CR, Karavirta L, Thomson RL, Robertson EY, Davison K, Buckley JD. Contextualising parasympathetic hyperactivity in functionally overreached athletes with perceptions of training tolerance. *Int J Sports Physiol Perform.* 2016;11(5):685-692.
12. Aubry A, Hausswirth C, Louis J, Coutts AJ, Le Meur Y. Functional overreaching: the key to peak performance during the taper? *Med Sci Sports Exerc.* 2014;46(9):1769-1777.
13. Crowcroft S, McCleave E, Slattery K, Coutts AJ. Assessing the measurement sensitivity and diagnostic characteristics of athlete-monitoring tools in national swimmers. *Int J Sports Physiol Perform.* 2017;12(2):S2-95.
14. Colin Kenttä G, Hassmén P. Overtraining and recovery: A conceptual model. *Sports Med.* 1998;26(1):1-16.
15. Plews DJ, Laursen PB, Le Meur Y, Hausswirth C, Kilding AE, Buchheit M. Monitoring training with heart rate variability: How much compliance is needed for valid assessment? *Int J Sports Physiol Perform.* 2013;9(5):783-790.
16. Wallace LK, Slattery KM, Coutts AJ. Establishing the criterion validity and reliability of common methods for quantifying training load in athlete's. *J Strength Cond Res.* 2014;28(8):2330-2337.
17. Foster C, Daines E, Hector L, Snyder AC, Welsh R. Athletic performance in relation to training load. *Wis Med J.* 1996;95(6):370-374.
18. Hopkins WG, Hawley JA, Burke LM. Design and analysis of research on sport performance enhancement. *Med Sci Sports Exerc.* 1999;31(3):472-485.
19. Pettitt RW. The standard difference score: A new statistic for evaluating strength and conditioning programs. *J Strength Cond Res.* 2010;24(1):287-291.
20. Zeger SL, Liang K, Albert PS. Models for longitudinal data: a generalized estimating equation approach. *Biometrics.* 1988:1049-1060.
21. Pan WK. Akaike's information criterion in generalized estimating equations. *Biometrics.* 2001;57(1):120-125.
22. Fawcett T. An introduction to ROC analysis. *Pattern Recognit Lett.* 2006;27(8):861-874.

23. Shanteau J. Competence in experts: The role of task characteristics. *Organ Behav Hum Decis Process.* 1992;53:252-262.
24. Hooper SL, Mackinnon LT, Howard A, Gordon RD, Bachmann AW. Markers for monitoring overtraining and recovery. *Med Sci Sports Exerc.* 1995;27(1):106-112.
25. Buchheit M. Sensitivity of monthly heart rate and psychometric measures for monitoring physical performance in highly trained young handball players. *J Sports Med.* 2015;36(5):351-356.
26. Robertson S, Bartlett JD, Gastin PB. Red, Amber or Green? Athlete monitoring in team sport: the need for decision support systems. *Int J Sports Physiol Perform.* 2017;12(2):S2-73.
27. Bourdon PC, Cardinale M, Murray A, Gastin P, Kellmann M, Varley MC, Gabbett TJ, Coutts AJ, Burgess DJ, Gregson W, Cable NT. Monitoring athlete training loads: consensus statement. *Int J Sports Physiol Perform.* 2017;12(Suppl 2):S2-161.
28. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
29. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Front Physiol.* 2014;5(73).
30. Chalencon S, Busso T, Lacour JR, Garet M, Pichot V, Connes P, Gabel CP, Roche F, Barthélémy JC. A model for the training effects in swimming demonstrates a strong relationship between parasympathetic activity, performance and index of fatigue. *PloS one.* 2012;7(12):e52636.
31. Wallace LK, Slattery KM, Coutts AJ. A comparison of methods for quantifying training load: relationships between modelled and actual training responses. *Eur J Appl Physiol.* 2014;114(1):11-20.
32. Gilbert WD, Trudel P. Learning to coach through experience: Reflection in model youth sport coaches. *J Teach Phys Educ.* 2001;21(1):16-34.
33. Goldberg LR. Man versus model of man: A rationale, plus some evidence, for a method of improving on clinical inferences. *Psychol Bull.* 1970;73(6):422.

Chapter 7

Discussion and Summary

In high performance sport, decisions around training content are typically developed through a process whereby the coaches expertise and recent observations are contextualised with athlete monitoring data to make informed decisions about the athlete's current status (i.e. performance readiness) [1]. Therefore, high performance sporting programs make substantial investments to develop and implement athlete monitoring systems to assist coaches and support staff understand how each athlete is responding to training [2-9]. Despite the extensive reviews supporting the usefulness of athlete monitoring systems [2-4,8,10-19], no study has assessed if these systems contribute to coaching or support staff's assessment of an athletes' readiness to perform. Therefore, a series of studies were conducted to explore athlete monitoring variables and a coach's subjective assessment to assess performance change in highly trained swimmers.

ASSESSING PERFORMANCE CHANGES

Athlete Monitoring Tools

In high performance athletes, there are numerous factors that influence performance outcomes including physiological and psychological state [20]. This thesis provided insight into the use and limitations of athlete monitoring tools to assess performance change in highly trained swimmers. The common findings of Study 1, 2 and 4 identified the poor diagnostic accuracy of athlete monitoring tools when used both in isolation or as part of a multi-factorial approach to identify performance change. Specifically, in Study 1 no single monitoring tool was able to accurately predict a change in performance outside of an athlete's average race results within a season. However, Study 1 showed numerous subjective questionnaires and heart rate (HR) measures had a good signal-to-noise ratio representing an athlete's acute changes in fitness and fatigue. These findings provided both the reliability and typical weekly variance of athlete monitoring tools for more objective measurement of a true change outside of normal for the individual. These results demonstrate athlete monitoring tools have clear seasonal and week-to-week fluctuations, however in isolation cannot accurately identify performance changes.

