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Training loads and player wellness in youth sport: Implications for illness

Thomas Sawczuk

A thesis submitted in partial fulfilment of the requirements of Leeds Beckett University for the degree of Doctor of Philosophy

September 2019

ABSTRACT

Despite the athlete monitoring cycle becoming increasingly popular within sport, very little evidence exists with regards to the relationships present between its measures or its relationship with illness incidence in youth athletes. The aim of this thesis was to evaluate the true predictive ability of an integrated athlete monitoring cycle model, incorporating measures of the training dose (training load), training recovery (sleep) and training response (wellness questionnaires (DWB and PRS), countermovement jumps and salivary IgA (s-IgA)), with regards to illness incidence in youth athletes. Study 1 outlined the reliability and usefulness of DWB (poor/marginal), PRS (poor/marginal) and CMJ (good/useful). Despite study 1's findings, study 2 showed that CMJ was not suitable for use as a training response measure in youth athletes. Studies 3 and 4 supported the use of the sleep quality subscale as a training recovery measure rather than within the DWB training response measure (which was reduced to the four item $DWB_{no\text{-}sleep}$). The overall $DWB_{no\text{-}sleep}$ score, fatigue, stress and mood were statistically related to the training recovery, whereas only muscle soreness was related to the training dose. Statistically, PRS was related to both the training dose and recovery. Despite the presence of these statistical relationships, only the effect of training load, including match exposure, on PRS was practically interpretable. Unfortunately, technical issues prevented the true predictive ability of an integrated athlete monitoring cycle model with regards to illness incidence being tested. However, study 5 showed that s-IgA measures could not accurately predict illness in youth athletes. Furthermore, analysis of the longitudinal trends of s-IgA, $DWB_{no\text{-}sleep}$ and PRS showed that the subjective fatigue/wellness measures were more responsive to qualitative events than objective measures of immune function. Overall, the results of this thesis provide support for the use of the integrated athlete monitoring cycle in youth athletes, particularly when subjective training response measures are included. However, future research needs to consider the true predictive ability of the proposed integrated athlete monitoring cycle model with regards to illness incidence.

DECLARATION

I hereby confirm that this is my own work. The thesis, or any part thereof, has not been previously submitted for any degree or comparable award.

_____

Thomas Sawczuk

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A PhD is a weird and wonderful journey. As authors, we are lauded for conducting a series of independent research studies; however, anyone who has completed a research study will be acutely aware that they are always the result of a team effort. With that in mind, there are a number of people, I would like to acknowledge for their help over the duration of this PhD.

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LIST OF ABBREVIATIONS

ACWR: Acute:chronic workload ratio

ANOVA: Analysis of variance

AU: Arbitrary units

AUC: Area under the curve

CI: Confidence interval

Cm: Centimetres

CMJ: Countermovement jump

CV: Coefficient of variation

DWB: Daily wellness questionnaire (McLean et al., 2010)

$DWB_{no\text{-}sleep}$: Daily wellness questionnaire (McLean et al., 2010) with sleep quality subscale removed.

e.g.: For example

EEG: Electroencephalography

EOG: Electrooculography

EMGsub: Electromyography of the submentalis

ES: Effect size

GPS: Global positioning system

HIGH: High frequency resistance training group

HPA: Hypothalamic-pituitary-adrenal

HR: Heart rate

i.e.: That is

IgA: Immunoglobulin A

IMTP: Isometric mid-thigh pull

IQR: Interquartile range

Low: Low frequency resistance training group

LQ: Lower quartile

m: Metres

m^2: Metres squared (area)

m/s^2: Metres per second squared (acceleration)

MBI: Magnitude-based inferences

MIF: Maximal isometric force

mL: Millilitres

N: Newtons

NHST: Null hypothesis significance testing

OR: Odds ratio

POMS: Profile of Mood States (McNair et al., 1971)

PRS: Perceived Recovery Status scale (Laurent et al., 2010)

RPE: Rating of perceived exertion

SD: Standard deviation

s-IgA: Salivary IgA

s-RPE: Session-RPE

SAM: Sympathetic-adrenal-medullary

SRI: Self-reported illness

SRI_{day}: Random forest model predicting incidence of SRI on day of saliva sampling

SRI_{2wk}: Random forest model predicting incidence of SRI within two weeks of saliva sampling

SRI_{4wk}: Random forest model predicting incidence of SRI within two weeks of saliva sampling

SWC: Smallest worthwhile change

TE: Typical error

TRIMP: Training impulse

UK: United Kingdom

UQ: Upper quartile

URI: Upper respiratory infection

URTI: Upper respiratory tract infection

USA: United States of America

USQ: Undergraduate Stress Questionnaire (Ensel, 1986)

W: Watts

WURSS-21: Wisconsin Upper Respiratory Symptom Survey 21 (Barrett et al., 2009)

PUBLICATIONS

The following articles were published alongside completion of this thesis:

Sawczuk, T., Jones, B., Scantlebury, S., Weakley, J., Read, D., Costello, N., Darrall-Jones, J. D., Stokes, K., Till, K. (2018) Between-day reliability and usefulness of a fitness testing battery in youth sport athletes: Reference data for practitioners, *Measurement in Physical Education and Exercise Science*, 22(1), p11-18.

Sawczuk, T., Jones, B., Scantlebury, S., Till, K. (2018) Relationships between training load, sleep duration and daily well-being and recovery measures in youth athletes, *Pediatric Exercise Science*, 30(3), p345-352.

Sawczuk, T., Jones, B., Scantlebury, S., Till, K. (2018) The influence of training load, exposure to match play and sleep duration on daily wellbeing measures in youth athletes, *Journal of Sports Sciences,* 36(21), p2431-2437.

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CONFERENCE PROCEEDINGS

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Chapter 1 Introduction

1.1 Youth Sport

Youth sport is the global term applied to any athletic program that provides a systematic sequence of practices and contests for children and youths (Seefeldt et al., 1993). It is estimated that 80.7% of young people aged 5-15 participate in youth sport in the United Kingdom (UK; DCMS, 2016) and approximately 7.8 million students aged 14-18 participate in high school sports in the United States of America (USA; Comstock et al., 2017). Within youth sport, contests typically occur at chronological age group level (e.g. under 7s, under 11s, under 16s etc) and finish at either the under 18 or under 23 age groups dependent upon the rules of the sport. However, despite youth sport participants experiencing key phases of social, psychomotor and physical development, research within this cohort is limited relative to its adult equivalent (Bergeron et al., 2015; Difiori et al., 2014; Mountjoy et al., 2008).

1.1.1 The professionalisation of youth sport

Recently, interest in youth sport performance, particularly within the areas of talent identification and development, has markedly increased (Rongen et al., 2015). This increase in interest may have been driven by Ericsson and colleagues' (1993) seminal finding that 10,000 hours of deliberate practice are required in order for an individual to master a skill. Ericsson and colleagues (1993) argued that unlike previous suggestions that talent was innate, mastery in specific skills could be achieved if a minimum of ten years of 'intensive practice' was completed. The 10,000 hours of deliberate practice rule was subsequently critiqued for being too simplistic (Crust, 2010) and for not accounting for the diverse range of practice activities (e.g. deliberate practice, deliberate play and unstructured activity) which may be required for elite performance to be achieved (Cobley & Baker, 2010). However, despite these concerns surrounding the validity of the rule, there has been significant investment within the professional sport academy system, resulting in programmes such as the Premier League's Elite Player Performance Plan

(EPPP), which caters for as many as 12,500 talented youth soccer players alone. These academies aim to start training youth athletes as early as possible within their sporting careers in the hope of obtaining the 10,000 deliberate training hours previously suggested as necessary to attain elite sporting performance (Ericsson et al., 1993). However, the dropout rate of youth soccer players from academies is extraordinarily high. For example, an eight year old entering a professional soccer academy is believed to have a 1 in 200 (0.5%) chance of playing professional soccer (Crane, 2017). The chances of a sixteen year old within the academy system remaining in the sport are greater, but there is still only a 50% likelihood that they will be playing soccer at a professional level at the age of 18 and only a 25% chance they will remain there by the age of 21 (Crane, 2017).

In response to such a large percentage of dropouts from high performance youth sport, there has been a cultural shift towards providing an academic education alongside the athlete's pursuit of sporting excellence so that individuals are appropriately educated for working life if they don't become professional athletes (Taylor et al., 2016). This approach has long been evident in the USA, where collegiate athletes are provided with a university education prior to entering the draft system for professional sports, but has recently become more prominent in the UK, as an increasing number of professional sports academies partner with private schools to provide full time education to academy athletes with integrated sports coaching via school sport scholarships (e.g. the Welsh Rugby Union with Rydal Penrhos school and Watford Football Club with the Harefield Academy). Alongside these professional academy affiliated school sports scholarships, private schools have independently begun to offer sports scholarships to talented youth athletes. These schools aim to attract talented youth athletes, who are aware that their chances of becoming professional athletes are limited but still wish to play at a high level whilst continuing to focus on their academic studies so that they can obtain a place at a good university. These school funded scholarship schemes also allow the school to develop an identity outside of their academic achievements and provide them with marketing material

for future students (Radtke & Coalter, 2007). Examples of school funded sports scholarship schemes within the UK include Myerscough College in Lancashire and Queen Ethelburga's Collegiate in North Yorkshire.

The key difference between the two forms of sport scholarships is the method by which academic lessons are integrated into the programme (Radtke & Coalter, 2007). Within professional academy affiliated school sports scholarship schemes, there is more specialist teaching provision, allowing teaching hours to be more flexible and providing greater opportunity for sport specific training to occur. Conversely, in school funded sport scholarship schemes, students' academic education is more strictly integrated within the school's normal timetable and so must take place at specific times. Both types of scholarship cater for the sporting needs of the athlete within the school day, but in professional academy affiliated scholarship schemes these sporting requirements are usually prioritised when scheduling difficulties arise, whereas in school funded sports scholarship schemes, the academic requirements usually remain the priority (Radtke & Coalter, 2007). Consequently, there is a greater likelihood that sports training sessions will be cancelled in school funded sports scholarship schemes if youth athletes fail to adhere to academic deadlines.

1.1.2 Consequences of the professionalisation of youth sport

The professionalisation of youth sport via professional sport academies and school sports scholarships is undoubtedly beneficial from the perspective of providing participants with increased exposure to deliberate practice within their sport. Indeed, it has recently been shown that as many as 15% of UK international athletes previously received a school sports scholarship (Ofsted, 2014), a figure which rises to 82% when considering German 2002 Winter and 2004 Summer Olympic medallists (Radtke & Coalter, 2007). However, as well as increasing the potential for sporting success, the increasing professionalisation

of youth sports also increases the prevalence of early specialisation, enhances the likelihood of excessively high training loads occurring and increases the psychological pressure placed upon youth athletes (Bergeron et al., 2015; Lloyd et al., 2015).

The risk of early specialisation and excessively high training loads within sports academies and school sport scholarship schemes can occur in tandem (Lloyd et al., 2015). Early specialisation occurs when a participant trains exclusively in one sport, at the expense of developing motor skills from other sports which may indirectly benefit them in the sport they wish to excel at (Güllich & Emrich, 2014; Mostafavifar et al., 2013). This is becoming increasingly common in sports academy and school sport scholarship environments, even for traditionally late specialising sports such as soccer and rugby (Lloyd et al., 2015). Participating in school sport scholarships also increases the risk of excessively high training loads as participants are sometimes expected to train and participate in multiple competitions (e.g. for their club and school) concurrently (Lloyd et al., 2015). The restriction of training to one sport has been associated with an increased risk of overuse injuries, which is only exacerbated when excessive training loads are also experienced (Difiori et al., 2014). Similarly, excessively high training loads can result in youth athletes experiencing the overtraining syndrome, burnout and other issues, such as illness and excessive fatigue (Bergeron et al., 2015; Meeusen et al., 2013).

In addition to the increased physical demands associated with sports academies and school sport scholarship schemes, increased psychological pressure is placed on the participating athletes (Malina, 2010). Amongst the multiple sources of pressure a youth athlete may experience, possibly the most prevalent sources are the pressure to succeed imposed upon the athlete by coaches or parents, or the fear of failure imposed upon the athlete by themselves (Bergeron et al., 2015; Malina, 2010; Siesmaa et al., 2011). Adding these demands to the already unique social, maturational and academic (particularly when coursework or examination deadlines are close) pressures experienced by youth

athletes (Mountjoy et al., 2008) presents significant psychological stress for the athlete. It has been highlighted that stress can significantly affect recovery for up to 96 hours following an exhaustive training protocol (Stults-Kolehmainen et al., 2014). Furthermore, psychological stress (r = 0.39) has recently shown correlations with changes in immune function following exercise equivalent to those of physical stress (r = -0.37; Edwards et al., 2018). Consequently, not only can the physical stress imposed upon a youth athlete affect their response to training, their psychological stress can also have an effect. It is therefore imperative that both the training load and response of youth athletes is regularly monitored and evaluated (Bergeron et al., 2015).

1.1.3 Applied research in youth sport

The issue of training load and response monitoring is one of several issues relating to positive and negative adaptations to training that can be studied when researchers and practitioners collaborate within an applied sport setting. Recently, it has become increasingly common to embed researchers within sports teams allowing meaningful research questions to be asked and answered within applied sport (Jones et al., 2019; Malone et al., 2019). Examples of issues which have been considered by the researcher/practitioner relationship in sports teams include the physical qualities of youth rugby players (Till et al., 2017), the peak running demands of match play (Whitehead et al., 2018) and the relationship between training loads and soft tissue injury incidence (Hulin et al., 2014; Hulin et al., 2016; Williams et al., 2016). However, to the author's knowledge, no research using this researcher/practitioner relationship has been published in youth athletes from school sport scholarship schemes. Given the growing influence of these schemes within the development of elite athletes (Ofsted, 2014; Radtke & Coalter, 2007), and the potential from which the frameworks considered could be adapted to other full time education environments (e.g. the American collegiate system), there is considerable scope for their consideration within the literature. Throughout this thesis, the

author was embedded as a researcher/practitioner within a school funded sports scholarship scheme environment helping to fill this gap and provide insights relevant to researchers and practitioners alike.

1.2 Adverse outcomes to the training process

The two key goals of athlete monitoring are to maximise performance and minimise the likelihood of adverse outcomes occurring (Saw et al., 2017). Adverse outcomes to the training process include injury, illness and the overtraining syndrome (Meeusen et al., 2013; Schwellnus et al., 2016; Soligard et al., 2016). Much of the literature within youth athletes has focussed on the risk of injury. Indeed, a PubMed search of articles up to the 31st December 2018 using the terms “youth sport injury” returns 1301 search items, far in excess of “youth sport illness” (91) and “youth sport overtraining” (15). Such interest is merited given that previous research has indicated that 1.7 million time loss injuries occur per year in American high schools (Comstock et al., 2012). However, it should be noted that within youth sport, approximately 50% of these injuries (range 46-54%) are overuse by nature (Luke et al., 2011; Rejeb et al., 2017; Valovich McLeod et al., 2011). Given appropriate training load monitoring, it should therefore be possible to avoid approximately half of these injuries. Similarly, given appropriate training load monitoring, it should be possible to avoid the overtraining syndrome occurring in youth athletes as this is also typically associated with excessively high training loads (Meeusen et al., 2013). However, avoiding the onset of illness is a more nuanced issue.

As discussed in the previous section, changes in immune function, and thus the risk of illness incidence (Fahlman & Engels, 2005; Neville et al., 2008), appear to be equally distributed between physical and psychological stressors. Consequently, these fluctuations are caused, at least in part by factors outside of the practitioner’s control. For example, psychological stress from life demands, sleep disturbances and poor nutritional

choices have been associated with an increased risk of illness (Walsh, 2018). All of these issues could occur in youth athletes given their unique set of life demands (Mountjoy et al., 2008) and immature coping skills (Compas et al., 2014). However, given that a virus can lie dormant for up to three weeks prior to illness onset (Schwellnus et al., 2016), it is possible that any of these stressors could cause a change in the youth athlete's training response prior to an illness episode occurring. Furthermore, it is possible that this change in the youth athlete's training response could be identified as a warning sign for illness via the athlete monitoring cycle and acted upon by practitioners prior to illness onset to reduce the illness burden experienced by youth athletes.

1.3 The athlete monitoring cycle

The athlete monitoring cycle (Gabbett et al., 2017) is depicted in Figure 1.1. It is based on the principles of the fitness-fatigue and supercompensation models (Banister, 1991; Bompa & Haff, 2009) and provides a framework by which practitioners can monitor athletes. The framework separates training into a dose-response model. The training dose allows the researcher and/or practitioner to evaluate what training the athlete did, whereas the training response enables the researcher and/or practitioner to consider how the athlete is coping with the training dose imposed using surrogate measures of performance.

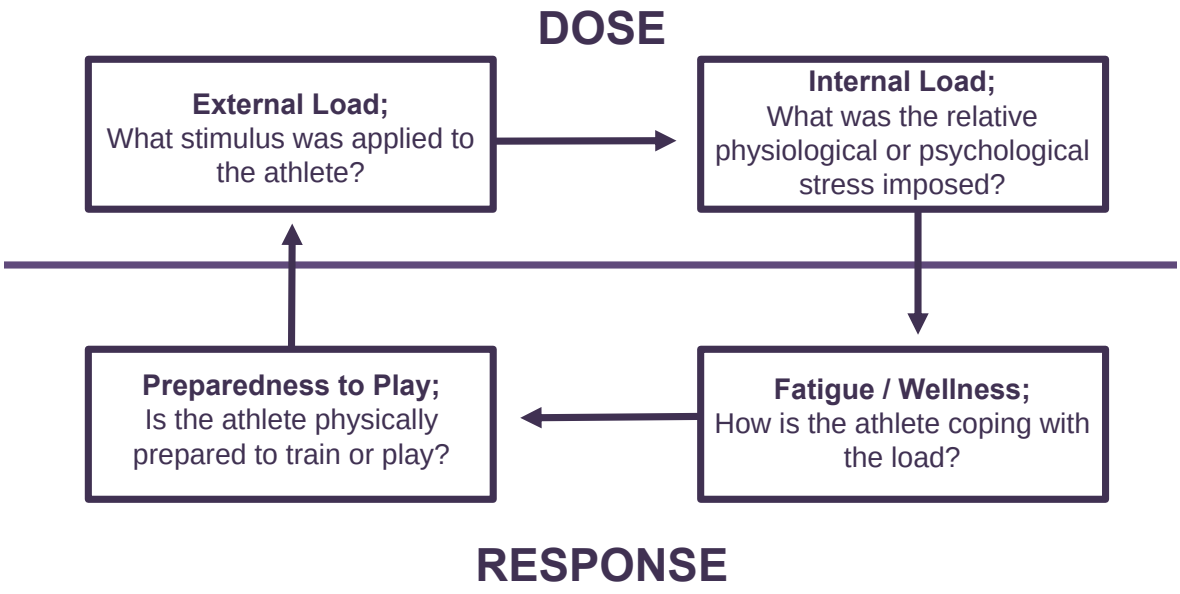


Figure 1.1: Training dose-response model of athlete monitoring. Figure adapted from Gabbett et al. (2017).

Despite providing a logical interpretation of the fitness-fatigue and supercompensation models (Banister, 1991; Bompa & Haff, 2009), the athlete monitoring cycle could be considered limited by its simplicity. This simplicity allows practitioners to monitor the aspect of the training process that they are in control of (i.e. the training dose) and understand how the athlete is responding to it (i.e. the training response). However, by failing to account for other factors related to the training response, it is impossible to deduce whether any fluctuations in an athlete's training response relative to normal are meaningful in practice.

Perhaps the two most relevant factors related to the training response omitted by Gabbett and colleagues' (2017) model are the training recovery experienced by the athlete and their underlying life stress. The omission of a training recovery measure is particularly surprising given that knowledge surrounding the importance of an athlete's recovery to performance has become widespread in recent years (Davenne, 2009; Mah et al., 2011; Mah et al., 2019; Taylor et al., 2016). Alongside the importance of evaluating the training recovery experienced by an athlete within monitoring models, there is increasing evidence

that the underlying life stress experienced can affect both their perceptions of the training dose imposed (Morgan, 1994), and the extent to which they are able to recover from a training bout (Stults-Kolehmainen et al., 2014). It could therefore be argued that athlete monitoring models should provide greater information with regards to these factors, allowing them to provide a more integrated understanding of the athlete's response to training. Figure 1.2 provides a graphical representation of this integrated athlete monitoring cycle.

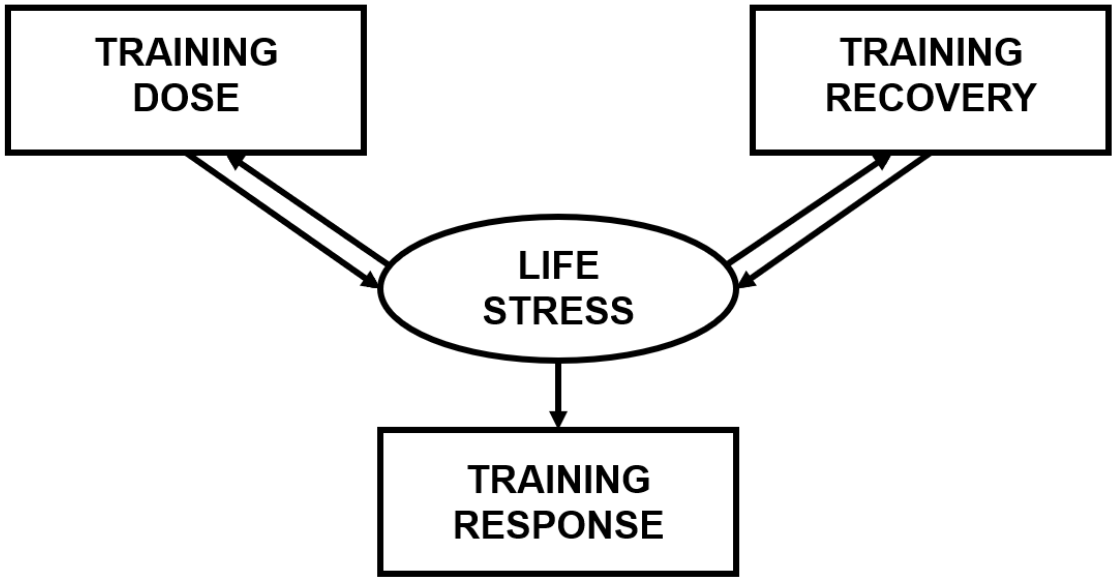


Figure 1.2: An integrated athlete monitoring cycle incorporating the training recovery and underlying life stress alongside the training dose and response.

In the integrated athlete monitoring cycle, the moderating effect of life stress on the training dose (Morgan, 1994) and training recovery (Stults-Kolehmainen et al., 2014) is accounted for, alongside the relationship all three measures hold with the training response. The inclusion of this additional information is pivotal as it allows further information to be gleaned with regards to the training response. This is important as, with all aspects of the training dose being equal, it is likely that an athlete will show a worse response to training if their recovery is compromised or if they have an increase in their

underlying life stress. Without access to information surrounding these factors, researchers/practitioners may consider the response to training maladaptive and unnecessarily modify the training dose. However, by obtaining all relevant information, the athlete's poor response to the training bout could be explained and the training dose could be modified or maintained appropriately. The factors considered within the integrated athlete monitoring cycle are outlined below and their relationships with illness incidence are evaluated.

1.3.1 The training dose

The training dose refers to the stimulus imposed upon an athlete. As shown in Figure 1.1, this can be evaluated via either the external or internal training load. The external training load refers to the absolute workload completed by the athlete in any given training session (Impellizzeri et al., 2005). It can be measured for field sessions using either global positioning system (GPS) or notational analysis. Resistance-based training sessions can be evaluated using linear position transducers or notational analysis. The internal training load outlines the physiological strain placed upon an athlete by the session (Impellizzeri et al., 2005). This can be measured using heart rate monitors and ratings of perceived exertion (RPE).

Evidence of a relationship between training load and illness incidence in youth athletes is uncertain (Anderson et al., 2003). However, multiple studies have indicated that spikes in training load could be related to illness incidence in youth athletes (Fahlman & Engels, 2005; Putlur et al., 2004). Despite these studies showing a relationship between spikes in training load and illness incidence in youth athletes, it is possible that the increase in illness risk may be due to factors outside of, but related to, the increased training load (Jones et al., 2017). For example, it may also be related to the sleep disturbances and psychological stress associated with intensive training, which affect immune function via the same mechanism as the training load imposed upon the athlete (Gunnar & Quevedo,

2007). Unfortunately, no study has considered these factors alongside training load, so this theory cannot be confirmed.

1.3.2 The training recovery

It is possible that the addition of a training recovery measure to the integrated athlete monitoring cycle could detect sleep disturbances leading to illness incidence. The training recovery experienced by an athlete is a complex and multifaceted phenomenon, influenced by sleep (Fullagar, Duffield et al., 2015), diet (Halson, 2014) and the use of recovery strategies (Brown et al., 2017; Poppendieck et al., 2016; Versey et al., 2013). However, given that calculation of accurate food diaries to assess diet in youth athletes is difficult (Kolodziejczyk et al., 2012) and that insufficient sleep appears to be more detrimental to a youth athlete's recovery than the use of recovery strategies (Fox et al., 2019), sleep will be considered as a measure of the training recovery in this thesis.

Sleep can be measured either objectively (via polysomnography or actigraphy) or subjectively (via sleep logs/diaries). Furthermore, it can be measured in terms of its duration or its quality. The relationship between self-reported sleep duration and illness has been shown twice in adult populations (Cohen, et al., 2009; Fitzgerald et al., 2018), but there is no research in youth athletes. Cohen and colleagues (2009) found that adults from the general population who slept seven hours or less per night were three times more likely to succumb to the common cold when exposed to the virus than those whose average sleep duration over a two week period was greater than eight hours. Although it is not possible to conduct such a well-controlled study within a performance environment, Fitzgerald and colleagues (2018) observed that only average weekly sleep duration was significantly associated with subsequent illness incidence when modelled alongside other measures of the training dose and recovery including: GPS derived total distance and sprint distance, and subjective sleep quality. It is therefore possible that within youth sport

when training load is well controlled, the training recovery experienced by the athlete may provide a better indication as to future illness incidence.

1.3.3 Life stress

Moderating the relationship between the training dose, training recovery and training response is the underlying life stress experienced by the athlete. The underlying life stress experienced by an athlete is related to perceptions of training intensity (Morgan, 1994) and the speed with which they recover from a training bout (Stults-Kolehmainen et al., 2014). Furthermore, it affects immune function to the same magnitude and along the same biological pathway as physical stress (Edwards et al., 2018; Gunnar & Quevedo, 2007). It is therefore pivotal that life stress is accounted for within the integrated athlete monitoring cycle.

Unfortunately, it is difficult to conceptualise a single scale to capture the underlying life stress a person is experiencing (Gunnar & Quevedo, 2007; Neil et al., 2011). In the context of an integrated athlete monitoring cycle model, this is partly due to the cognitive appraisal aspect of stress (i.e. every individual will appraise a stressor in a different manner, which makes it difficult to quantify the impact it would be expected to have on them, positively or negatively, within a single scale entity), but also due to the influence of stress on the training dose, recovery and response factors which are measured. To this end, if stress has a negative moderating impact on any other factor and is measured alone, any negative consequence may be measured twice within the model. It may therefore be more appropriate to consider the life stress as an explanatory factor within the model rather than measuring it quantitatively.

1.3.4 The training response

Related to the training dose, training recovery and underlying life stress is the training response. The training response allows researchers and practitioners to evaluate how an athlete is coping with the current training dose and consider whether they are ready for a further training stimulus to be imposed upon them. According to Gabbett and colleagues' (2017) athlete monitoring cycle, it can be evaluated using fatigue/wellness measures (e.g. subjective wellness questionnaires and salivary IgA (s-IgA) testing) or preparedness to play measures (e.g. countermovement jump (CMJ) performance).

Research considering the relationship between the training response and illness incidence varies dependent on the measure considered. For example, there is strong evidence that s-IgA is related to illness incidence as Neville and colleagues (2008) identified a three week transient drop in the measure prior to illness onset in elite adult yachtsmen and Fahlman and Engels (2005) found s-IgA secretion rate to be the only significant predictor of illness incidence in their regression model in collegiate American Football players. Unlike s-IgA, the evidence for subjective wellness questionnaires is mixed. Watson and colleagues (2017) found no significant relationships between the previous day's wellness and subsequent illness in female collegiate soccer players, but Thornton and colleagues (2016) found that, alongside training load, a decrease in wellness measures of less than 7.25 AU increased the accuracy of their illness prediction model with professional rugby league players. However, despite indicating statistical relationships were present between fatigue/wellness measures and illness incidence, the predictive ability of the models evaluated in all these studies was poor (Fahlman & Engels, 2005; Neville et al., 2008; Thornton et al., 2016).

1.3.5 An integrated athlete monitoring cycle model to predict illness

It is perhaps unsurprising that previous studies considering measures of the training response have failed to identify strong predictive relationships with illness incidence because, generally, they have not considered the integrated nature of the athlete monitoring cycle (Fahlman & Engels, 2005; Neville et al., 2008; Thornton et al., 2016; Watson et al., 2017). Although no study has yet confirmed the relationship in youth athletes, fatigue/wellness and preparedness to play measures, as measures of the training response, are expected to fluctuate in line with the training dose and recovery experienced by the athlete. For example in adult athletes, Thorpe and colleagues (2015) reported a large and significant negative correlation between high speed running distance and the fatigue subscale of a wellness questionnaire in professional soccer players. Similarly, Montgomery and Hopkins (2013) identified 'clear and small' increases in muscle soreness in response to s-RPE training load, with an additive small effect on muscle soreness also present upon exposure to match play in Australian Rules football players. Consequently, it is expected that fatigue/wellness and preparedness to play measures will reduce in response to training or match play (Gallo et al., 2017; Roe, Till et al., 2016), but this fluctuation does not necessarily mean that an athlete will suffer from an adverse outcome, such as illness, or that they are even at greater risk of one occurring.

It is more likely that negative fatigue/wellness responses will be predictive of future illness incidence if they are present when they are not expected (i.e. when they are unrelated to the training dose or recovery experienced by the athlete). When this occurs, it is possible that life stress factors outside of the training process (e.g. social, academic or maturational stressors in youth athletes) may be adding to the overall stress experienced by the athlete potentially exposing them to a greater risk of illness incidence (Walsh, 2018). Unfortunately, no study has yet evaluated the training response against the training dose and recovery in this manner and used these results to try and predict illness

incidence in adult or youth athletes. Consequently, there is scope for a series of studies within youth athletes identifying the relationships between measures of the training dose, recovery and response before using these relationships to try and predict illness incidence.

1.4 Statistical analyses

This series of studies evaluating the ability of the integrated athlete monitoring cycle to predict illness incidence in youth athletes will be split into three distinct sections, which will each require different statistical analyses. The first section will calculate the reliability of the training response measures considered within this thesis; the second will evaluate the relationships between measures within the integrated athlete monitoring cycle and identify the most appropriate measures to use within youth athletes; and the third will evaluate the ability of an integrated athlete monitoring cycle model, which accounts for the results of the first two sections, to predict illness incidence in youth athletes.

1.4.1 Reliability of training response measures

The first section will consider the reliability of the training response measures considered within this thesis. The most commonly used fatigue/wellness measure is subjective wellness questionnaires, which have regularly shown poor reliability in the literature (Gastin et al., 2013; Roe, Darrall-Jones et al., 2016; Thorpe et al., 2015), whereas the most commonly considered preparedness to play measure is countermovement jumps (CMJ), which have shown good reliability within the literature (Cormack et al., 2008; Roe, Darrall-Jones et al., 2016). These reliability values will be considered alongside the relationships found in the second section within the integrated model attempting to predict illness incidence in the third section.

1.4.2 Relationships between measures within the integrated athlete monitoring cycle

After identifying the reliability of the training response measures present within the integrated athlete monitoring cycle, the relationships between these measures and the training dose and training recovery will be evaluated. Given the final aim of evaluating the predictive ability of an integrated athlete monitoring cycle model with regards to illness incidence, it will be important to provide results which are both more practically interpretable than is currently common within the literature (Montgomery & Hopkins, 2013; Rowell et al., 2017; Thorpe et al., 2015) and provide individualised coefficients, which have not previously been considered within the literature.

Typically within the literature, the raw coefficient from statistical analyses is divided by the between subject standard deviation to provide a Cohen's *d* effect size (e.g. Rowell et al., 2017) or the covariance matrix is used to provide a correlation coefficient, *r* (e.g. Thorpe et al., 2015). This method of standardisation is completed at a group level and is particularly important within the analysis of subjective fatigue/wellness questionnaires where the scales can vary between studies, so the standardised effect is necessary to compare between studies. However, to consider an integrated athlete monitoring cycle model, it is important to consider both the practically interpretable relationships between the measures (i.e. what is the expected change in the dependent variable in raw units due to the effect of the independent variable) and how these relationships vary between individuals. These practically interpretable changes are provided by Thorpe and colleagues (2015) at a group level, but not at an individual level, and are generally not provided within the literature (Buchheit et al., 2013; Rowell et al., 2017). Furthermore, these relationships have never been considered further to establish how they can be used to predict illness (or any other adverse outcome measure).

As the relationships between measures of the integrated athlete monitoring cycle have not been considered within the youth athlete literature, these relationships will first be confirmed using statistical analyses previously employed within the adult sport literature (Rowell et al., 2017; Thorpe et al., 2015). Following confirmation the relationships exist within youth sport, statistical analyses which provide more practically interpretable and individual results will be considered so that an integrated athlete monitoring cycle model can be evaluated in the third section.

1.4.3 Predictive ability of an integrated athlete monitoring cycle model with regards to illness

Upon completion of the first two sections of analysis, it will be possible to establish the expected change in fatigue/wellness and preparedness to play measures in response to the training dose and recovery experienced by the athlete. The reliability values from the first section will be added to and subtracted from the expected changes to provide a range of expected values the training response may hold. This range of expected values will then be used to evaluate whether the observed changes in the training response measures are due to the training dose and recovery experienced by the athlete or other factors. It is hypothesized that any negative fluctuations from the range of expected responses may represent an increase in life stress and/or a negative adaptation to the training dose and recovery experienced and may therefore be predictive of illness incidence (Walsh, 2018).