Therefore, Study 2 examined the efficacy of a multi-factorial monitoring system to identify both short term (i.e. compared to the most recent previous race results) or longitudinal (i.e. compared to the athlete's first race of the season) changes in race performance. The results from Study 2 provide conceptual support for the use of a multi-factorial model to improve the accuracy of identifying performance changes compared to any monitoring tool in isolation. Similar to previous studies [21-23], Study 2 identified combining multiple athlete monitoring tools improved the diagnostic accuracy to assess decrements in performance. Specifically, these measures included contextualising HRV with athlete perceptions of fatigue or training completed to improve the assessment of decrements in performance. However, the prediction models had a weaker diagnostic accuracy when assessing the likelihood of a short-term decrement in performance compared to the longitudinal model. Indeed, the present findings showed that the directional changes in HRV measures must be specific to both the training phase and psychological state. Therefore, to improve the prediction of performance changes and identify athlete readiness, alternative monitoring tools that have a clear directional change related to performance outcomes may be more appropriate than HRV measures in linear models. For example, the use of a standardised warm up measuring a power output at a prescribed heart rate or RPE may have a stronger relationship to a change in performance [24]. However, these findings have yet to be investigated within swimming.

The results from Study 2 are the first to highlight the use of subjective questionnaires combined with and individual athlete intercept to assess improvements in performance. These findings also provided support for the use of the total quality recovery scale (TQR) to identify a likely improvement in performance. However, no physiological variables (HR-derived measures) or training measures (training load or weekly distance) in this study improved the accuracy of the models to identify improvements in performance. This may be due to the association between changes in subjective questionnaires and training load. Furthermore, while several studies have identified the usefulness of HRV-derived indices to explain an athlete's training response [25-27], studies that have contextualised changes in HR indices with subjective measures have been relatively short term training studies [21-23,28]. Furthermore, the discussion of these studies was focused towards contextualising changes in HR measures relevant to training phase and psychological state to identify functional overreaching. As such, contextualising changes in HR measures with training phase and psychological state may be more useful to identify a likely decrement in performance.

Taken collectively, the present findings support the improved accuracy of a multi-factorial monitoring approach through combining both HR measures and psychological or training measures compared to any single monitoring tools in isolation when assessing decrements in performance. However, the weaker diagnostic accuracy from the short-term performance changes identified the limited practicality to assess an athlete's readiness to perform from the most recent previous race result. Therefore, Study 4 assessed if combining multiple athlete monitoring with a coach prediction could improve the practicality of monitoring tools to assess changes in an athlete's readiness to perform.

Coach Assessment

The development of athlete training programs are often guided from a coaches experiential knowledge, intuition and subjective assessment of an athlete's current performance [1,29]. However, the accuracy of coaches' subjective assessment of their athlete's ability to perform has not been empirically assessed. The results of these studies provide initial evidence to support an experienced swim coach's professional judgements and skilled intuition to accurately identify changes in swim performance. The findings from Study 3 showed a very strong association of coach predicted to actual athlete race results. Following from these findings, Study 4 identified the high diagnostic accuracy of a coach's subjective assessment to identify both improvements and decrements in their athlete's performances. Additionally, as shown in Figure 7:1 when comparing the results of the monitoring tools assessed throughout Studies 1, 2 and 4, none were able to improve on a coach prediction of performance. Collectively, these results provide evidence of a coach's subjective assessment and professional judgement to identify their athlete's readiness to perform.

However, it is important to acknowledge that the present results are limited to the high-performance swim squad who collaborated on this thesis. Indeed, as swimming is a highly controllable training and competition environment, there is consistent feedback available to the coach through direct observations [4]. This environment provides an ideal environment to develop expertise, skilled intuition and well considered professional judgements. However, there should be some scepticism in skilled intuitions and professional judgements due to the potential to be hindered by inherent biases. These situations arise from a lack of skilled intuition, inexperience or when an unfamiliar environment or situation presents [30].