In order to establish the predictive ability of this integrated athlete monitoring cycle model with regards to illness in youth athletes, a machine learning based approach will be necessary. A machine learning based approach is necessary because it allows a model's performance to be tested on data it has not previously been exposed to enabling its true predictive ability to be evaluated (Breiman, 2001b). This approach was previously used by

Thornton and colleagues (2016) to show that the athlete monitoring cycle could predict self-reported illness incidence in elite adult rugby league players with 74% accuracy. Employing a similar machine learning based approach within this thesis to test the integrated athlete monitoring cycle model's ability to predict illness in youth athletes would therefore be appropriate.

1.5 Aims of this thesis

The overarching aim of this thesis is to evaluate the true predictive ability of an integrated athlete monitoring cycle model with regards to illness incidence in youth athletes. The thesis will achieve this overarching aim with the following study objectives:

1. Evaluate the between-day reliability and usefulness of fatigue/wellness and preparedness to play measures in youth athletes across multiple sports.
2. Evaluate the relationships between measures of the integrated athlete monitoring cycle in youth athletes using statistical analyses previously employed in elite adult sport studies.
3. Evaluate the relationships between measures of the integrated athlete monitoring cycle in youth athletes using statistical analyses providing more practically interpretable results.
4. Explore the use of different sleep indices as measures of training recovery within the integrated athlete monitoring cycle.
5. Use the identified relationships between measures of the integrated athlete monitoring cycle to predict illness incidence in youth athletes.

Chapter 2 Literature Review

2.1 Search strategy

An initial review of the literature was conducted using the PubMed electronic database of academic publications. Multiple combinations of some/all of the following groups of keywords were used to identify relevant literature: a) ‘youth’, ‘adult’, ‘senior’, ‘junior’, ‘adolescent’ b) ‘sport’; c) ‘dose’, ‘recovery’, ‘response’; d) ‘training’, ‘sleep’, ‘immune’, ‘fatigue’, ‘wellness’, ‘wellbeing’, ‘neuromuscular’; e) ‘load’, ‘duration’, ‘intensity’, ‘volume’, ‘quantity’, ‘quality’, ‘index’, ‘function’, ‘questionnaire’ f) ‘objective’, ‘subjective’; g) ‘injury’, ‘illness’, ‘overtraining’. The search was limited to articles published in English between 01/01/1980 and 31/12/2018, and included any studies published online ahead of print at this cut-off point. A secondary review of the literature was also conducted, with the same search terms, using the SPORTdiscus and Google Scholar electronic databases to identify any additional research not found during the initial review.

Given the broad scope of this thesis, it was important to evaluate all aspects of athlete monitoring prior to focussing on the adverse outcome of illness incidence. In total, 4516 articles were identified by the search of which 2398 were related to injury, 676 to illness and 212 to overtraining. 1230 evaluated the relationship between measures of the athlete monitoring cycle. Following justification of illness incidence as the adverse outcome of focus for this thesis in section 2.3, only the 1906 articles relating to illness and the relationships between measures of the athlete monitoring cycle were used. This figure was further reduced to 641 when only those articles which provided information relevant to an applied sport setting were considered.

2.2 Theoretical concepts underpinning athletic performance

Prior to discussing methods of evaluating a youth athletes’ training load and response to training, it is important to consider the theoretical concepts underpinning athletic performance. The most prominent model of athletic performance is the fitness-fatigue

model (Banister, 1991), which can be simplified to the supercompensation curve (Bompa & Haff, 2009). Both models will be discussed in this section.

2.2.1 The fitness-fatigue model

The fitness-fatigue model (Banister, 1991) conceptualises the influence of a training bout on an athlete's levels of fitness and fatigue. The impact of a bout of training on these physical characteristics can be used to derive the individual's expected performance (Figure 2.1). In Figure 2.1, the blue rectangle represents a training bout (for example a resistance training session, or a high intensity interval session). Following the training bout, the dashed lines show the sharp increase in fatigue and slower increase in fitness experienced by the athlete. Initially, the increased fatigue masks the increase in fitness causing a reduction in performance (red line) and a potential increase in injury risk (blue line). However, following an appropriate period of recovery the fatigue experienced by the athlete dissipates faster than the increase in fitness. Consequently, performance is enhanced beyond the previous level. However, if too much recovery is provided between training bouts, the enhancement in fitness gained from the training bout is lost and performance will fall again. This negative impact of too much recovery on performance is best shown via the supercompensation curve.

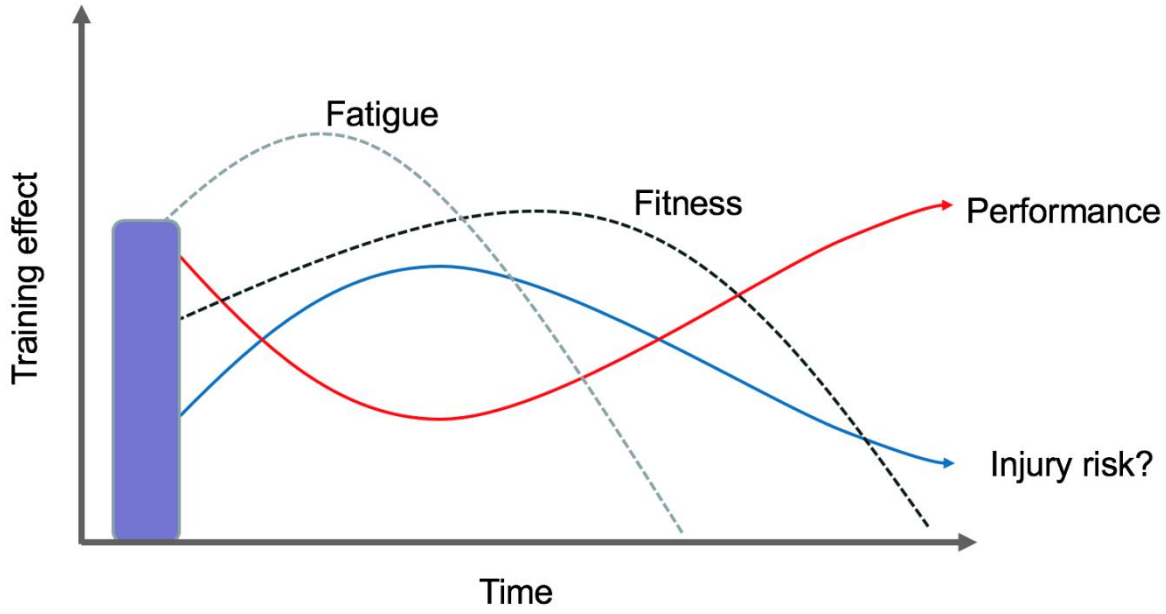


Figure 2.1: The fitness-fatigue model. Figure adapted from Fitz-Clarke et al. (1991)

2.2.2 The supercompensation curve

Figure 2.2 depicts the supercompensation curve (Bompa & Haff, 2009) in response to appropriately spaced training bouts (green curve) and with too little recovery between bouts (red curve). The supercompensation curve effectively extends the red performance line from the fitness-fatigue model (Figure 2.1). Like the fitness-fatigue model, there is a reduction in performance below the base level in response to experiencing a load stimulus. However, following a period of recovery, performance will recover and improve beyond the initial base level (i.e. supercompensate) if appropriate time is given between stimuli. The green curve shows the gradual improvement in performance beyond an athlete's base level that can be expected when appropriate periods of recovery are provided, whereas the red curve shows the gradual decline expected when insufficient recovery is experienced. Alongside the gradual decline in performance expected when insufficient recovery is provided, there is also an increased risk of the athlete experiencing adverse outcomes (i.e. injury, illness and overtraining).

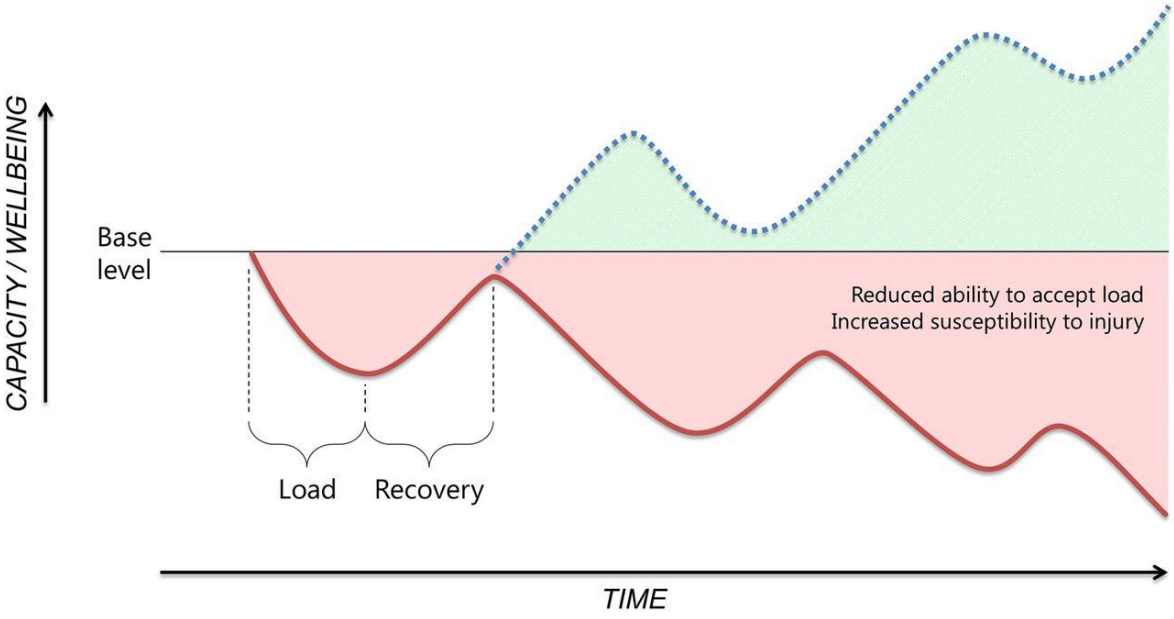


Figure 2.2: The supercompensation curve. Figure adapted from Soligaard et al. (2016)

2.2.3 Limitations

The fitness-fatigue model and supercompensation curve are excellent tools for practitioners to use in their planning and evaluation of training load. However, recent research suggests that their sequential approach (i.e. that physical training load reduces performance, before sufficient physical recovery allows it to progress above the original level) is too simplistic and disregards the impact of other stressors within a youth athlete's life.

Sections 1.1.1 and 1.1.2 highlighted the social, academic, maturational and performance related stressors encountered by youth athletes, particularly those on school sports scholarship schemes. Although difficult to quantify, it could be argued that these stressors provide a second element of 'load' which an athlete must cope with on a daily basis. It may therefore be more appropriate to consider this 'life stress' alongside or in addition to the training load normally considered by practitioners within both models. Perhaps because it is difficult quantify, limited research has considered the impact of life stress on the recovery of performance post-training. However, its impact, evaluated via the

Undergraduate Stress Questionnaire (USQ; Ensel, 1986), on the recovery of neuromuscular performance was recently assessed over 96 hours following an exhaustive leg press resistance training bout (Stults-Kolehmainen et al., 2014). Stults-Kolehmainen and colleagues (2014) found that although life load wasn't significantly associated with changes in performance measures including maximal isometric force (MIF), jump height and cycling power pre to post an exhaustive leg press regime, it was related to the recovery of some of these measures in the subsequent four days of recovery. Table 2.1 shows the recovery of the three physical performance variables from before and after the leg press protocol to 96 hours post-exercise. It is split into LOW and HIGH groups, based on the median Perceived Stress Scale (Cohen & Williamson, 1988) score from the initial familiarisation test.

In Table 2.1, the contrast in recovery between high and low stress groups is stark, particularly with regards to MIF. In the high stress group, MIF recovers by 64.6% in the 96 hours post-exercise, which only just compares favourably to the 60.3% increase in MIF 1 hour post-exercise for the low stress group and is a lot less than the 93.4% recovery experienced by the low stress group at the same 96 hour timepoint. Furthermore, even when accounting for other variables associated with muscular function and recovery (i.e. recent exams, fitness, fat free mass, training experience, workload, and reduction in force), the USQ (a measure of life event stress) moderated the recovery time relationship in MIF (p = 0.032 for linear relationship; p = 0.021 for quadratic relationship). Similar to MIF, the recovery profiles of jump height and cycling power were markedly blunted in HIGH stress compared to the LOW stress group; however when all other recovery variables were accounted for, no significant moderating relationship was found with USQ for either jump height (p = 0.497 for linear relationship; p = 0.391 for quadratic relationship) or cycling power (p = 0.856 for linear relationship; p = 0.919 for quadratic relationship). These conflicting findings (i.e. that life stress moderates the recovery of maximal neuromuscular function, but does not influence the more 'applied' performance

measures of jump height and cycling power) provide contradictory evidence as to whether life stress should be considered within performance models, but the growing evidence that it may be related to adverse outcomes of the training process (Andersen & Williams, 1988; Meeusen et al., 2013; Walsh, 2018) provides a strong rationale that it should at least be considered within athlete monitoring processes, even if it is not quantitatively evaluated.

In addition to the influence of life stress as an added burden on an athlete, there is an increasing amount of focus within the literature on understanding the sleep experienced by athletes and how this can be optimised to enhance performance or minimise adverse training outcome risk (Fullagar, Skorski et al., 2015; Halson, 2014; Taylor et al., 2016). Within the fitness-fatigue and supercompensation models, recovery is considered to be solely time dependent, however there is growing evidence that youth athletes experience widely varying sleep with 41% of Dutch youth athletes classified as ‘poor sleepers’ and 12% identified as having sleep disorders (Knufinke et al., 2018). Furthermore, there is growing evidence that training and match play schedules can influence adult sleep schedules, limiting sleep durations when match play occurs in the evening, or training sessions begin early the following morning (Fullagar, Duffield et al., 2015; Juliff et al., 2015; Sargent et al., 2014). Alongside training and match play demands, mobile phone usage and academic deadlines are two key factors which may influence the sleep schedules of youth athletes (Taylor et al., 2016; Twenge et al., 2017). Consequently, it cannot be assumed that the recovery experienced by youth athletes is uniform in nature and there is strong rationale for the inclusion of sleep as a quantifiable measure of recovery within athlete monitoring models.

Table 2.1: Recovery of physical outcome variables broken down into low and high groups. Table adapted from Stults-Kolehmainen et al. (2014)

		Hours Post Protocol					
	Pre	**0**	**1**	**24**	**48**	**72**	**96**
Low							
MIF (N)	2939.1 (1064.0)	1514.1 (635.5)	2427.1 (1089.5) *60.3%*	2745.9 (1093.1) *81.4%*	2958.8 (1024.5) *95.4%*	2827.4 (1005.2) *86.7%*	2928.6 (1076.9) *93.4%*
Jump (cm)	45.6 (11.9)	38.1 (11.7)	N/A	45.0 (11.5) *18.1%*	49.6 (9.1) *30.2%*	45.8 (12.1) *20.2%*	47.5 (9.8) *24.7%*
Cycle (W)	1319.7 (367.5)	1067.8 (275.6)	N/A	1337.3 (297.7) *25.2%*	1385.2 (207.4) *29.7%*	1322.9 (281.5) *23.9%*	1455.8 (356.6) *36.3%*
High							
MIF (N)	2801.8 (1039.5)	1658.8 (554.1)	2330.1 (719.8) *38.2%*	2497.9 (999.2) *48.1%*	2489.5 (844.5) *47.7%*	2598.5 (938.5) *54.1%*	2775.0 (1079.8) *64.6%*
Jump (cm)	41.7 (12.1)	36.4 (8.8)	N/A	40.4 (12.7) *11.0%*	38.6 (10.2) *6.0%*	43.9 (12.4) *20.6%*	41.1 (11.2) *12.9%*
Cycle (W)	1344.3 (413.7)	1152.9 (371.2)	N/A	1293.9 (413.1) *12.2%*	1301.2 (365.3) *12.9%*	1358.2 (380.4) *17.8%*	1357.8 (401.8) *17.8%*

N.B.: MIF = maximum isometric force; Jump = maximum squat jump height; Cycle = maximum cycling power. Pre = Familiarisation testing score. Percentages denote percentage improvement from 0 hours post-protocol. Jump and cycle were not measured one hour post-protocol.

2.3 Adverse outcomes of the training process

One of the key goals for all practitioners working within sport is to assist their athletes in the achievement of peak sporting performance (Saw et al., 2017). However, this goal is achieved subject to numerous factors outside of the control of sport science and strength and conditioning support staff (e.g. technical, tactical and other contextual factors). Consequently, there has been a shift within the sports science literature towards identifying processes by which athlete availability can be maximised, so that athletes are given the opportunity to try and achieve their performance goals. Maximising athlete availability is usually a function of minimising the incidence of adverse outcomes to the training process (Schwellnus et al., 2016; Soligard et al., 2016).

The importance of maximising athlete availability with regards to performance goals has recently been identified in both individual (Raysmith & Drew, 2016) and team (Podlog et al., 2015) sports. In a comprehensive five year study of elite adult individual track and field athletes, Raysmith and Drew (2016) found completion of greater than 80% of training weeks was the most sensitive threshold to identify those athletes who achieved their self-reported key performance goals over the course of that season (AUC 0.72; 95% CI 0.64-0.81). Indeed, the likelihood of these athletes achieving their performance goals was seven times greater than those who completed less than 80% of training weeks (RR = 7.16; 95% CI 1.84-27.89). Similarly, Podlog and colleagues (2015) observed a small negative correlation between player-games missed and percentage of games won by any given team during an NBA season (r = -0.29, p < 0.0001) in their 25 year longitudinal study. However, it is possible that this underestimates the relationship given the importance of the missing player was not accounted for within the analysis. This theory is strengthened by the same authors' conclusions that 48% of teams with less than 100 player-games missed were able to achieve a 'strong' season (identified as winning greater than 60% of their games), whereas only 10% of those teams with more than 300 player-

games missed were able to achieve the feat (Podlog et al., 2015). Unfortunately, there is no research in youth sport identifying the importance of athlete availability to athletic development or performance; however, it is logical to assume that the relationship would be maintained within this cohort and that minimising the incidence of adverse outcomes (i.e. injury, illness and overtraining) should be a target for practitioners.

2.3.1 Injury

Although it is difficult to be fully certain of incidence rates due to various methodological and definition issues (Fuller et al., 2007), the most common adverse outcome to training experienced within sport is injury. In their five year study, Raysmith and Drew (2016) reported 77% of 123 time loss adverse outcomes were a result of an athlete sustaining an injury, whereas it is estimated that 1.7 million time loss injuries occur per academic year in American high schools (Comstock et al., 2012). It is therefore unsurprising that a brief search of PubMed for the terms “youth sport injury” returns 1301 items, far in excess of “youth sport illness” (91) and “youth sport overtraining” (15).

Injuries can be split into several categories including time loss *vs* medical attention, acute *vs.* overuse, and contact *vs* non-contact (Fuller et al., 2006; Fuller et al., 2007). Differentiating between the type and method of injury in this way is particularly important as the injuries of interest differ between youth and adult athletes based on the risk factors specific to each population group. Recently, the main focus of interest for elite adult sport has been non-contact, soft tissue injuries via the acute:chronic workload ratio (Hulin et al., 2016; Williams et al., 2016). However, within youth sport approximately 50% (range 46-54%) of injuries are overuse by nature (Luke et al., 2011; Rejeb et al., 2017; Valovich McLeod et al., 2011). Given the specific risk factors of overuse injuries in youth athletes (described below), it is likely that the difference in injury importance between population groups is related to the challenges of maturation and growth spurts alongside early

specialising training schedules (Difiori et al., 2014). As a consequence of their extremely high prevalence within youth sport, only overuse injuries will be considered within this section.

2.3.1.1 Overuse injuries

There is no clear consensus as to the cause of an overuse injury, however it is generally considered to be the result of training excessively at submaximal intensities without allowing sufficient recovery for musculoskeletal structures (Difiori et al., 2014). Figure 2.2 depicted the impact repeated loadings with minimal recovery could have on an athlete's performance, but the red shaded area could also represent increased risk of adverse outcomes, such as injury risk. The issue from a practitioner's perspective is understanding how much training is excessive, increasing the risk of injury, and how much training is too little, hindering an athlete's progress. At youth level, the issue is further exacerbated by the demands maturation places on the body, which helps to explain why apophyseal injuries, particularly around the knee, are the most common injury complaint in this population (Witvrouw et al., 2000).

In a recent review, Difiori and colleagues (2014) identified the various intrinsic (i.e. biological characteristics and psychosocial traits) and extrinsic (i.e. external forces related to the sport and biomechanical considerations) risk factors for overuse injuries. Although the authors categorised them in this way, the risk factors can also be grouped according to how they can be accounted for, and which member of the support team (strength and conditioning coach/physiotherapist or sport scientist) would be required to make changes to their training programmes to minimise the risk of injury. Using these categories, there is one unchangeable risk factor: growth and maturation. Growth and maturation is an intrinsic risk factor, during which there is a loosening and weakening of musculoskeletal structures, potentially increasing the impact any individual training session may have upon their functioning and injury risk (Alexander, 1976). Although it is impossible to change the

timing of growth and maturation, it is possible that maintaining awareness of its presence, for example via peak height velocity testing, may be beneficial to help with scheduling decisions and reduce the risk of injury. However, there is little research considering the impact of changes in training load, made according to maturation status, on overuse injury so it unclear whether changes should be made on this basis.

Whereas the impact of changing training load according to maturation status on overuse injury incidence is unclear, the impact of excessive training loads on injury incidence is well known (Cuff et al., 2010; Emery, 2003; Rose et al., 2008). For example, Rose and colleagues (2008) identified a linear relationship between number of hours trained and risk of self-reported injury in 2873 high school students. Evaluating relative to those participants who had 0 hours of training exposure per week, the authors found that 7-10 hours per week of training exposure resulted in a four times greater risk of self-reported injury (RR = 4.33; 95% CI 3.13-6.00), 11-15 hours per week had a five times greater risk of injury (RR = 4.96; 95% CI 3.57-6.88) and greater than 16 hours per week was associated with an almost nine times greater risk of injury compared to zero training hours (RR = 8.52; 95% CI 5.82-12.47). The impact of load on injury risk manifests itself through two risk factors: the loads, and the schedules experienced by the athlete, both of which should be considered by the sport science support staff. In practice, the two factors are related as the training load is usually dictated by the schedule. In adult sport, this is not an issue because most athletes play for one team or under one coach; however, in youth sports, where athletes can participate at both school and club level and in multiple matches per week (Phibbs et al., 2018b), it is common for coaches at school and club level to expect their players to play for them. Consequently, athletes within youth sport can easily complete significantly more training and match play than that perceived by their coaches, increasing their risk of injury (Lloyd et al., 2015).

Finally, there are three risk factors which should be considered by the strength and conditioning staff and physiotherapists: previous injury history, anatomical alignment and biomechanical considerations. Each of these risk factors is categorised as such because they pre-dispose an athlete to injury, but the impact of the risk factor can be reduced with appropriate strength and conditioning or rehabilitation work. For example, poor rehabilitation from a previous injury is regularly identified as one of the biggest risk factors for future injuries (Emery et al., 2005; Kucera et al., 2005). Indeed, Kucera and colleagues (2005) found that over three seasons, youth soccer players with one previous injury had a two and a half times greater risk of injury (RR = 2.57; 95% CI 2.00-3.29) and players with two or more previous injuries had a three times greater risk of suffering injury (RR = 2.97; 95% CI 2.28-3.86) than those who had no previously succumbed to an injury. Alongside the influence of previous injuries, physical conditioning support staff should be wary of the impact of anatomical alignment and biomechanical factors on injury incidence rates. During growth and maturation, limb lengths and moments of inertia can change incredibly quickly affecting co-ordination and musculoskeletal balance, and increasing the risk of injury (Hawkins & Metheny, 2001; Malina & Bouchard, 1991). Consequently, practitioners should be aware that even at the same training loads, due to either maturation or previous injury related factors, the risk of injury can vary dramatically both within and between athletes.

2.3.2 Illness

Despite not occurring as frequently as injury ((Raysmith and Drew (2016) reported it accounted for only 23% of time loss events in their study), illness is an important ailment that researchers and practitioners should be wary of. However, as highlighted in section 1.2, it is heavily under-researched in youth sport, with only 91 articles on PubMed compared to 1301 for injury. It is possible that this is due to the common acceptance that athletes at both senior and youth level will succumb to illness from time to time when

training or competing, but that the toughest athletes will train and compete through it (Engebretsen et al., 2013; Ruedl et al., 2012; Schwellnus et al., 2016). Recent studies have established such thinking to be counterproductive as Schwellnus and colleagues (2008) identified decreased exercise performance could be prevalent for up to four days following clinical recovery from upper respiratory tract illness (URTI). Furthermore, Van Tonder and colleagues (2016) observed that distance runners who start an endurance race with an acute illness episode are 1.6 times more likely to fail to finish than those who did not experience illness (RR = 1.60; 95% CI 0.99-2.44). If the worst case scenario from Schwellnus and colleagues (2008) of four days of reduced performance following clinical recovery from illness is added to the median illness burden of 1.5 weeks provided by Raysmith and Drew (2016), this potentially provides a two week window by which performance may be reduced in youth athletes for each episode of illness. Although this may not sound like a large amount, when extrapolated for one illness event per year over an athletic development period of five to ten years, it results in 2.5-5 months of training potentially being hindered and can start to have a significant impact on the physical development achieved by the athletes.

Illness is a broad term for any ailment experienced by an athlete including respiratory, systemic, gastrointestinal and genitourinary issues. Of these, upper respiratory tract infections (URTI's) are the most common within athletes, accounting for around 50% of the total illness incidence (Engebretsen et al., 2013; Ruedl et al., 2012; Schwellnus et al., 2016). URTI is the blanket term for upper respiratory illnesses including coughs, colds, headaches and fever. During an episode of URTI, athletes may experience some or all of these symptoms (Spence et al., 2007); however, succumbing to any of these illnesses is a result of the same pathway within the human body so they are grouped together within research (Schwellnus et al., 2016; Walsh, 2018).

2.3.2.1 Illness mechanisms

It is widely agreed that illness occurs when the body is unable to cope with the stress imposed upon it (Schwellnus et al., 2016; Walsh, 2018). Within sport science, the quantification of the stress imposed on athletes has normally been limited to physical stress via the training load imposed upon the athlete (Moraes et al., 2017; Morgans et al., 2014). However, it has recently been suggested that the psychological stress of life demands could also influence the risk of illness, by depressing immune function either prior to or alongside the effects of physical stressors such as the training load experienced (Walsh, 2018).

Figure 2.3 outlines the pathway by which immune function is depressed in response to the demands of exercise and life. It shows that an important mediator of the impact of exercise and life demands on immune function is the cognitive appraisal of these stressors. If the stressor is perceived to be challenging, there is a stress response, which occurs via either the sympathetic-adrenal-medullary (SAM; Frankenhaeuser, 1986) or hypothalamic-pituitary-adrenal (HPA; Stratakis and Chrousos, 1995) axis. These effector limbs are activated in the same manner whether the perceived stressor is physical or psychological (Gunnar & Quevedo, 2007).

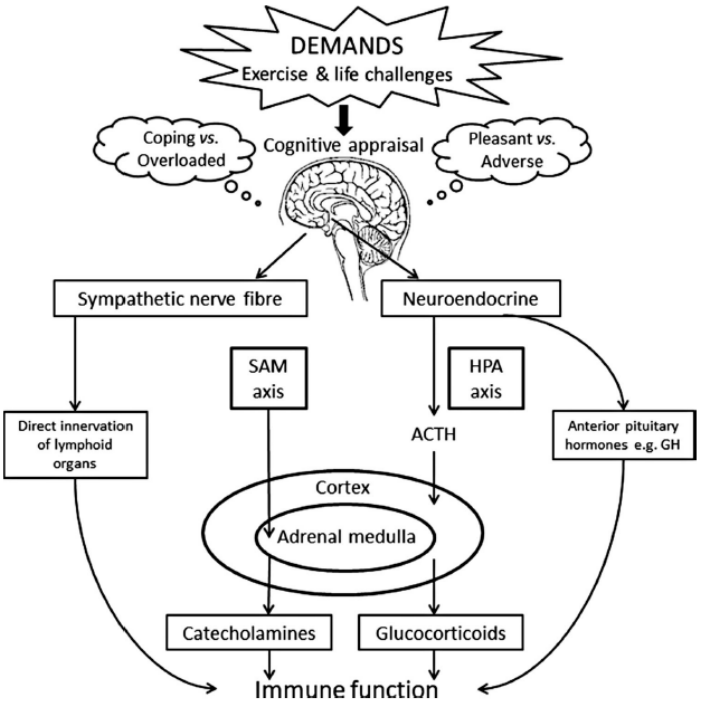


Figure 2.3: Schematic of influence of exercise and life demands on immune function. Figure adapted from Walsh et al. (2018).

The SAM axis controls the 'fight or flight' response to stress through the secretion of adrenaline and noradrenaline. These catecholamines are secreted from the adrenal medulla, via direct innervation from sympathetic preganglionic neurons within the spinal cord (Tsapatsaris & Breslin, 1989) and have a half-life of approximately 1-3 minutes. Consequently, the SAM axis 'fight or flight' response is commonly identified as the short-term response to stress (Esler et al., 1990). The HPA axis, on the other hand, is slower acting and controls the levels of cortisol circulating in the body. It can take approximately 25 minutes for circulating glucocorticoid circulations to peak (Kloet, de, 1991), which is in part due to the blood borne messenger system employed by the axis. Unlike the SAM axis, which controls circulation of catecholamines via direct innervation, the HPA axis controls the secretion of glucocorticoids from the adrenal cortex through hormones secreted from the hypothalamus (corticotropin-releasing hormone) and the anterior pituitary gland (adrenocorticotropic hormone). In addition to this, the majority of glucocorticoid actions on the body occur via gene expression (Kloet, de, 1991), so it is

logical that the HPA axis acts much more slowly, and is considered the body's long-term response to the stress imposed (Gleeson et al., 2013).

It is through the actions of the HPA axis in response to physical and psychological stress that immune function is progressively reduced, and risk of illness is increased. Sustained activation of the HPA axis leads to an increase in the amount of cortisol secreted and, subsequently, a decrease in the number of circulating leukocytes (Dhabhar, 2008). This suppression of the body's ability to re-distribute leukocytes (Dhabhar, 2008), combined with diminished s-IgA concentrations (Evans et al., 1995) reduces the ability of the immune system to protect against infections. However, it should be noted that alongside the traditionally considered physical and psychological stressors of exercise and life demands, any action which chronically increases the amount of cortisol in the body can cause the same changes to immune function. To this end, it is unsurprising that both sleep deprivation, and poor nutrition practices were also recently identified as risk factors for reduced immune function and increased illness risk in athletes (Walsh, 2018).

2.3.3 The overtraining syndrome

Unlike injury and illness, which have both been identified as important restrictors of athlete availability (Raysmith & Drew, 2016), the overtraining syndrome is much less important. Indeed, Brink and colleagues (2012) recently suggested that only 7% of youth footballers suffer from the condition. These numbers are much smaller than the 60% females and 64% males experiencing the condition within elite adult athletes and 33% of non-elite adult runners (Morgan et al., 1988; Morgan et al., 1987). These differences may be due to an increased prevalence of overuse injuries in youth athletes ensuring that athletes succumb to injury before they suffer from mental distresses within training programmes (see section 2.3.1) but may also be due to the difficulty of defining the overtraining syndrome.

The difficulty in defining the overtraining syndrome lies within the theoretical concepts of performance enhancement explained within section 2.2. The overtraining syndrome is characterised by perceptions of fatigue and performance decrements, both of which are expected following an intense training session. However, the time required to recover from these symptoms, and the presence of other symptoms such as illness, poor sleep and severe mood disturbances appears to help decipher whether an athlete is suffering from the overtraining syndrome (Meeusen et al., 2013). In their consensus statement, Meeusen and colleagues (2013) argued there are two stages before the overtraining syndrome: functional overreaching and non-functional overreaching. Functional overreaching is the decrement in performance expected by traditional models of performance enhancement (Banister, 1991; Bompa & Haff, 2009) and results in fatigue lasting a few days to a week. Non-functional overreaching is an extension of functional overreaching, whereby fatigue and performance decrements last for weeks to months, and other symptoms such as sleep disorders, increased illness incidence and mood disturbances are present. The difference between non-functional overreaching and the overtraining syndrome is difficult to define (Meeusen et al., 2013), but usually results in performance decrements that last for months. As the overtraining syndrome is still not fully understood, it is difficult to outline all the risk factors to its prevalence, however it is, by definition, caused by excessively high training loads (Meeusen et al., 2013).

2.3.4 Summary

The previous three subsections have identified the three adverse outcomes associated with the training process that researchers should study and practitioners should attempt to avoid in order to maximise athletic development and performance. Two (overuse injuries and the overtraining syndrome) appear to be related to excessively high training loads. Consequently, if training load is appropriately managed, it should be possible to avoid the incidence of these issues. Illness, on the other hand, may be caused by factors outside

the practitioner's control. Psychological stress from life demands, sleep disturbances and poor nutritional choices have also been associated with an increased risk of illness (Walsh, 2018), and all of these have an increased chance of occurring within youth athletes. In sections 1.1.1 and 1.1.2, the unique life demands imposed on youth athletes within school sport scholarship schemes were highlighted. These unique demands, alongside the immature coping skills available to youths (Compas et al., 2014) provide a clear mechanism by which numerous stressful events could be appraised negatively and activate the HPA axis. In addition to this psychological stress, the amount of sleep reported by youths is continually decreasing (Twenge et al., 2017). In their study, Twenge and colleagues (2017) found that adolescents were 17% more likely to report less than seven hours of sleep per night than in 2009. Given that Cohen and colleagues (2009) previously reported that adults who slept for less than seven hours on average were nearly three times more likely to develop a cold than those who slept for eight hours or more (RR = 2.94; 95% CI 1.18-7.30), this provides another clear mechanism by which illness incidence could occur in youth athletes.

Unfortunately, despite the mechanisms by which illness risk could be enhanced in youth athletes, there is no study evaluating the relationship between illness and athletic development or performance in this population. Given the multitude of factors affecting athletic development, including training age, genetics and maturation, this is perhaps unsurprising (Bergeron et al., 2015; Faigenbaum et al., 2009; Lloyd et al., 2016; Mountjoy et al., 2008). However, given illness has previously been associated with failure to reach performance goals in adult athletes (Raysmith & Drew, 2016), and that the incidence of illness remains constant between youth and adult athletes (Engebretsen et al., 2013; Ruedl et al., 2012), there is sufficient evidence to believe that athletic development and performance could be compromised by illness in youth athletes and that further research to identify methods by which it can be predicted and avoided are required.