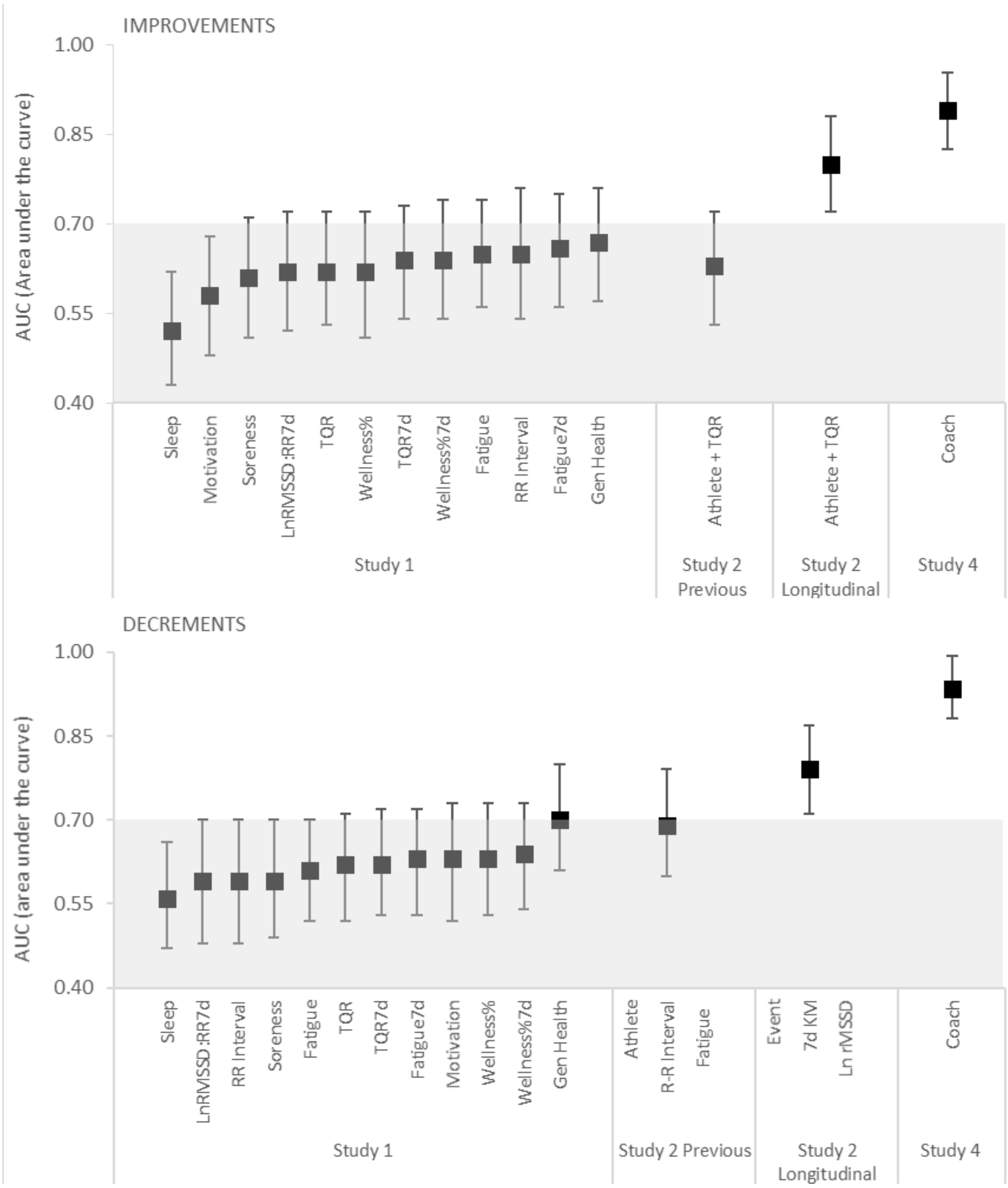

Figure 7:1 A comparison of all athlete monitoring tools, models and coach predictions to assess both improvements and decrements in performance. *AUC- Area under the curve, TQR – Total quality recovery, Ln rMSSD – Log transformed root mean squared of the consecutive R-R interval differences, Study 2 Previous- Model assessing performance change from previous race result, Study 2 Longitudinal – Model assessing performance change from first race result of the season, Coach – Coach subjective assessment of athlete performance. Grey shading identifies a "good" diagnostic accuracy (AUC).*

ASSISTING THE TRAINING PROCESS

The consistent discrepancy between coach planned to athlete reported training intensity may demonstrate a coach's poor understanding of an athlete's physical capacity, or an athlete's inappropriate implementation of the prescribed training session. These differences may lead to poor training control resulting in unexpected training induced fatigue, non-functional overreaching or poor performance [31]. Similar to previous studies [32-34], Study 3 identified the discrepancy of coach planned to athlete reported training intensity and subjective questionnaires. However, this investigation showed that a change in perceived fatigue could assist to identify a likely discrepancy between the coach planned to athlete reported session rating of perceived exertion (sRPE). As such, the reporting of perceived fatigue may assist to highlight a small likely discrepancy between the coach planned to athlete reported sRPE. However, the diagnostic accuracy of perceived fatigue in isolation to identify this discrepancy was weak. Therefore, the discrepancy of coach expected to athlete reported subjective questionnaires suggests the ongoing use of these measures could provide addition information and assist a coach to understand the individual athlete's training response. Although, no measures assessed in isolation could accurately identify a discrepancy of coach planned to athlete reported sRPE.

AN INTEGRATED APPROACH

The collective findings from this thesis support the use of athlete monitoring tools to provide objective data quantifying an athlete's response to training but had a poor assessment of performance changes. The results from Study 1,2 and 4 showed that athlete monitoring tools have limited practicality to assess how an athlete will perform compared to a coach's subjective assessment. Although the very strong relationship of coach prediction to actual athlete results in Study 3 and 4 support a swim coach's strong professional judgement to assess performance change. However, the discrepancies of coach expected to athlete reported perceived fatigue, TQR and sRPE in Study 3, and the good signal-to--noise ratio of monitoring variables in Study 1 show that monitoring tools may quantify acute changes in fitness and fatigue based on an athlete's response to training. Based on these observations, Figure 7:2 shows a conceptual model of an integrated approach to training prescription through combining both a coaches' observation (subjective feedback) and the use of athlete monitoring data to compliment a coaches' understanding of the training process (objective feedback).