2.4 The athlete monitoring cycle

In an attempt to maximise the availability of athletes for training and match play, thus enhancing athletic performance and development, practitioners regularly monitor the workload their athletes are subjected to, and how they respond to it. This has been termed the athlete monitoring cycle (Gabbett et al., 2017). The athlete monitoring cycle builds upon the principles of the fitness-fatigue (Figure 2.1; Banister, 1991) and supercompensation (Figure 2.2; Bompa and Haff, 2009) models, allowing practitioners to try and identify their athletes' positions along the performance curve, without maximally testing their performance. To achieve this goal, it utilises the training dose-response model depicted within Figure 2.4.

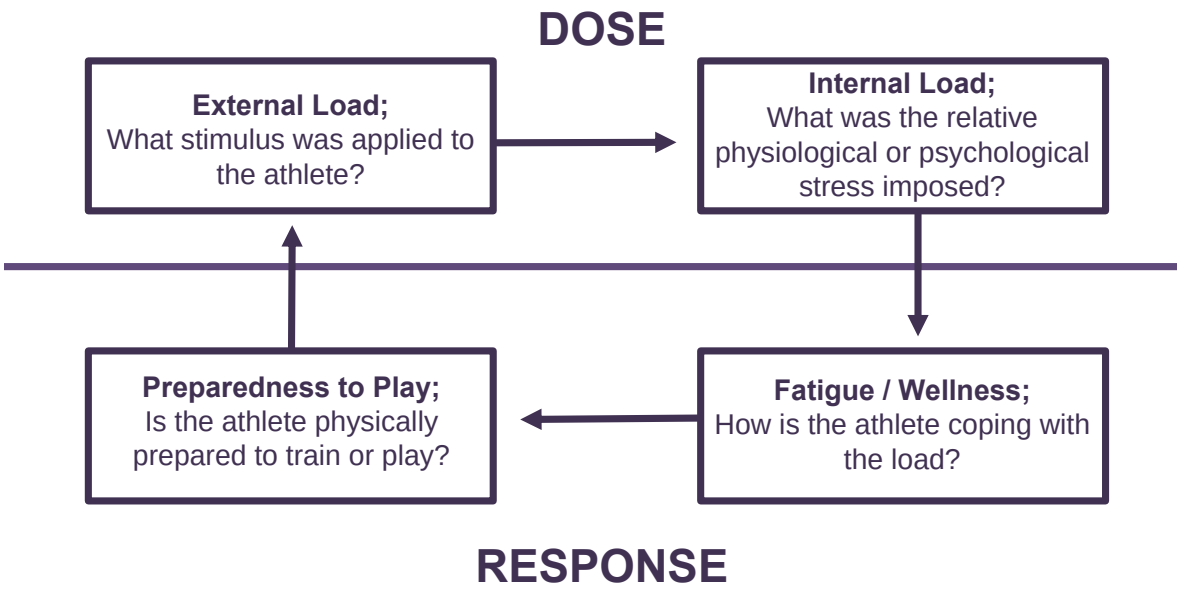


Figure 2.4: Training dose-response model of athlete monitoring. Figure adapted from Gabbett et al. (2017)

The training dose-response model proposes that an athlete should be monitored by understanding both the training dose (i.e. what the athlete did) and the training response (i.e. how the athlete felt or performed after the training dose). Understanding the dose allows the practitioner to evaluate the stimulus imposed upon the athlete, whereas

evaluating the response allows the practitioner to use surrogate measures of performance to try and place the athlete at an appropriate point on the supercompensation curve.

Although the athlete monitoring cycle provides a best-case scenario where objective and subjective measures are monitored and evaluated to provide a global understanding of the training process, the cycle can still be employed if only one measure (objective or subjective) of the dose and response categories is used. Consequently, the choice of measure(s) used in either category is usually dependent upon the time available for athlete monitoring processes, the cost of the equipment and personal/research-based preferences of the practitioner in question (Akenhead & Nassis, 2016; Saw et al., 2015; Taylor et al., 2012).

2.4.1 Limitations

As previously stated, the athlete monitoring cycle builds upon the foundations of the fitness-fatigue and supercompensation models (Banister, 1991; Bompa & Haff, 2009). Building upon these theoretical concepts allows for a logical interpretation of the impact training load has on fatigue/wellness and readiness to play measures. However, the simplistic nature of the cycle fails to quantify the training recovery experienced by the athlete and disregards the importance of life stress (highlighted in section 2.2.3.

There are several possible reasons why these training recovery and life stress factors are not included within traditional performance and monitoring models. These range from the logistical challenges of conceptualising a suitable measure of life stress to inaccuracies within the calculation of nutritional diaries and the scientific challenge of a lack of research (until recently) considering the importance of stress to performance and recovery in athletes (Bandini et al., 1990; Halson, 2014; Hardy, 1999; Walsh, 2018).However, given their importance to performance enhancement (Halson, 2014; Stults-Kolehmainen et al.,

2014) and role in an athlete's susceptibility to illness (Cohen, et al., 2009; Edwards et al., 2018), it is pivotal that both the training recovery and life stress are accounted for within an athlete monitoring cycle that provides an understanding of the athlete's susceptibility to illness. Figure 2.5 depicts the integrated athlete monitoring cycle, which includes these measures.

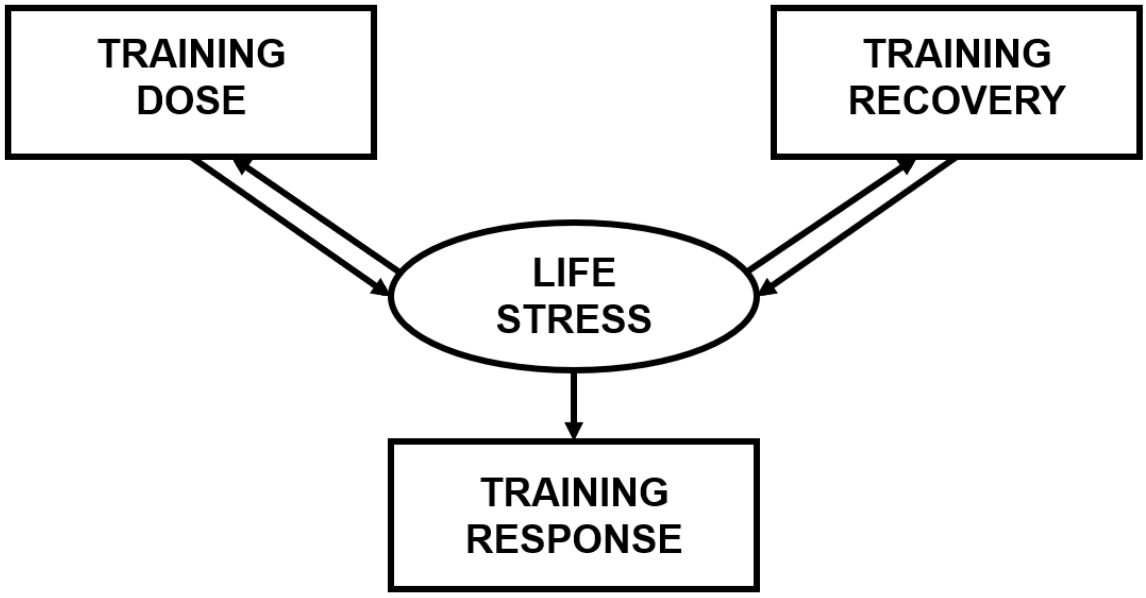


Figure 2.5: Integrated athlete monitoring cycle previously depicted in Figure 1.2.

2.4.2 The integrated athlete monitoring cycle

The integrated athlete monitoring cycle (Figure 2.5) provides a framework by which the relationships between the training dose, training recovery and training response are considered alongside the moderating influence of life stress. By obtaining further information, practitioners are able to make better informed decisions with regards to training scheduling. For example, suppose an athlete experiences a high training load on the same day over two consecutive weeks, with no training in between. In week one, they may respond well with no change to their fatigue/wellness or preparedness to play scores. Conversely, in week two, there may be a significant reduction in these response measures. By solely evaluating the training dose, practitioners may identify this as an

indication that the athlete is showing signs of maladaptation to the training load prescribed and reduce the training dose. However, if the training recovery and/or life stress experienced by the athlete is quantified, it is possible that these measures could help to provide an explanation for the difference in responses. It may be that the athlete suffered disrupted sleep post-training session in week two, resulting in their negative response to training. Conversely, the athlete's response may be affected by an important academic examination. In both these cases, rather than reducing the training dose blindly, practitioners would be able to modify or maintain the training dose appropriately using all the information available.

Within the integrated athlete monitoring cycle, the training dose (external or internal training load measures) and training response (fatigue/wellness and preparedness to play measures) can be measured according to Gabbett and colleagues' (2017) athlete monitoring cycle. Unfortunately, obtaining a single measure for either the training recovery or life stress experienced by the athlete is much more difficult.

The training recovery experienced by an athlete is a complex and multifaceted phenomenon, influenced by sleep (Fullagar, Duffield et al., 2015), diet (Halson, 2014) and the use of recovery strategies (Brown et al., 2017; Poppendieck et al., 2016; Versey et al., 2013). However, given that calculation of accurate food diaries to assess diet in youth athletes is difficult (Kolodziejczyk et al., 2012) and that insufficient sleep appears to be more detrimental to a youth athlete's training recovery than the use of recovery strategies (Fox et al., 2019), sleep will be considered as a measure of the training recovery in this thesis.

Like the training recovery, conceptualising a measure of life stress is difficult. This is party due to the cognitive appraisal element of stress (Gunnar & Quevedo, 2007; Neil et al., 2011) and partly due to the influence of stress on the training dose, recovery and

response factors which are measured. To this end, if stress has a negative moderating impact on any other factor and is measured alone, any negative consequence may be measured twice within the model. It may therefore be more appropriate to consider the life stress as an explanatory factor within the model rather than measuring it quantitatively.

The following sections will discuss the literature surrounding training load (as a measure of the training dose - section 2.5), sleep (as a measure of the training recovery – section 2.6), fatigue/wellness measures (section 2.7) and preparedness to play measures (section 2.8). Following this, the incorporation of life stress as an explanatory factor, alongside the previously discussed measures, will be evaluated in section 2.10.

2.5 Training load

As indicated within section 2.4, training load is the most commonly used measure of the training dose (Akenhead & Nassis, 2016; Taylor et al., 2012). An athlete's training load refers to any organised physical training that they have completed and can be categorised as either an external or internal training load (Impellizzeri et al., 2005). It is now commonplace for athletes to perform field-based training (i.e. technical and tactical training sessions) and resistance-based training (i.e. strength and conditioning sessions). Consequently, this section will identify measures of external and internal training load within both types of sessions (field and resistance-based). Furthermore, the relationship between training load and the adverse training outcome of illness incidence will be discussed. Finally, their appropriateness for use within the youth athlete monitoring cycle will be considered before the relationship between training load and measures of the training response are evaluated in section 2.7 (fatigue/wellness measures) and section 2.8 (preparedness to play measures).

2.5.1 External training load

The external training load provides the absolute workload completed by an athlete in any given training session (Impellizzeri et al., 2005). There are two key methods by which the external training load of field-based sessions can be analysed: global positioning system (GPS) analysis; and notational analysis. The external training load of resistance-based training sessions can also be analysed via two key methods: linear position transducers; and notational analysis.

2.5.1.1 Global positioning system analysis

Microtechnology devices incorporating GPS, accelerometer, magnetometer and gyroscope data are used for GPS analysis. These devices are usually enclosed within vests worn by athletes and situated between their shoulder blades when participating in field-based training sessions or match play. The GPS unit determines the position of the athlete by calculating the distance from a network of satellites that orbit the planet (MacLeod et al., 2009). A minimum of four satellite signals are required to provide a three-dimensional location (Dobson & Keogh, 2007) but the accuracy of this location, and any further data derived from it, is dependent upon numerous factors including: the manufacturer and model of the microtechnology device; sampling rate; firmware and software used; interunit reliability; minimum effort duration; number of connected satellites; and horizontal dilution of precision (Malone et al., 2017).

The importance of standardising the manufacturer, model, sampling rate, firmware and software of microtechnology devices has recently been shown across multiple studies. For example, Jennings and colleagues (2010) showed that the distance measured by Catapult MinimaxX Team 2.5 GPS units varied against the actual measurement dependent on the sampling frequency employed by the unit in question. Over twenty metres at sprinting pace, the 1-Hz unit's standard error of the estimate was 22.3 ± 4.7%, whereas that of a 5-

Hz unit was only 17.0 ± 3.6%. Similarly, Roe and colleagues (2017) showed that the extent to which maximal sprint speed derived from 10-Hz GPS units (Catapult Optimeye S5) differs from a 50-Hz radar gun (Stalker Acceleration Testing System II) is dependent upon the software used to access the data. They found that speeds identified using the Catapult Openfield system had a *small* typical error of the estimate (1.87%, 1.67-2.18%), whereas when values were derived using the Catapult Sprint system, the typical error of the estimate became *moderate* (1.95%, 1.70-2.32%).

Alongside these internal factors, the speed measured by the unit can also influence its validity. Jennings and colleagues (2010) showed 5-Hz GPS units' standard error of the estimate for the distance measured increased from walking speed (9.8 ± 2.0%) to sprinting speed (11.9 ± 2.5%) over forty metres. However, the same authors identified that the measurement error decreased as the distance covered increased from ten to forty metres. For example, the standard error of the estimate was 30.9 ± 5.8% for the 5-Hz unit over ten metres, which dropped to 17.0 ± 3.6% over twenty metres, and 11.9 ± 2.5% over forty metres. These differences may be attributable to the increased accuracy shown by GPS measures in response to constant speed running (Varley et al., 2012), and their inability to accurately measure accelerations greater than 4 m/s^2 (Akenhead et al., 2014).

Following the multiple reliability and validity studies performed on numerous different versions of microtechnology devices, it is becoming clear that the use of GPS within sport to quantify the external training load of athletes in field-based sessions is appropriate (Malone et al., 2017). However, practitioners should be aware that errors may occur frequently at high speeds and in periods of quick accelerations (Akenhead et al., 2014; Jennings et al., 2010). Furthermore, regardless of the manufacturer, model or firmware used, there can be significant variability between units (Johnston et al., 2014; Johnston et al., 2012). Consequently, it has been recommended that the same unit is used throughout the process when longitudinally monitoring an athlete (Malone et al., 2017).

2.5.1.2 Field-based training notational analysis

Notational analysis within field-based training involves a practitioner manually coding the actions completed by an athlete. Such analysis can be completed 'live' or via retrospective video analysis and is now generally known as performance analysis (Hughes 2004). The actions involved can be specific to the individual sport, so a rugby practitioner may consider rucks, mauls, carries and line breaks; whereas a soccer practitioner may be more interested in tackles, dribbles and shots on target. However, whilst these actions are important for understanding the technical performance of the athlete in question, their use within longitudinal training load monitoring is limited with the exception of any collision-based measure, which can vastly increase the recovery time required by the athlete (Costello et al., 2018; Roe, Darrall-Jones, Till et al., 2017). Consequently, a more appropriate use for notational analysis within longitudinal monitoring could be to detail sets and reps for small sided games or sprint interval sessions. However, more detailed information of this type can be gleaned from microtechnology devices (Malone et al., 2017), limiting the usefulness of notational analysis within field-based sessions for longitudinal athlete monitoring.

2.5.1.3 Linear position transducers

Although traditionally evaluated solely by notational analysis (see below, section 2.5.1.4), interest in the field of resistance-based training monitoring, particularly via the monitoring of exercise repetition velocity, has significantly increased in recent years (Pareja-Blanco et al., 2014; Randell et al., 2011; Sanchez-Medina & Gonzalez-Badillo, 2011). Intuitively, this shift in monitoring resistance training activities is similar to the shift observed in field-based training with microtechnology devices measuring the actual speeds and distances run for each athlete rather than practitioners observing each player completing a 90-minute soccer match and identifying them as experiencing the same workload.

Measuring exercise repetition velocity has become more common since linear position transducers became widespread (Jovanović & Flanagan, 2014). A linear position transducer is comprised of a central processing unit and a retractable measuring cable, which is normally attached to a barbell whilst the exercise takes place. The central processing unit is connected to a computer, which can calculate the velocity and acceleration of the bar based on the displacement of the retractable measuring cable (Jovanović & Flanagan, 2014). Recently, the validity of the most prominent linear transducer (GymAware Power Tool) was confirmed against a force plate (AMTI BP6001200) over six different back squat training intensities (20, 40, 60, 80, 90 and 100% of 1 repetition maximum). In this study, Banyard and colleagues (2017) observed correlations in excess of $r = 0.90$ between the GymAware linear position transducer and the force plate for the mean velocity, peak velocity, mean force, peak force, mean power and peak power of the back squat. Furthermore, the between day coefficient of variation of the transducer for squat jump (3.25%) and countermovement jump (0.74%) show it to be a reliable measure (Wadhi et al., 2018).