This conceptual model supports the collection, analysis and reporting of both training load, physiological and subjective measures to quantify the individual training response *(as shown in Study 1 and 3)* and complement both the reflective process and assist in refining coach expertise. Furthermore, this approach demonstrates how observations and data collected at each training session can contribute to medium and long-term planning of training programs. It is proposed that through using athlete monitoring tools (quantifying training load and the athlete's training response) aligned with the context of the phase of the season, that a more robust (informed) decision-making process will be developed.

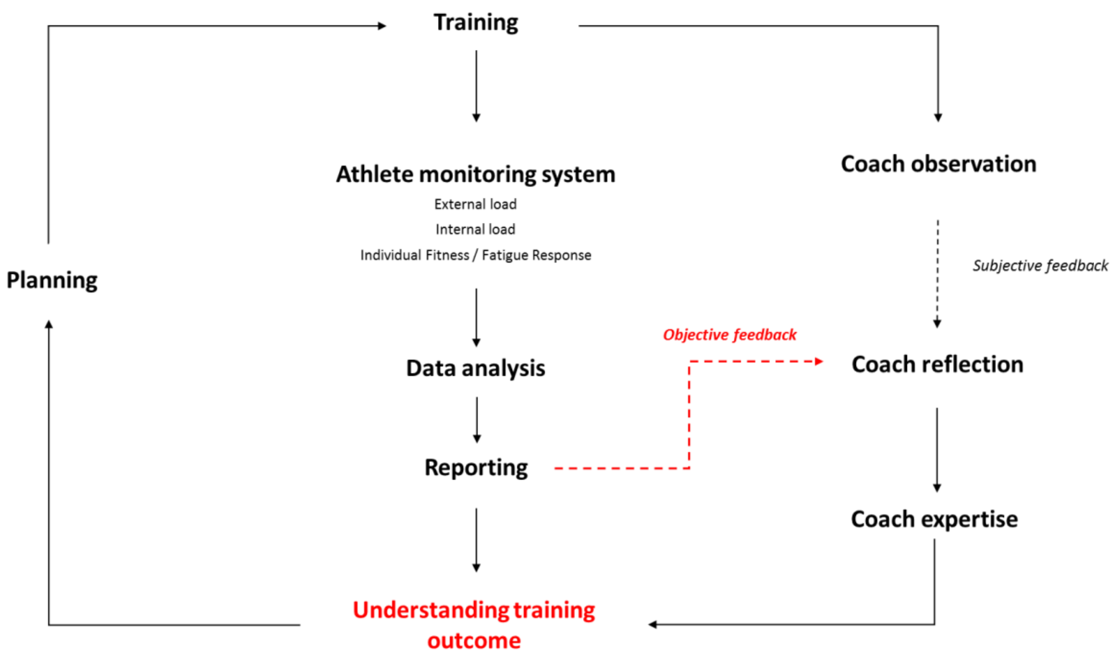

Figure 7:2 An integrated approach of athlete monitoring tools and coach expertise to inform a coach decision-making and planning of training prescription.

LIMITATIONS

Due to the applied approach taken in this thesis, the findings are limited to a small group of highly trained swimmers. Indeed, the relationship of coach predictions and athlete monitoring systems to performance outcomes may vary in an alternative sport setting such as the team sport environment or coaches with different levels of experiences. Likewise, only a select number of athlete monitoring tools were assessed in this thesis. It was impractical for the implementation of multiple subjective questionnaires and physiological measures for longitudinal data collection on the same group of athletes. A comparison of a wider array of subjective questionnaires and physiological measures would have allowed for a more in-depth understanding of the varying relationship of these monitoring tools to performance changes. Furthermore, both the single item, multi-factorial athlete monitoring models and coach predictions are yet to be validated on an out of sample population. These findings provide a proof of concept for a coaches' strong subjective assessment and skilled intuition of performance outcomes, however as mentioned are yet to be validated on both coaches and athletes of different levels of expertise and sports. Due to the uneven distribution of performance outcomes and repeated measure design, performance outcomes in this thesis were pooled and converted to a dichotomous outcome. These models could provide the probability of a directional change in performance, although it was not specific on the magnitude of performance changes. Finally, whilst novel, the studies in this thesis were only observational in design and therefore do not provide the same level of evidence as randomised control trials that would examine the efficacy of various athlete monitoring systems or coaches. Further studies should aim to assess if the collection and reporting of athlete monitoring systems contributes to improve on a coaches' assessment of their athlete's performance or the training process.

PRACTICAL APPLICATIONS

The findings from this thesis provided evidence to support a coach's professional judgement and skilled intuition to assess performance changes in highly trained swimmers. Furthermore, the use of athlete monitoring tools may assist a coach have a more comprehensive understanding of their athlete's response to training. Specifically, key practical applications from this thesis include:

- Caution should be taken with the interpretation of any single monitoring tool to assess performance change due to the poor diagnostic accuracy.
- Validation of monitoring tools and assessment of the typical variation should be validated with each sport.
- After accounting for each athlete TQR can assist to identify improvements in performance.

- Combining HR-derived measures (R-R interval or Ln rMSSD) with either psychological state or training volume can improve the diagnostic accuracy to identify decrements in performance.
- There is a consistent discrepancy of coach planned to athlete reported sRPE, perceived fatigue and TQR even in a homogenous population of highly trained swimmers.
- The use of perceived fatigue can only explain a small likely difference between coach planned to athlete reported sRPE.
- Interpreting coach subjective assessments in isolation has potential for inherent biases, therefore objective data may assist to negate these possible issues.

REFERENCES

1. Kiely J. Periodization paradigms in the 21st century: evidence-led or tradition-driven. *Int J Sports Physiol Perform.* 2012;7(3):242-250.
2. Bourdon PC, Cardinale M, Murray A, Gastin P, Kellmann M, Varley MC, Gabbett TJ, Coutts AJ, Burgess DJ, Gregson W, Cable NT. Monitoring athlete training loads: consensus statement. *Int J Sports Physiol Perform.* 2017;12(Suppl 2):S2-161.
3. Robertson S, Bartlett JD, Gastin PB. Red, Amber or Green? Athlete monitoring in team sport: the need for decision support systems. *Int J Sports Physiol Perform.* 2017;12(2):S2-73.
4. Borresen J, Lambert MI. The quantification of training load, the training response and the effect on performance. *Sports Med.* 2009;9:779-795.
5. Jobson SA, Passfield L, Atkinson G, Barton G, Scarf P. The analysis and utilization of cycling training data. *Sports Med.* 2009;39(10):833-844.
6. Foster C, Daines E, Hector L, Snyder AC, Welsh R. Athletic performance in relation to training load. *Wis Med J.* 1996;95(6):370-374.
7. Mujika I. Quantification of training and competition loads in endurance sports: methods and applications. *Int J Sports Physiol Perform.* 2017;12(2):2-9.
8. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med.* 2014;44(2):139-147.
9. Saw A, Halson S, Mujika I. Monitoring athletes during training camps: Observations and translatable strategies from elite road cyclists and swimmers. *Sports.* 2018;6(63).
10. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and external training load: 15 years on. *Int J Sports Physiol Perform.* 2019(00):1-4.
11. Lambert MI, Borresen J. Measuring training load in sports. *Int J Sports Physiol Perform.* 2010;5:406-411.
12. Lambert M, Borresen J. A theoretical basis of monitoring fatigue: a practical approach for coaches. *Int J Sports Sci Coach.* 2006;1(4):371-388.
13. Morgan WP, Brown DR, Raglin JS, O'connor PJ, Ellickson KA. Psychological monitoring of overtraining and staleness. *Br J Sports Med.* 1987;21(3):107-114.
14. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
15. Taylor K, Chapman DW, Cronin JB, Newton MJ, Gill N. Fatigue monitoring in high performance sport: A survey of current trends. *J Aus Strength Cond.* 2012;20(1):12-23.
16. Vanrenterghem J, Nedergaard NJ, Robinson MA, Drust B. Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Med.* 2017;47(11):2135-2142.
17. Hooper SL, MacKinnon LT. Monitoring overtraining in athletes. Recommendations. *Sports Med.* 1995;20(5):321-327.
18. Coyne JC, Haff GG, Coutts A, Newton RU, Nimphius S. The current state of subjective training load monitoring—a practical perspective and call to action. *Sports Med - Open.* 2018;4(1):58.
19. Ward P, Coutts AJ, Pruna R, McCall A. Putting the ‘i’ back in team. *Int J Sports Physiol Perform.* 2018:1-14.
20. Mann TN, Lamberts RP, Lambert MI. High responders and low responders: Factors associated with individual variation in response to standardized training. *Sports Med.* 2014;44(8):1113-1124.
21. Bellenger CR, Karavirta L, Thomson RL, Robertson EY, Davison K, Buckley JD. Contextualising parasympathetic hyperactivity in functionally overreached athletes with perceptions of training tolerance. *Int J Sports Physiol Perform.* 2016;11(5):685-692.

22. Aubry A, Hausswirth C, Louis J, Coutts AJ, Buchheit M, Le Meur Y. The development of functional overreaching is associated with a faster heart rate recovery in endurance athletes. *PloS one.* 2015;10(10):e0139754.
23. Aubry A, Hausswirth C, Louis J, Coutts AJ, Le Meur Y. Functional overreaching: the key to peak performance during the taper? *Med Sci Sports Exerc.* 2014;46(9):1769-1777.
24. Lamberts RP. Predicting cycling performance in trained to elite male and female cyclists. *Int J Sports Physiol Perform.* 2014;9(4):610-614.
25. Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? *Front Physiol.* 2014;5(73).
26. Bellenger CR, Fuller JT, Thomson RL, Davison K, Robertson EY, Buckley JD. Monitoring athletic training status through autonomic heart rate regulation: A systematic review and meta-analysis. *Sports Med.* 2016:1-26.
27. Plews DJ, Laursen PB, Kilding AE, Buchheit M. Heart rate variability in elite triathletes, is variation in variability the key to effective training? A case comparison. *Eur J Appl Physiol.* 2012;112(11):3729-3741.
28. Thomson RL, Bellenger CR, Howe PR, Karavirta L, Buckley JD. Improved heart rate recovery despite reduce exercise performance following heavy training: A within-subject analysis. *J Sci Med Sport.* 2015;In Press.
29. Viru A, Viru M. *Nature of training effects.* Philadelphia: Lippincott Williams and Wilkins; 2000.
30. Bowes I, Jones RL. Working at the edge of chaos: Understanding coaching as a complex, interpersonal system. *Sport Psychol.* 2006;20(2):235-245.
31. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, Raglin J, Rietjens G, Steinacker J, Urhausen A. Prevention, diagnosis and treatment of the overtraining syndrome: Joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). *Eur J Sport Sci.* 2013;13(1):1-24.
32. Wallace LK, Slattery KM, Coutts AJ. The ecological validity and application of the session-RPE method for quantifying training loads in swimming. *J Strength Cond Res.* 2009;23(1):33-38.
33. Barroso R, Cardoso RK, do Carmo EC, Tricoli V. Perceived exertion in coaches and young swimmers with different training experience. *Int J Sports Physiol Perform.* 2014;9:212-216.
34. Brink MS, Frencken WGP, Jordet G, Lemmink KAPM. Coaches' and players' perceptions of training dose: Not a perfect match. *Int J Sports Physiol Perform.* 2014;9(3):497-502.