Alongside its confirmed reliability and validity, the linear position transducer and the exercise velocities derived from it have differentiated between the training adaptations made over as few as six weeks (Pareja-Blanco et al., 2014). The authors found that over the training period, participants who were asked to maintain a maximal intended velocity (actual mean velocity across all reps: 0.80 ± 0.13 m/s) obtained significantly greater improvements in lower body strength (1 repetition maximum squat increase 18.0% vs 9.7%, ES = 0.36; ±0.35, *likely* small) and power (countermovement jump increase 8.9% vs 2.4%, ES = 0.38; ±0.23, *very likely* small) than those who attempted to maintain a half-maximal velocity (actual mean velocity across all reps: 0.43 ± 0.07 m/s). Consequently, in addition to their potential use as a monitoring tool for the external load of resistance-based training, linear position transducers could be used as measures for potential performance gain. However, despite these two possible uses, the requirement of attaching the

transducers to a barbell limits their usefulness within youth athlete environments where a large number of athletes have low training ages and may not be able to perform exercises such as barbell squats and bench presses. Furthermore, despite interest in velocity based training increasing recently, the literature is still in its infancy (Pareja-Blanco et al., 2014; Randell et al., 2011; Sanchez-Medina & Gonzalez-Badillo, 2011).

2.5.1.4 Resistance-based training notational analysis

The use of notational analysis within resistance training sessions is still widespread (Kraemer & Fleck, 2014). Usually, notation of resistance training loads includes details on the exercise performed, the weight lifted (in absolute or percentage of one repetition maximum terms), and the number of repetitions and sets completed. The weight lifted can be multiplied by the number of repetitions to provide the total volume load, a global measure of the intensity of the training session (Kraemer & Fleck, 2014). The use of total volume load as a measure of resistance-based training load is well established within sport (Bourdon et al., 2017).

Notational analysis within resistance training sessions is convenient from an equipment perspective and allows each athlete to fill in their own details at the end of their training session. Despite this, there are two key issues with the use of notational analysis in youth sport. The first of these is the requirement for expensive technology if the system is to be centralised as a measure of the training dose and compared to training response measures. Usually within strength and conditioning programmes, data is input onto a paper spreadsheet and a total volume load is calculated from this after it has been manually input into computer programme (e.g. Microsoft Excel). Unfortunately, such an approach is impractical in school sport scholarship schemes where as many as thirty or forty athletes can simultaneously complete a training session. In this situation, either each athlete would have to input their data directly into an online spreadsheet using expensive equipment, which isn't easily available in high quantities (e.g. iPads), or the strength and

conditioning coach would have to input the data for each individual manually, which would have a significant and unrealistic time cost. The second key issue is the large enhancement in weightlifting performance that can be observed in the very early stages of a youth athlete's resistance training career. This increase in performance capacity would be accompanied by a similarly large increase in total volume load, which could skew the overall training dose measured, hindering attempts to accurately compare it to the training response. Consequently, within school sports scholarships it may be more appropriate to use notational analysis within resistance training sessions to measure athletic development, via fitness testing procedures, rather than as a training dose measure to compare against the training response.

2.5.2 Internal training load

The internal training load details the physiological strain placed upon an individual athlete by a training session (Impellizzeri et al., 2005). Although the prime determinant of an athlete's internal training load is the activities completed within the training session (i.e. the external training load), there are other influencing factors including: fitness levels, genetic predisposition to the activities in question, perceptions of stress and fatigue, and sleep deprivation/disruption (Haddad et al., 2013; Impellizzeri et al., 2005). It could therefore be argued that the internal training load provides a more global understanding of the effect of a training session on any individual athlete than the external training load (Coyne et al., 2018). The two most prominent methods of evaluating an athlete's internal training load are heart rate monitoring and RPE's.

2.5.2.1 Heart rate monitoring

Heart rate monitoring provides a popular and objective method by which the internal load of an athlete can be measured (Achten & Jeukendrup, 2003). It is based on the assumption that a linear relationship is present between heart rate (HR) and steady state work output (Arts & Kuipers, 1994) and has been extended to provide a measure of the

internal training load via Banister's training impulse (TRIMP; Banister, 1991), the summated HR zone score (Edwards, 1993) and Lucia's TRIMP (Lucia et al., 2003). Each of these measures uses a weighting scale relating to different zones of heart rate (e.g. above 90% of max HR or above the ventilatory threshold HR), to provide a single score for the training stress of a single session.

The use of HR data to provide a single measure of internal training load is tempting for practitioners, not least because it provides an objective understanding of the physiological demand placed upon the athlete (Achten & Jeukendrup, 2003). Despite this, each of the three HR measures described above can be individually criticised with regards to their appropriateness for youth sport and school sports scholarship schemes (Banister, 1991; Edwards, 1993; Lucia et al., 2003). For example, both Banister's (1991) and Lucia's (2003) TRIMP require laboratory-based measures for their TRIMP calculations, which is impractical within school sports scholarship schemes where large numbers of athletes are usually monitored. On the other hand, the summated HR zone score (Edwards, 1993) does not require laboratory-based measures but has been criticised as it does not appear to be based on physiological measures and has not been validated in the literature (Borresen & Lambert, 2009). Alongside these concerns surrounding the session load calculation, the use of HR data requires practitioners to account for the day-to-day variation in heart rate, which can be as high as six beats per minute (Lambert et al., 1998). This can be affected by numerous factors including stress, environmental conditions, medication and hydration status (Borresen & Lambert, 2009) and provides a further challenge practitioners must overcome when attempting to obtain meaningful data from HR measures.

2.5.2.2 Ratings of perceived exertion

RPE's refer to the self-reported intensity of a training session experienced by an athlete. They are based on the fundamental assumption that athletes inherently understand the

physiological stress that their bodies experience during exercise (Borresen & Lambert, 2009; Coyne et al., 2018). Whilst traditionally used in laboratory studies via the 6-20 RPE scale (Borg et al., 1987), the use of RPE's has been advanced in recent years with the introduction of the session-RPE (s-RPE) method of quantifying the internal training load (Foster et al., 2001). The s-RPE typically uses the Borg category-ratio 10 RPE scale (Table 2.2) and multiplies the value obtained for the session intensity by the session duration to provide an overall measure of the session load (Foster et al., 2001). Although originally identified for use 30 minutes following exercise completion, recent studies have identified a 48 hour window post-training session within which the s-RPE can be provided accurately in youth athletes (Christen et al., 2016; Phibbs et al., 2017).

Table 2.2: Borg category-ratio 10 scale (Foster et al., 2001)

Rating	Descriptor
1	Very, Very Easy
2	Easy
3	Moderate
4	Somewhat Hard
5	Hard
6	-
7	Very Hard
8	-
9	-
10	Maximal

The usefulness of the s-RPE method has been shown across multiple modes of training, but the information provided by s-RPE is not a direct replacement for objective measures of internal training load. Impellizzeri and colleagues (2004) found that individual s-RPE correlations with Banister's TRIMP method ranged from $r = 0.50$ to $r = 0.77$, correlations with the summated HR zone method ranged from $r = 0.54$ to $r = 0.77$, and correlations with Lucia's TRIMP ranged from $r = 0.61$ to $r = 0.85$ in field-based soccer training sessions. The large correlations observed suggest that s-RPE measures are strongly related to HR measures, but also suggest that HR measures only account for approximately 50% of the variation in s-RPE responses. Similarly, Day and colleagues

(2004) found that s-RPE significantly differentiated between low (50% one repetition maximum), medium (70% one repetition maximum) and high (90% one repetition maximum) resistance training sessions. Despite this, numerous factors have been identified, which can influence the s-RPE score, including the exercise order, different muscle groups used and training age of the individuals (McGuigan et al., 2004; Sweet et al., 2004).

These deviations from objective measures of the physiological stress experienced by athletes are unsurprising given the complex determinants of exercise intensity experienced, including hormonal concentrations, substrate concentrations and personality traits (Williams & Eston, 1989). Therefore, provided the athlete responds honestly and is not influenced by factors such as team selection worries or peer pressure, it is reasonable to conclude that s-RPE is the most accurate of measure of internal training load as it provides a global overview of the perception of load the athlete believes they have experienced (Coyne et al., 2018; Saw et al., 2017).

2.5.3 Relationship with illness

Interest in the relationship between training load and illness incidence has grown since Nieman and colleagues (1990) identified significant relationships between weekly running volume and self-reported illness symptoms. The authors noted that participants running more than 97km per training week had a significantly greater risk of succumbing to at least one illness episode in the two months prior to the Los Angeles marathon than those completing 32km or less per training week (OR = 2.0, 95% CI 1.2-3.4, p = 0.045). Conversely, there was no significant difference between the four training distance categories from <32km to >97km, and the control group (p = 0.63) indicating that extremely high training loads may have been required for self-reported illness episodes to occur in this population group. Training to this extent is extremely unlikely to occur in

youth athletes, suggesting that the importance of training load to illness in this population group is limited. Indeed, Table 2.3 confirms that the mean weekly training load appears to have little relationship with illness incidence in team sport athletes (Anderson et al., 2003). However, there does appear to be a relationship between spikes in training load and illness incidence (Cunniffe et al., 2011; Fahlman & Engels, 2005; Piggott et al., 2008; Putlur et al., 2004). For example, Piggott and colleagues (2008) noted that over a 15-week preseason period, 42% of illnesses in a group of Australian Rules football players were preceded by a spike in s-RPE training load. Similarly, Putlur and colleagues (2004) reported that 55% of illnesses were preceded by spikes in s-RPE training load in their nine week preseason period with female collegiate soccer players.

Table 2.3: Overview of studies considering the relationship between training load and illness incidence.

Authors	Cohort	Methods	Conclusions
(Anderson et al., 2003)	12 female basketball players *(age = 18-22 years)*	Training load (s-RPE) and illness incidence (time-loss only) collected daily over 20-week season. Weekly training load 1400-6000 AU[a]	No correlation between total weekly training load and illness incidence (r = 0.10)
(Cunniffe et al., 2011)	30 professional rugby union players *(age = 26.4 ± 1.0 years, height = 185.6 ± 3.6 cm, body mass = 102.2 ± 10.9 kg)*	Training load (s-RPE) and illness incidence (self-reported) collected daily over 48-week season Weekly training load 4000-12000 AU[a]	No statistical analysis, but periods of intense conditioning work (i.e. spikes in training load) occurred concurrently with reductions in immune function and preceded increases in illness incidence.
(Fahlman & Engels, 2005)	75 varsity American football players *(age = 20.5 ± 1.5 years, height = 170.0 ± 2.0 cm, body mass = 96.5 ± 18.6 kg)*	Illness incidence (medical attention) collected weekly and evaluated against unmeasured training load eight times over 49-week study (approximately weeks 1, 6, 17, 26, 28, 33, 43, 49)	Percentage of athletes suffering from illness significantly greater at timepoints 2, 3, 6 and 7 – all occurred after periods of increased physical stress (p < 0.001)
(Piggott et al., 2008)	16 professional Australian Rules football players *(age = 23.8 ± 5.1 years, height = 188.9 ± 7.4 cm, body mass = 90.9 ± 9.2 kg)*	Training load (s-RPE) and illness incidence (time-loss only) collected daily over a 15-week preseason period Weekly training load 2945 ± 922 AU	42% of illnesses could be explained by a >10% increase (spike) in training load within the previous seven days
(Putlur et al., 2004)	14 female soccer players *(age = 19.8 ± 1.0 years, body mass = 65.9 ± 7.3 kg)*	Training load (s-RPE) and illness incidence (self-reported) collected daily over a 9-week preseason period Weekly training load 2100-6800 AU[a]	55% of illnesses could be explained by a previous spike in training load

N.B: [a] Exact value not provided in text so approximated from data within manuscript.

The association between spikes in training load and illness incidence is likely a consequence of an athlete failing to maintain an appropriate balance between the training dose imposed and the training recovery experienced during periods where the training load is greater than that which the athlete is adapted to. Jones and colleagues (2017) recently suggested failure to maintain this balance may be due to factors outside of, but related to, the increased training load (e.g. sleep disturbances or the psychological stress associated with completing heavy training periods). Added weight is given to this theory as sleep disturbances and psychological stressors affect immune function via the same HPA axis as the physical stressor of training load (section 2.3.2.1). Furthermore, it provides significant support for the implementation of training load and illness monitoring within youth athletes given the multiple stressors they are exposed to alongside their training endeavours (Mountjoy et al., 2008).

2.5.4 Practical considerations when measuring training load in youth sport

The athlete monitoring cycle suggests that both external and internal training load should be evaluated to provide details of the training dose (Gabbett et al., 2017). Comparing the internal load (e.g. s-RPE or HR measures) to the external load (e.g. GPS analysis) has recently been proposed as a possible method of evaluating fitness changes within an athlete (Delaney et al., 2018). However, no research has proven that both external and internal measures are required as part of the athlete monitoring cycle, or that using both helps a practitioner to deduce an athlete's training response more accurately. There are a number of factors practitioners must consider when deciding which measure(s) of training load to use within their athlete monitoring cycles (Saw et al., 2017). Within school sports scholarship schemes, multiple teams can train and compete at the same time, and all teams are usually supervised by one strength and conditioning coach limiting the feasibility of some training load monitoring options. Consequently, the most prominent factors these youth sport practitioners consider when introducing athlete monitoring cycle

measures are the time and monetary cost of implementation, and the ease of use (Bergeron et al., 2015; Murray, 2017).

The requirement that athlete monitoring measures are easy to use is the key barrier to the use of any external training load measure in youth sports. Across multiple sports, the importance of training load metrics (e.g. high-speed running, collision and jump counts) varies. For example, although high speed running and collision counts are important in rugby, jump counts are a more accurate measure of the external load experienced in netball (Chandler et al., 2014; Costello et al., 2018; Read et al., 2017). Although such variation is easy to account for using microtechnology devices or notational analysis due to the flexibility they provide in terms of variables collected, it is also time consuming. Furthermore, when multiple athletes train at the same time, it is impractical to ensure each athlete has their own microtechnology GPS device from a cost perspective, which can severely hamper the reliability of the distances and speeds monitored (Johnston et al., 2014; Johnston et al., 2012; Malone et al., 2017). These issues are further exacerbated within school sports scholarship environments where athletes participate in numerous sessions outside of their scholarship commitments for clubs, regional or national teams (Phibbs et al., 2018). It is very difficult to account for these additional sessions using either microtechnology devices or notational analysis, indicating that a self-report measure of the training load experienced (i.e. s-RPE) is more appropriate (Saw et al., 2015).

The s-RPE can be used globally across all field-based and resistance-based training sessions ensuring that a single measure of the daily training load can be devised regardless of the mode of training completed. Furthermore, the accuracy of s-RPE has been validated for up to 48 hours post-training session completion (Phibbs et al., 2017; Scantlebury et al., 2018). Practitioners can therefore be confident that they can validly obtain it from athletes at any point in the 48 hours post-training session, which is an

invaluable asset when evaluating large groups of individuals with limited resources. Consequently, s-RPE will be used as the measure of training load within this thesis.

2.6 Sleep

In section 2.2.3, it was proposed that sleep should be added to the athlete monitoring cycle as a measure of training recovery. The importance of sleep as a recovery method for athletes has only recently been explored (Fullagar, Duffield et al., 2015; Halson, 2014; Taylor et al., 2016), but this new understanding of its importance has resulted in a dramatic increase in the number of published articles over the last ten years. According to a PubMed search of “sleep sport”, 84 articles were published in 2010, whereas in 2018, 486 articles were published, representing a six-fold increase.

There are two aspects of sleep: duration and quality. Whereas sleep duration is easy to define as the amount of sleep experienced by an individual, it is much more difficult to define sleep quality. This difficulty is likely due to the number of indices of sleep that can be measured and how they interact with each individual’s unique physical and psychological characteristics (Krystal & Edinger, 2008). However, despite an inability to provide a global definition for sleep quality, there is a growing body of evidence suggesting that it is hindered by athletic training to a greater extent than sleep duration (Leeder et al., 2012; Pitchford et al., 2017). For example, Leeder and colleagues (2012) discovered significant differences between elite athletes and age and sex matched non-athletic controls in numerous sleep quality metrics including sleep efficiency (athletes 80.6 ± 6.4% *vs.* controls 88.7 ± 3.6%, $p < 0.05$), fragmentation index (athletes 36.0 ± 12.4 *vs.* controls 29.8 ± 9.0, $p < 0.05$), and sleep latency (athletes 18.2 ± 16.5 mins *vs*. controls 5.0 ± 2.5 mins, $p < 0.05$), but not in the time asleep sleep duration metric (athletes 6 hours 55 mins ± 43 mins *vs*. controls 7 hours 11 mins ± 25 mins, $p = 0.27$).

Sleep can be measured either objectively, via polysomnography or actigraphy, or subjectively, via self-reported sleep logs. Both methods of assessing sleep will be discussed below. Furthermore, the relationship between sleep and illness, and the appropriateness of each method for use within youth sport will be considered. The relationship between sleep and measures of the training response will be evaluated in section 2.7 (fatigue/wellness measures) and section 2.8 (preparedness to play measures).

2.6.1 Objective measures

2.6.1.1 Polysomnography

The gold standard of sleep measurement is polysomnography. Polysomnography evaluates sleep architecture by measuring three variables essential to determining the sleep stage of the participant: electroencephalography (EEG), electrooculography (EOG) and electromyography of the submentalis (EMGsub). These measurements require small metal discs with thin wires to be attached to the scalp (EEG), around the eye (EOG) and near any muscle belly (EMGsub) and evaluate the brain wave patterns, eye movement and muscle tone of the participant respectively (Vaughn & Giallanza, 2008). Researchers can also measure physiological variables such as heart rate, blood pressure and respiratory function to help confirm the sleep stage identified (Vaughn & Giallanza, 2008).