Chapter 8

Summary and Future Directions

THESIS SUMMARY

Despite the ubiquitous nature of athlete monitoring tools in high performance sport, it is currently unknown if these systems can be used to assess an athlete's readiness to perform in training or competition. Although there are an extensive number of research papers reporting how athlete monitoring systems can be implemented into high performance programs [1-14], no studies had previously assessed if the use of a monitoring system could improve on an experienced coach's subjective assessment of athletic performance. Furthermore, no studies had assessed the accuracy of coach observations and the subjective assessment of an athlete's performance. Finally, it was also unknown if a coach's subjective assessment of their athlete's readiness to perform is improved when athlete monitoring tools are integrated with coach expertise. Therefore, this thesis assessed the accuracy of an athlete monitoring system and coach subjective assessments to identify athlete readiness to performance and performance changes in highly trained swimmers.

The studies within this thesis built on the knowledge and practical application of athlete monitoring systems in high performance sport. Specifically, this thesis assessed the prediction accuracy of athlete monitoring tools to identify performance changes *(Study 1 and 2)* and provided objective information on an athlete's training response *(Study 1 and 3).* Furthermore, initial evidence was provided on the accuracy of a coach's subjective assessment of their athlete's readiness to perform *(Study 3 and 4)* and ability to quantify the expected training responses *(Study 3).* Finally, the ability of monitoring tools to improve on a coach's prediction of their athlete's performances was also examined *(Study 4).*

The findings of the current thesis contribute to the prior knowledge base on contextualising multiple athlete monitoring tools to identify performance change in highly trained athletes. Indeed, when comparing results from Study 1 and 2, multi-factorial models had higher

diagnostic accuracy to identify both longitudinal improvements and decrements in performance. However, when aiming to assess short term changes in performance there were weaker results. Therefore, while these findings support the concept of a multi-factorial approach, there is still limited accuracy in the practical application of these models to identify short term performance changes. In contrast, the results from Study 3 and 4 demonstrated the high diagnostic accuracy of a coach's subjective assessment of their athlete's performance. These results provide initial support to quantify a swim coach's professional judgement and skilled intuition when assessing athletic performance. These findings may provide a benchmark for future research aiming to contribute to a coach's understanding of performance change. However, the results from Study 3 also identified a poor relationship between coach expected to athlete reported subjective questionnaires and training intensity. As such, a coach may be provided with unknown or unexpected information of how their athletes are responding to training through the reporting of monitoring variables with a good signal-to-noise ratio (shown in Study 1). As such, this thesis provided evidence to support a coach's subjective assessment of athletic performance in highly trained swimmers. However, the use of athlete monitoring tools may assist a coach to have a more comprehensive understanding of their athlete's response to training.

FUTURE RESEARCH

To expand on the findings of this thesis and develop a greater understanding of coaches' subjective assessment of athlete performances and the role of monitoring systems in assessing an athlete's readiness to perform, it is suggested that further research should investigate:

- Multi-centre studies on coaches' subjective assessment of athletic performance across multiple sports, differing levels of expertise and predicting different outcomes (e.g. training adaptations, race results, pacing strategies etc.). While this thesis provided new information on the use of both coach predictions and athlete monitoring data, multi-centre studies will provide larger data sets for a more comprehensive analysis.
- Assess the multi-factorial models in an out of sample population in both swimmers and across sports to identify potential cross over of these conceptual models. Although the findings from this study provide initial evidence supporting athlete monitoring systems to identify performance change, they have not been assessed on an independent group of athletes.
- Explore the development of coaching expertise and skilled intuition within swimming and other sports. It is currently not known if this strong subjective assessment found within this thesis is applicable across difference sports, where coaches may have less frequent observations of their athletes, or in less controllable training or competition environments.
- The role that regularly reporting athlete monitoring data has on the development or inhibition of coaching expertise and skilled intuition. While it is commonly believed that the use of monitoring may assist coaches in the decision-making process, it is unknown if the long-term reporting of athlete monitoring data may inhibit a coach's development of expertise. It is currently unknown if coaches may become reliant on "data" with frequent reporting suppressing coaches' professional judgement and skilled intuition.

- Assess the sensitivity and specificity of athlete monitoring tools and their diagnostic accuracy for other important outcomes in sport such as injury and illness. While this thesis aimed to assess the predictive accuracy of athlete monitoring and performance changes, there is still limited evidence supporting these measures and their prediction accuracy to identify illness and injury in high performance athletes.

REFERENCES

1. Bourdon PC, Cardinale M, Murray A, Gastin P, Kellmann M, Varley MC, Gabbett TJ, Coutts AJ, Burgess DJ, Gregson W, Cable NT. Monitoring athlete training loads: consensus statement. *Int J Sports Physiol Perform.* 2017;12(Suppl 2):S2-161.
2. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and external training load: 15 years on. *Int J Sports Physiol Perform.* 2019(00):1-4.
3. Borresen J, Lambert MI. The quantification of training load, the training response and the effect on performance. *Sports Med.* 2009;9:779-795.
4. Lambert MI, Borresen J. Measuring training load in sports. *Int J Sports Physiol Perform.* 2010;5:406-411.
5. Lambert M, Borresen J. A theoretical basis of monitoring fatigue: a practical approach for coaches. *Int J Sports Sci Coach.* 2006;1(4):371-388.
6. Morgan WP, Brown DR, Raglin JS, O'connor PJ, Ellickson KA. Psychological monitoring of overtraining and staleness. *Br J Sports Med.* 1987;21(3):107-114.
7. Robertson S, Bartlett JD, Gastin PB. Red, Amber or Green? Athlete monitoring in team sport: the need for decision support systems. *Int J Sports Physiol Perform.* 2017;12(2):S2-73.
8. Saw AE, Main LC, Gastin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: a systematic review. *Br J Sports Med.* 2016;50(5):281-291.
9. Taylor K, Chapman DW, Cronin JB, Newton MJ, Gill N. Fatigue monitoring in high performance sport: A survey of current trends. *J Aus Strength Cond.* 2012;20(1):12-23.
10. Vanrenterghem J, Nedergaard NJ, Robinson MA, Drust B. Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Med.* 2017;47(11):2135-2142.
11. Halson SL. Monitoring training load to understand fatigue in athletes. *Sports Med.* 2014;44(2):139-147.
12. Hooper SL, MacKinnon LT. Monitoring overtraining in athletes. Recommendations. *Sports Med.* 1995;20(5):321-327.
13. Coyne JC, Haff GG, Coutts A, Newton RU, Nimphius S. The current state of subjective training load monitoring—a practical perspective and call to action. *Sports Med - Open.* 2018;4(1):58.
14. Ward P, Coutts AJ, Pruna R, McCall A. Putting the ‘i’ back in team. *Int J Sports Physiol Perform.* 2018:1-14.

Chapter 9

Appendix

HUMAN RESEARCH ETHICS COMMITTEE APPROVAL

Research.Ethics@uts.edu.au

Wed 08/04/2015 10:40
To:
Aaron.Coutts@uts.edu.au; Stephen Crowcroft; Erin Louise McCleave; Research.Ethics@uts.edu.au

Dear Applicant,

Thank you for your response to the Committee's comments for your project titled, "Man versus Machine: Assessing the proof of concept for the implementation of an athlete monitoring system in well-trained swimmers.". Your response satisfactorily addresses the concerns and questions raised by the Committee who agreed that the application now meets the requirements of the NHMRC National Statement on Ethical Conduct in Human Research (2007). I am pleased to inform you that ethics approval is now granted.

Your approval number is UTS HREC REF NO. 2014000842

Your approval is valid five years from the date of this email.

Please note that the ethical conduct of research is an on-going process. The National Statement on Ethical Conduct in Research Involving Humans requires us to obtain a report about the progress of the research, and in particular about any changes to the research which may have ethical implications. This report form must be completed at least annually, and at the end of the project (if it takes more than a year). The Ethics Secretariat will contact you when it is time to complete your first report.

I also refer you to the AVCC guidelines relating to the storage of data, which require that data be kept for a minimum of 5 years after publication of research. However, in NSW, longer retention requirements are required for research on human subjects with potential long-term effects, research with long-term environmental effects, or research considered of national or international significance, importance, or controversy. If the data from this research project falls into one of these categories, contact University Records for advice on long-term retention.

You should consider this your official letter of approval. If you require a hard copy, please contact Research.Ethics@uts.edu.au.

To access this application, please follow the URLs below:

- if accessing within the UTS network: http://rmprod.itd.uts.edu.au/RMENet/HOM001N.aspx
- if accessing outside of UTS network: https://remote.uts.edu.au , and click on "RMENet - ResearchMaster Enterprise" after logging in.

We value your feedback on the online ethics process. If you would like to provide feedback please go to: http://surveys.uts.edu.au/surveys/onlineethics/index.cfm

If you have any queries about your ethics approval, or require any amendments to your research in the future, please do not hesitate to contact Research.Ethics@uts.edu.au.

Yours sincerely,

Professor Marion Haas

Chairperson

UTS Human Research Ethics Committee

C/- Research & Innovation Office

University of Technology, Sydney

E: Research.Ethics@uts.edu.au

I: http://www.research.uts.edu.au/policies/restricted/ethics.html

P: PO Box 123, BROADWAY NSW 2007

[Level 14, Building 1, Broadway Campus]

CB01.14.08.04

COACH INFORMED CONSENT

I ________________________________ *(participant's name)* agree to participate in the research project "Man versus machine: Assessing the proof of concept for the implementation of an athlete monitoring system" being conducted by Stephen Crowcroft at the Faculty of Health, University of Technology, Sydney (UTS) and the NSW Institute of Sport (NSWIS). I understand the purpose of the study is to investigate the physiological and perceptual changes of an athlete leading into competitions, the association to changes in performance and to compare an athlete's response against coaches expected outcomes. I understand that I have been asked to participate in this research project due to my current status as a coach of highly trained competitive swimmer. I am aware that my participation in this research may involve up 5 minutes of my time at the beginning of each week and 2 minutes daily until April 2016. I also understand that there are possible risks for my athletes who will be participating in this study. These possible risks are:

1. **Risk of infection during blood and saliva sample collection:** There is a slight risk of infection when blood samples are withdrawn during pinprick or while collecting saliva samples. However, this risk will be minimised through all capillarised blood sampling from pinprick and passive saliva samples be undertaken by trained personnel under sterile conditions using standard procedures

2. **Fatigue from testing:** The exercise protocols in the present study may be demanding. It is anticipated that your athletes may feel general fatigue from physical testing completed in this study. However, this fatigue will be no greater than your athletes normally endure during competition or training.