Although recognised as the gold standard of sleep architecture measurement and considered to be relatively non-invasive, polysomnography still requires the attachment of multiple wires to the human body and a mask to be worn. The use of such equipment requires a laboratory setting, which could impact the sleeping habits of participants, particularly adolescents who may be affected by the laboratory environment to a greater extent than adults (Keenan, 1992). Furthermore, the equipment would be extremely expensive if used regularly across large numbers of participants concurrently.

Consequently, it is inappropriate for use within youth sport environments where daily monitoring of sleep is incorporated within the integrated athlete monitoring cycle.

2.6.1.2 Actigraphy

In response to the difficulties associated with use of polysomnography in longitudinal studies, actigraphy-based measures have been adopted with increasing regularity (Peake et al., 2018). Actigraphy is a non-invasive method of identifying sleep-wake patterns using a small accelerometer, which measures bodily movements. A computer algorithm uses data from these bodily movements to identify stages of the sleep-wake cycle (e.g. sleep, deep sleep, light sleep and wake). However, the algorithms used are specific to each watch so it is pivotal that all watches are individually validated (Evenson et al., 2015).

The validity of actigraphy watches is measured using their sensitivity and specificity to identify different stages of sleep rather than using traditional correlation coefficients. Sensitivity evaluates the ability of actigraphy watches to correctly identify epochs of sleep scored as such by polysomnography. Specificity identifies those correctly coded epochs of wake as scored by polysomnography (Meltzer et al., 2012). Multiple studies have shown that actigraphy watches can accurately identify an individual as sleeping (sensitivity = 0.96-0.97), but their ability to identify different stages of sleep or elements of sleep architecture is limited. For example, the ability of different actigraphy watches to accurately code wake (specificity = 0.37-0.61) and rapid eye movement sleep (accuracy = 0.61-0.74) is poor and varies dependent on the watch measured (de Zambotti et al., 2015; 2018; 2019). Similarly, there is wide variability between watches in their estimation of indices of sleep quality such as wake after sleep onset. In the same three studies as above, the mean bias for wake after sleep onset against polysomnography was reported as 5 ± 19 minutes (de Zambotti et al., 2018), 2 ± 21 minutes (de Zambotti et al., 2019) and 31 ± 32 minutes (de Zambotti et al., 2015).

This uncertainty surrounding the validity and reliability of actigraphy watches is perhaps unsurprising given they only provide proxy measures of sleep quality via accelerometer readings. Krystal and Edinger (2008) suggested the use of these accelerometers may result in two key measures of sleep quality (sleep-onset delay and prolonged night-time awakenings) being misclassified as participants will usually remain motionless at this time and thus be classified as sleeping. Given that both of these measures are related to the total sleep time experienced by an individual, this may explain why the specificity (i.e. ability to detect wake) of actigraphy measures is frequently lower than the sensitivity (i.e. ability to detect sleep) de Zambotti et al., 2015; 2018; 2019). In addition to this, logistical challenges such as the monetary cost (approximately £100 per unit), the time required to filter and download results, and issues with data collection due to participants forgetting to wear/start the watches or other important events (e.g. academic examinations) taking prominence limit the usefulness of actigraphy watches as longitudinal measures of sleep within youth athletes on school sports scholarship schemes (Caia et al., 2018; Kölling et al., 2016; Meltzer et al., 2012).

2.6.2 Subjective measures

Recently, the potential benefits of using self-reported sleep measures in longitudinal monitoring has been highlighted (Knufinke et al., 2018). Self-reported measures of sleep are regularly used within longitudinal health studies (Cohen et al., 2009; Lauderdale et al., 2008) and provide an understanding of the quantity and quality of sleep an athlete believes they have experienced. Such information is important as the interaction between objective indices of sleep and perceptions of sleep varies between individuals (Krystal & Edinger, 2008). Indeed, subjective measures of sleep could be more important than objective measures as individuals suffering from sleep disorders, e.g. insomnia, cannot always be identified based on objective measures of sleep alone (Krystal & Edinger, 2008).

2.6.2.1 Sleep duration

Three studies have considered the validity of self-reported sleep duration against actigraphy based measures, with conflicting findings (Caia et al., 2018; Kölling et al., 2016; Lauderdale et al., 2008). The first of these studies by Lauderdale and colleagues (2008) reported a limited relationship between self-reported sleep duration and actigraphy measured sleep duration (r = 0.60). However, both Caia et al. (2018) and Kolling et al. (2016) reported almost perfect relationships between the two measures (r = 0.85-0.90). There are several possible explanations for these discrepancies. The first of which involves the cohort utilised for each study. In both Kolling and colleagues' (2016) and Caia and colleagues' (2018) studies, athletic populations were utilised. Lauderdale et al. (2008), on the other hand, considered the general population. It is possible, given the reproducibility between the studies of Caia and Kolling, that athletic populations are better able to identify their total sleep time than the general population (Caia et al., 2018; Kölling et al., 2016). However, no research has specifically attempted to prove/disprove this theory.

An alternative explanation is that the lack of congruency between studies is due to the different equipment used. The difference in technology used between the studies is particularly interesting given that there were 8-10 years between the studies. In the validity studies reported in section 2.6.1.2, the mean bias in total sleep time reduced as the studies advanced in chronological order from approximately 27 minutes in 2015 to 9 minutes in 2018 (de Zambotti et al., 2015; 2018). This 18 minute difference in mean bias, achieved over three years, is similar to the difference between Kolling and colleagues' (2016) mean bias of 18.7 minutes and Lauderdale and colleagues' (2008) mean bias of 35 minutes achieved over eight years. Consequently, the difference in correlation between actigraphy and self-reported measures could be due to reductions in the error of the

actigraphy measure as technology and algorithms develop rather than due to changes in the self-reported measure.

Finally, the difference in the questions used between studies could have influenced the findings. Lauderdale and colleagues (2008) question: *"What is your best estimate of how much actual sleep you got"* is subtly different to the question used in the other two studies, who asked the participant to estimate their sleep duration based on the time they turned the lights off (Caia et al., 2018; Kölling et al., 2016). The use of this anchor ('when they turned the lights off') may have helped to standardise the start point of sleep duration relative to Lauderdale and colleagues (2008) less precise question. Indeed, this anchoring process could be taken further to include a defined point by which sleep duration ends, which could further enhance the validity of self-reported sleep duration (Cohen et al., 2009).

2.6.2.2 Sleep quality

Unlike self-reported sleep duration, the relationship between self-reported sleep quality and actigraphy based measures of sleep quality is not good. For example, Caia and colleagues (2018) reported small correlations between actigraphy measured sleep efficiency and self-reported sleep quality on a 5-point and 10-point likert scale (r = 0.22; ±0.06, and r = 0.28; ±0.06 respectively). Similarly, Kolling and colleagues (2016) only observed moderate relationships (r = 0.32-0.35) between self-reported sleep onset latency and their sensewear armband actigraphy calculated measure. The regularly observed poor relationship between actigraphy calculated and self-reported measures of sleep quality has led to a number of publications utilising actigraphy as a measure of sleep quality in athletes (Leeder et al., 2012; Pitchford et al., 2017; Thornton et al., 2017). However, although objectively accurate, changes in these measures (e.g. sleep onset latency or sleep efficiency) do not necessarily relate to changes in athletes' perceptions of sleep quality because these perceptions are multifactorial and individual by nature (Krystal

& Edinger, 2008; Ramlee et al., 2017). For example, suppose that two athletes suffer from increased sleep onset latency, relative to normal, over multiple nights. In this situation, it is likely that an athlete who is more affected by sleep onset latency will report a lower sleep quality score than an athlete who is more reactive to changes in the frequency of night-time awakenings. Consequently, it could be argued that the gold standard of sleep quality should be the athlete's individual perception, rather than any objective measure which may not influence their specific individual response.

2.6.3 Relationship with illness

Despite a growing understanding of the importance of sleep as a measure of recovery for athletes, research surrounding its relationship with illness incidence is limited as the majority of research to date has focussed on the relationship between training load and illness. There are, though, three studies which have specifically evaluated the relationship between sleep and susceptibility to illness, one of which took place in sport (Cohen et al., 2009; Fitzgerald et al., 2018; Prather et al., 2015). There are no studies in youth sport.

It is the work of Sheldon Cohen and colleagues in the general population that provides the basis by which sleep is considered to be related to susceptibility to illness (Cohen et al., 2009; Prather et al., 2015). In the first of these studies, Cohen and colleagues (2009) calculated the average sleep duration and sleep quality of participants over fourteen days using the Pittsburgh Sleep Quality Index (Buysse et al., 1989). Participants were then quarantined and exposed to nasal drops of rhinovirus, the predominant cause of the common cold. In the following five days, participants whose average sleep duration was less than seven hours per night in the two weeks preceding inoculation were three times more likely to develop a cold than those whose average sleep duration was greater than eight hours (OR = 2.94, 95% CI 1.18-7.30). Similarly, those who reported less than 92% sleep efficiency (defined as the percentage of time asleep from bed time until sleep end)

were five and a half times more likely to develop a cold than those with greater than 98% sleep efficiency (OR = 5.50, 95% CI 2.08-14.48). In another study, where sleep was assessed for seven days using actigraphy prior to exposure to the rhinovirus nasal spray, Prather and colleagues (2015) identified a cut-off point of five or six hours as more appropriate. They found that those sleeping less than five hours per night had a four and a half times greater risk (OR = 4.50, 95% CI 1.08-18.69) and those sleeping between five and six hours per night had a four and a quarter times greater risk (OR = 4.24, 95% CI 1.08-16.71) of developing a cold than those sleeping more than seven hours per night. This small discrepancy in the cut-off points is likely due to the tendency for individuals to over-estimate self-reported sleep durations *vs.* actigraphy measures (described in section 2.6.2.1). Interestingly, neither sleep efficiency (p = 0.258) nor sleep fragmentation (p = 0.715) were associated with susceptibility to illness when measured via actigraphy, providing further support for the use of self-reported sleep quality measures highlighted in section 2.6.2.2. In all cases, the significant relationships held when previously identified risk factors such as age, viral specific antibody and psychological stress levels were accounted for, confirming the importance of measuring sleep when attempting to avoid adverse outcomes to training and enhance athlete availability.

Unfortunately, it is not possible to perform such a well-controlled study within performance sport as coaches would not allow their athletes to be intentionally exposed to viruses as it risks hindering their performance or development. Consequently, the only study to consider the relationship between sleep and illness risk in sport, alongside the known training load stressor is observational by nature (Fitzgerald et al., 2018). In their 40-week study in Australian Rules football, Fitzgerald and colleagues (2018) found only weekly average sleep duration to be significantly associated with subsequent illness incidence (OR = 0.49, 95% CI 0.25-0.94, p = 0.032) when modelled alongside various measures of training stress and recovery including: GPS derived total distance and sprint distance, and self-reported sleep quality. Such a finding is particularly important because all measures

of the training dose and recovery were identified as significantly associated with subsequent illness incidence in univariate models prior to their inclusion within the multivariate model. Taken together, these results highlight the importance of considering both training load and sleep measures when attempting to minimise the risk of illness in athletes.

2.6.4 Practical considerations when measuring sleep in youth sport

The integrated athlete monitoring cycle proposed in Figure 1.2 (and repeated in Figure 2.5) suggests that a training recovery measure (e.g. sleep) should be considered alongside the training dose (e.g. training load) when evaluating the training response (e.g. fatigue/wellness or preparedness to play measures) of any athlete. Similar to the training load imposed upon an athlete, the sleep experienced can be measured either objectively or subjectively. Unfortunately, despite suggestions that self-reported measures may provide a more accurate indication of the sleep experienced by an athlete (Krystal & Edinger, 2008; Ramlee et al., 2017), there is little research considering how both measures relate to outcome measures of the training process. Consequently, when considering the inclusion of sleep measures practitioners may wish to evaluate the options based on the same criteria suggested for training dose measures in section 2.5.4: time and monetary cost of implementation, and ease of use (Bergeron et al., 2015; Murray, 2017; Taylor, 2016).

When considering time and monetary cost, alongside ease of use, self-reported measures of sleep are the most logical option. Self-reported measures can easily be incorporated into a fatigue/wellness questionnaire or the participant can be asked for the information directly by a practitioner the morning following the night of interest. This option is not available for polysomnography or actigraphy-based measures which require participants to remember to wear watches or expensive equipment and start recording data at the

correct time. Although no research has specifically tested objective *vs.* subjective measures in youth athletes, it is reasonable to assume that expecting youth athletes to remember to wear the equipment and start recording data at the correct time is unlikely to occur with the regularity required for the integrated athlete monitoring cycle in practice. Consequently, self-reported measures of sleep will be used within this thesis.

2.7 Fatigue/wellness measures

By evaluating the training response, practitioners aim to evaluate both the extent to which the athlete is coping with the training dose imposed upon them and whether they are ready for another training stimulus to be applied. According to Gabbett and colleagues' (2017) athlete monitoring cycle model, the first of these questions (i.e. is the athlete coping with the training stress) is answered using fatigue/wellness measures. Like the training dose and recovery experienced by an athlete, fatigue and wellness measures can be monitored either objectively or subjectively. Objectively, it is possible to use biological measures such as cortisol, testosterone and s-IgA (McLean et al., 2010; Morgans et al., 2014; Rowell et al., 2018), whereas subjectively, fatigue/wellness questionnaires are more prominent (Saw et al., 2016; Taylor et al., 2012). Although all three biological measures have shown associations with the training dose imposed upon an athlete (Morgans et al., 2014; Rowell et al., 2018; Rowell et al., 2017), it is through the influence of cortisol on s-IgA via the HPA axis that immune function is compromised and the risk of illness is increased (see section 2.3.2.1). As this increased risk of illness is related to a reduction in s-IgA, rather than an increase in cortisol concentrations, it would be more logical to measure the immune measure (s-IgA) than its biological intermediary (cortisol). Therefore, in this section s-IgA will be evaluated as an objective measure of an athlete's fatigue/wellness and self-reported wellness questionnaires will be considered as a subjective measure. The rationale for the use of both measures within the context of

illness monitoring in youth athletes will be discussed as well as their relationships with the training dose (training load) and training recovery (sleep) experienced by the athlete.

2.7.1 Salivary IgA

In recent years, the use of s-IgA as an illness monitoring strategy has increased as it provides an objective and relatively non-invasive measure of athlete immune function (Brandtzaeg, 2003; Gleeson, 2007). These characteristics are demonstrated by the ease with which practitioners can obtain accurate estimates of s-IgA from small amounts of saliva (Brandtzaeg, 2003). S-IgA is secreted from the mucosa and has been called the 'first line of defence' against infection because approximately 90% of pathogens attempt to enter the body at its secretion location (Brandtzaeg, 2003; Brandtzaeg, 2013). The importance of IgA in the fight against foreign elements stems from its action as the key mediator in immune exclusion, which is the body's non-inflammatory adaptive mucosal surface protection. By mediating the protection of this mucosal area of approximately 400 m^2, s-IgA ensures that the vast majority of pathogens are destroyed before they are able to enter the body and cause harm (Brandtzaeg, 2003).

S-IgA can be measured as either a concentration or secretion rate. S-IgA concentration refers to the amount of IgA within an arbitrary amount of saliva (usually 1 mL). It is controlled by the sympathetic nervous system and increases in response to the release of catecholamines via increased expression of polymeric immunoglobulin receptor (Bishop, 2006). The s-IgA secretion rate provides the amount of IgA available at any time and is measured by multiplying the concentration by the amount of saliva entering the mouth (termed the 'flow rate'). Unlike IgA concentration, the saliva flow rate is controlled by the parasympathetic nervous system (Humphrey & Williamson, 2001). This innervation of the two aspects of s-IgA by opposing members of the nervous system usually results in complementary actions occurring which maintain appropriate levels of immune defence

during homeostasis and light exercise (Bishop et al., 2000; Brandtzaeg, 2003). However, in response to intensive exercise, the immune response can be compromised (Gleeson, 2007; McDowell et al., 1992).

2.7.1.1 Relationship with measures of training dose and recovery

Interest in the use of s-IgA as a monitoring tool has grown since significant changes were identified in response to intensive exercise (McDowell et al., 1992). In their study, McDowell and colleagues (1992) showed that s-IgA concentration decreased by 24.4% ($p < 0.05$) in a group of moderately active college males following an incremental treadmill test to exhaustion and remained depressed by 16.9% one hour after the test. Recently, Coad and colleagues (2015) observed similar results, showing that s-IgA concentration remains significantly depressed for up to 60-hours post-match play in Australian Rules football ($p < 0.05$). These findings have given rise to the 'open window' hypothesis, which suggests that this extended time period whereby immune function is depressed post-exercise provides an opportunity for pathogens to enter the body and predispose it to illness (Gleeson, 2007). Given athletes can perform repeated high intensity efforts as part of progressive adaptation programmes, it is unsurprising that practitioners have begun to consider the impact of training load on s-IgA measures.

Table 2.4 provides an overview of the studies evaluating the relationship between s-IgA and training load measures. The most interesting aspect of Table 2.4 is the observation that out of the eight studies identified, only three directly evaluated the relationship between training load and s-IgA (Moreira et al., 2011; Owen et al., 2018; Putlur et al., 2004). Furthermore, within these three studies, the only significant relationship observed between training load and s-IgA occurred in female collegiate soccer players (Putlur et al., 2004). In this study, a significant correlation between training monotony and s-IgA secretion rate was identified during week four of the nine-week study ($r = 0.75$). However, no relationship was observed during any of the other weeks and no correlation was

reported between average weekly s-RPE and s-IgA concentration or secretion rate in youth basketball players (Moreira et al., 2011), or between training intensity and s-IgA concentration in elite adult male soccer players (Owen et al., 2018).

Despite limited direct support for the relationship between training load and s-IgA, research has consistently identified reductions in s-IgA measures to occur in response to intensified training periods or match play (Cunniffe et al., 2011; Fahlman & Engels, 2005; Moraes et al., 2017; Moreira et al., 2011; Morgans et al., 2014). It has been suggested that the discrepancy between these findings is likely due to the complex, multifactorial nature by which immune function can be altered (Bishop & Gleeson, 2009). Section 2.3.2.1 depicted the influence physical and psychological stress, alongside sleep and diet, could have on immune function via the HPA axis. However, despite an underlying theoretical and laboratory-based understanding of this link, there is very limited field-based research considering the relationship between measures of the training dose and immune function. For example, although Edwards and colleagues (2018) recently showed that psychological stress, measured by the State-Trait Anxiety Inventory (Spielberger, 1983), is as important to the acute immune response to moderate intensity treadmill running as the physical stress itself, measured via HR monitoring, (psychological stress r = 0.39 *vs.* physical stress r = -0.37), no study has yet evaluated the long-term relationship between the two measures. Furthermore, despite Irwin's (2002; 2015) laboratory studies identifying relationships between sleep disturbances and various cellular based immune measures (including natural killer cells, cytokines and T-cells, which help mediate the production of IgA), the only current study to evaluate the relationship between sleep and s-IgA within sport showed no significant relationship between a sleep quality measure and s-IgA concentration (r value not provided; Owen *et al.*, 2018). Consequently, there is significant scope for future research evaluating the individual and interactional relationships between measures of the training dose (e.g. training load and psychological stress), measures of the training recovery (e.g. sleep) and s-IgA.

Table 2.4: Overview of studies considering the relationship between s-IgA and training load.

Authors	Cohort	Methods	Results
(Coad et al., 2016)	18 elite male Australian Rules football (AFL) players *(age = 24.0 ± 4.2 yrs, height = 187.0 ± 7.1 cm, body mass = 87.0 ± 7.6 kg)*	Saliva samples collected 36 hours post-match for 16 consecutive matches, over a 17-week time period. Baseline saliva sample collected 36 hours after the last pre-season AFL match. Match load measured using GPS PlayerLoad.	Compared to pre-season baseline, weeks 5 and 7-16 had substantially lower s-IgA concentrations (≥75% likelihood; $p < 0.05$ at weeks 5, 7, 9-11, 14-16). Mostly unclear differences in PlayerLoad when compared to previous week. Substantial increases at weeks 6 ($p < 0.05$) and 8 ($p < 0.05$); substantial decreases at weeks 4 ($p > 0.05$), 7 ($p < 0.05$) and 11 ($p < 0.05$).
(Cunniffe et al., 2011)	30 professional rugby union players *(age = 26.4 ± 1.0 years, height = 185.6 ± 3.6 cm, body mass = 102.2 ± 10.9 kg)*	Saliva samples collected 11 times over a 43-week period *(weeks 1, 6, 9, 14, 19, 24, 28, 34, 38, 41, 43).* Average weekly training load calculated using s-RPE method	General increasing trend for s-IgA concentration between weeks 1 and 43, with exception of one month drop in weeks 9 (20%), 28 (29%) and 38 (9%). Weeks 9 (onset of match play) and 38 (peak training intensity) coincided with changes in training load. Week 28 coincided with peak illness incidence.
(Fahlman & Engels, 2005)	75 varsity American football players *(age = 20.5 ± 1.5 yrs, height = 170.0 ± 2.0 cm, body mass = 96.5 ± 18.6 kg)*	Saliva samples collected 8 times over a 49-week period *(approximately week 1, 6, 17, 26, 28, 33, 43, 49).* No direct measure of training load	S-IgA concentration ($p = 0.005$) and secretion rate ($p = 0.001$) significantly lower at weeks 6, 17, 33 and 43. Weeks 6 and 33 coincided with intensive pre-season training, weeks 17 and 43 coincided with in-season period.
(Moraes et al., 2017)	23 male youth basketball players *(age = 15.8 ± 0.8 yrs, body mass = 82.7 ± 13.0 kg)*	Saliva samples collected 3 times over a 7-week period *(weeks 1,4,7)* Internal training load assessed using sessional-RPE - average weekly load used for analysis.	S-IgA concentration was significantly lower at end of tapering phase compared to both start ($p = 0.002$) and end ($p = 0.05$) of overloading phase. No difference in s-IgA concentration response to training between high and low fitness groups ($p = 0.344$).

		High and low fitness groups measured by Yo-Yo IR1 performance.	
(Moreira et al., 2011)	15 male basketball players *(age = 19.0 ± 0.6 yrs, height = 192.0 ± 10.0 cm, body mass = 92.0 ± 9.0 kg)*	Saliva samples collected pre and 1 week post a 4-week period *(weeks 1 and 5).* Internal training load assessed using sessional-RPE - average weekly load used for analysis.	S-IgA secretion rate significantly lower following four weeks of training ($p < 0.05$). No difference in s-IgA concentration. No correlation between training load and s-IgA measures. .
(Morgans et al., 2014)	21 elite male English Premier League professional soccer players *(age = 26.0 ± 4.0 yrs, height = 183.0 ± 7.0 cm, body mass = 80.9 ± 7.4 kg)*	Saliva samples collected on 7 occasions (two days post-match) over a 32-day period *(days 3, 8, 11, 14, 18, 25, 32).* Players split into two groups: >50% minutes played, <50% minutes played. Training load assessed via GPS measures.	Significant decline in s-IgA concentration at day 11 ($p = 0.001$), day 14 ($p = 0.003$) and day 18 ($p = 0.002$) relative to day 3. S-IgA concentration returns to baseline following 7 days rest before match 6 No significant differences in s-IgA concentration between player groups ($p = 0.79$) No difference in GPS measures between the 7 games (total distance $p = 0.43$; high intensity distance $p = 0.16$; sprint distance $p = 0.09$).
(Owen et al., 2018)	37 elite male international soccer players *(age = 24.9 ± 3.3 yrs, height = 182.5 ± 6.0 cm, body mass = 73.1 ± 6.2 kg)*	Saliva samples taken before 27 training sessions at international camps over a 2-year time period *(match day-4 to match day-1)*. Training intensity measured using the Borg CR-10 scale.	No correlation between RPE via the Borg CR-10 scale and s-IgA concentration ($p > 0.05$).
(Putlur et al., 2004)	14 female soccer players *(age = 19.8 ± 1.0 yrs, body mass = 65.9 ± 7.3 kg)*	Saliva samples collected weekly over a 9-week competition period. Training load measured using the sessional-RPE method via the Borg CR-10 scale.	S-IgA secretion rate and training monotony were correlated in week 4 ($r = 0.75$).

2.7.1.2 Relationship with illness

Table 2.5 details the studies considering the relationship between s-IgA and illness. Whereas the majority of studies evaluating the relationship between training load and s-IgA have utilised s-IgA concentration without considering s-IgA secretion rate, the balance of evidence shown in Table 2.5 suggests that the differentiation between s-IgA concentration and secretion rate is important with regards to the relationship observed with illness. Although some variability is present within the results provided in Table 2.5, there appears to be a key trend by which s-IgA concentration is related to illness incidence on a short-term basis, whereas s-IgA secretion rate appears to have a relationship in the longer term. This is best illustrated by the transient three week drop in s-IgA concentration identified by Neville and colleagues (2008) prior to illness incidence in elite adult yachtsmen and the findings of Fahlman and Engels (2005) that only s-IgA secretion rate was significantly associated with illness incidence in collegiate American football players, when all samples were collected a minimum of four weeks apart. Further support for the short-term importance of s-IgA concentration is provided by Orysiak and colleagues (2017) and Cunniffe et al (2011), who both showed it to be lower in athletes when suffering from illness *vs.* when considered healthy. However, although both these studies provided similar results, it is important to understand the limitation that an association when the athlete is already suffering from an illness does not necessarily mean that the measure is predictive. Indeed, only 48% of illnesses could be predicted by Neville and colleagues (2008) based on changes from the average healthy s-IgA concentration, and only 12-42% of the variation in illness incidence could be accounted for by changes in s-IgA secretion rate (Fahlman & Engels, 2005). It should also be noted that both of these 'predictive' qualities were assessed with data previously used to form the model rather than new incidences, limiting their validity as predictive measures (Fahlman & Engels, 2005; Neville et al., 2008). Consequently, although there appears to be a relationship between s-IgA concentration or s-IgA secretion rate and illness incidence, it is not yet clear which measure is more important or whether this changes dependent upon

the time of sampling. Furthermore, it is unclear whether this relationship is predictive, so it is uncertain whether s-IgA measures are useful from an athlete monitoring perspective.

It is possible that any associative or predictive relationships between s-IgA and illness would become clearer if some of the variability between the results of published articles could be removed. One method by which this could be achieved is by considering the definitions of illness employed by each study. Within the studies evaluated in Table 2.5, definitions of illness ranged from unvalidated (e.g. asking athletes to identify whether they were suffering from symptoms) and validated (e.g. the WURSS-21) self-reported logs to medical or throat swab identified illnesses. Such variation in definitions is unsurprising given the difficulty in conducting medium to long-term studies with accessibility to medical practitioners but does provide an additional element of uncertainty within the results as the number of illnesses observed is likely to vary between studies due to the definition of illness utilised. Furthermore, although it is unfair to criticise the use of self-reported illness within longitudinal studies, it is unhelpful to readers attempting to draw conclusions between studies when similar terms are used for unvalidated self-report illness measures as for those scientifically validated measures or diagnosed by medical practitioners. For example, despite both Cunniffe and colleagues (2011) and Neville and colleagues (2008) using the term upper respiratory illness (URI), one study utilised solely unvalidated self-report measures (Cunniffe et al., 2011), whereas the other confirmed the illnesses using a medically trained practitioner (Neville et al., 2008). It is therefore suggested that within future research studies, illnesses using unvalidated self-report measures are identified as self-reported illnesses to assist practitioners evaluating the evidence available.

Table 2.5: Overview of studies considering the relationship between s-IgA and illness incidence.

Authors	Cohort	Methods	Results
(Cunniffe et al., 2011)	30 professional rugby union players *(age = 26.4 ± 1.0 years, height = 185.6 ± 3.6 cm, body mass = 102.2 ± 10.9 kg)*	Saliva samples collected 11 times over a 43-week period *(weeks 1, 6, 9, 14, 19, 24, 28, 34, 38, 41, 43).* Upper respiratory illness (URI) incidence collected via a self-reported weekly log.	s-IgA concentration 15% lower during URI than where no URI present (P = 0.08) Percentage of players reporting URI increased from August to March, with peak in December, coinciding with lowest squad s-IgA concentration.
(Fahlman & Engels, 2005)	75 varsity American football players *(age = 20.5 ± 1.5 yrs, height = 170.0 ± 2.0 cm, body mass = 96.5 ± 18.6 kg)*	Saliva samples collected 8 times over a 49-week period *(approximately week 1, 6, 17, 26, 28, 33, 43, 49).* URTI incidence collected via weekly log and follow up interview with principal investigator and doctor (where necessary).	s-IgA secretion rate accounted for 12-42% (36-42% in high risk time points 2, 3, 6 and 7) in the variance of predicted number of colds. s-IgA concentration not significant within this model.
(Gleeson et al., 1999)	26 elite national level swimmers *(15 male, 11 female - age 16-24 yrs)*	Saliva samples collected pre- and post-testing session every month for 7 months (April-October). Daily infection logs were collected, and throat swabs were taken to identify episodes of infection.	Seasonal mean pre-training s-IgA concentration predictive of number of infections (24%, P = 0.006). Pre-season s-IgA concentrations also predictive of number of infections (12%, P = 0.048). From 85mg/L (0), a drop of 15 mg/L in seasonal mean pre-training s-IgA concentration associated with increase of 1 predicted infection up to maximum 3.
(Mortatti et al., 2012)	14 youth soccer players *(age = 18.5 ± 0.4 yrs, height = 177.7 ± 4.0 cm body mass = 72.4 ± 6.0 kg)*	Saliva samples collected 7 times over a 20-day period *(each separated by 3 days).* URTI incidence collected via weekly log and follow up interview with principal investigator and doctor (where	Significant increases in URTI across period 2 and period 6 (P < 0.05), which mirrored significant decreases in s-IgA concentration (-15%, P < 0.05 at period 2; -12%, P < 0.05 at period 6).

		necessary) - reported as percentage of participants suffering from symptoms (prevalence) and total number of days with URTI symptoms (incidence).	Significant correlation between s-IgA concentration and URTI incidence at match 2 (r = -0.60, P < 0.05) and match 6 (r = -0.65, P < 0.05).
(Neville et al., 2008)	38 male America's Cup yacht racing athletes *(age = 36 ± 7 yrs, body mass = 92 ± 12 kg)*	Saliva samples collected weekly over a 50-week period of sailing and training. URI recorded by team doctor - stringent criteria (required medication/time loss illness). Recurrent illnesses (any within one week of previous episode) not included in analysis.	Normalised to the healthy mean, s-IgA concentration was 28% lower during URI (P < 0.005). In the 3 weeks leading up to URI, s-IgA progressively decreased below mean healthy value before recovering 2 weeks post-illness. s-IgA concentration falling below 40% of healthy mean suggest 48% chance URI in 3 weeks, whereas below 70% only gave 28% chance. However, 38% of URI were preceded by values at or above healthy mean.
(Orysiak et al., 2017)	27 youth ice hockey players *(age = 16.5 ± 0.5 yrs, height = 181.0 ± 6.2 cm, body mass = 74.2 ± 9.9 kg)*	Saliva samples collected on 8 occasions over 21 weeks *(weeks 1, 4, 6, 8, 11, 14, 18, 21)*. URTI reported via WURSS-21 on a daily basis.	No difference in s-IgA concentration (P = 0.180) or secretion rate (P = 0.481) between healthy-prone (0-2 URTI episodes) and illness-prone (≥ 3 URTI episodes) athletes. s-IgA concentration significantly lower during periods of URTI relative to periods without (P = 0.002). s-IgA secretion rate showed no significant differences (P = 0.170).
(Putlur et al., 2004)	14 female soccer players *(age = 19.8 ± 1.0 yrs, body mass = 65.9 ± 7.3 kg)*	Saliva samples collected weekly over a 9-week competition period. Illnesses which limited performance in training or exercise session were self-reported	No correlation between s-IgA secretion rate and illness incidence. 82% of illnesses were preceded by a fall in s-IgA secretion rate. 55% of illnesses were preceded by a fall in s-IgA secretion rate and a rise in cortisol.

2.7.1.3 Summary of s-IgA literature

Although there is an increasing interest in the use of s-IgA as an athlete monitoring tool (Coad et al., 2015; Fahlman & Engels, 2005; Morgans et al., 2014; Neville et al., 2008; Owen et al., 2018; Putlur et al., 2004), there isn't yet a clear consensus as to how it may best be utilised. The applied sport literature has focussed on the changes to s-IgA concentration, which occur in response to individual training sessions (Coad et al., 2015), at the expense of considering the s-IgA secretion rate. This focus is perhaps logical given the short-term impact of exercise on s-IgA concentration (McDowell et al., 1992) and the reductions in s-IgA concentration that are present when athletes are ill relative to not ill (Cunniffe et al., 2011; Orysiak et al., 2017). However, it is still unclear from longitudinal studies whether it is the training load itself that causes these reductions in s-IgA or other stressors associated with the training process (Bishop & Gleeson, 2009; Moreira et al., 2011; Owen et al., 2018). Future research should aim to further establish the relationship between these stressors in a similar manner to Edwards and colleagues (2018) recent study considering the impact of physical and psychological stress on immune measures.

It is interesting that despite the uncertainty surrounding the mechanisms behind the relationship between training load and s-IgA, the immune response to training and future risk of illness is remarkably consistent between adult and youth athletes (Cunniffe et al., 2011; Moreira et al., 2011; Orysiak et al., 2017; Owen et al., 2018). For example, both Moreira and colleagues (2011) in youth basketball and Owen and colleagues (2018) in elite adult soccer observed no significant relationship between training load measures and s-IgA concentration in their longitudinal studies. Similarly, multiple studies in both adult and youth athletes have identified a significant difference between s-IgA concentration when athletes are ill or not ill (Cunniffe et al., 2011; Moreira et al., 2011; Moreira et al., 2014; Neville et al., 2008; Orysiak et al., 2017). However, despite this focus on s-IgA concentration, the evidence appears to suggest that s-IgA secretion rate has a better long-term relationship with illness incidence (Fahlman & Engels, 2005; Neville et al.,

2008). Furthermore, although research has shown associative relationships between both s-IgA concentration and s-IgA secretion rate with illness at different time points in the lead up to incidence, the predictive ability in both cases was poor (Fahlman & Engels, 2005; Neville et al., 2008). Consequently, future research is necessary to evaluate the true predictive ability of s-IgA measures with regards to illness (i.e. using data previously unseen by the model). This research could also establish whether there is a difference in importance between s-IgA concentration and secretion rate in the lead up to illness incidence as the associative research appears to imply.

2.7.2 Subjective wellness questionnaires

The use of short, subjective wellness questionnaires to monitor an athlete's response to training has now become widespread in sport (Saw et al., 2015). These questionnaires are cheap, time efficient and easy to implement across large groups, which