3. **Muscle strains:** There is a minor risk of suffering a muscular strain during the exercise completed during the studies. As the testing in some instances involves maximal force production, it is important for athletes warm up prior to exercise and warm down at the completion. Leading up to the maximal tests, it is expected that your athletes would perform activities that gradually aim to build up muscle temperature to ensure that injury risk is minimised during testing.

I understand that UTS attempts to ensure that the greatest of care will be taken by the researchers during the testing and training sessions. However, I acknowledge that UTS, its agents and employees will not be liable for any loss or damage arising directly or indirectly from these testing and training sessions. I acknowledge and accept that there are risks involved, including but not limited to discomfort, injury and, in extremely rare circumstances, death. I acknowledge and accept that my participation is entirely voluntary, and that UTS has accepted my participation in good faith without express implied warranty. I am aware that I can contact Stephen Crowcroft (M: +61 [redacted], E: Stephen.J.Crowcroft@student.uts.edu.au) or Professor Aaron Coutts- UTS PhD supervisor E: Aaron.coutts@uts.edu.au) if I have any concerns about the research. I also understand that I am free to withdraw my participation from this research project at any time I wish, without consequences, and without giving a reason. I agree that Stephen Crowcroft has answered all my questions fully and clearly. I agree that the research data gathered from this project may be published in a form that does not identify me in any way.

______________________________________ ____/____/____

Signature (participant)

______________________________________ ____/____/____

Signature (research or delegate)

ATHLETE INFORMED CONSENT

I ________________________________ *(participant's name)* agree to participate in the research project *"Man versus machine: Assessing the proof of concept for the implementation of an athlete monitoring system"* being conducted by Stephen Crowcroft at the Faculty of Health, University of Technology, Sydney (UTS) and the NSW Institute of Sport (NSWIS). I understand the purpose of the study is to investigate the physiological and perceptual changes of an athlete leading into competitions, there association to changes in performance and to compare an athlete's response against coaches expected outcomes. I understand that I have been asked to participate in this research project due to my current status as a highly trained competitive swimmer. I am aware that my participation in this research may involve up to 10 minutes of my time daily until April 2016. I also understand that there are possible risks in participating in this study. These possible risks are:

4. **Risk of infection during blood and saliva sample collection:** There is a slight risk of infection when blood samples are withdrawn during pinprick or while collecting saliva samples. However, this risk will be minimised through all capillarised blood sampling from pinprick and passive saliva samples be undertaken by trained personnel under sterile conditions using standard procedures.

5. **Fatigue from testing:** The exercise protocols in the present study may be demanding. It is anticipated that you may feel general fatigue from physical testing completed in this study. However, this fatigue will be no greater than you normally endure during competition or training.

6. **Muscle strains:** There is a minor risk of suffering a muscular strain during the exercise completed during the studies. As the testing in some instances involves maximal force production, it is important for the subject to warm up prior to exercise and warm down at the completion. Leading up to the maximal tests, you will perform activities that gradually aim to build up muscle temperature to ensure that injury risk is minimised during testing.

I understand that UTS attempts to ensure that the greatest of care will be taken by the researchers during the testing and training sessions. However, I acknowledge that UTS, its agents and employees will not be liable for any loss or damage arising directly or indirectly from these testing and training sessions. I acknowledge and accept that there are risks involved, including but not limited to discomfort, injury and, in extremely rare circumstances, death. I acknowledge and accept that my participation is entirely voluntary, and that UTS has accepted my participation in good faith without express implied warranty. I am aware that I can contact Stephen Crowcroft (M: +61 [redacted], E: Stephen.Crowcroft@uts.edu.au) or Professor Aaron Coutts- UTS PhD supervisor E: Aaron.coutts@uts.edu.au) if I have any concerns about the research. I also understand that I am free to withdraw my participation from this research project at any time I wish, without consequences, and without giving a reason. I agree that Stephen Crowcroft has answered all my questions fully and clearly. I agree that the research data gathered from this project may be published in a form that does not identify me in any way.

____ ____/____/____

Signature (participant)

____ ____/____/____

Signature (research or delegate)

ATHLETE MONITORING QUESTIONNAIRE

To be completed each morning before training

Time to bed: ______ **Waking time:** ______

Sleep quality:

1	Much worse than normal
2	worse than normal
3	normal
4	better than normal
5	much better than normal

Perceived Fatigue:

1	Much worse than normal
2	worse than normal
3	normal
4	better than normal
5	much better than normal

Total Quality Recovery:

6	
7	Very,very poor recovery
8	
9	Very poor recovery
10	
11	Poor recovery
12	
13	Reasonable recovery
14	
15	Good recovery
16	
17	Very good recovery
18	
19	Very, very good recovery
20	

Injury/ Illness:

1	Discomfort
2	Pain
3	Injury
4	Sick/illness
5	Other

Comments:

Sleep Quality:	
Total quality recovery:	
Perceived fatigue:	
Injury/ Illness rating:	

To be completed following each session by athletes

Rating of Perceived exertion

6	
7	Very, very light
8	
9	Very light
10	
11	Fairly light
12	
13	Somewhat hard
14	
15	Hard
16	
17	Very hard
18	
19	Very, very hard
20	

Session Type	
Total Distance Swum:	
High Intensity swimming:	
Session Duration:	
Session RPE	

Comments: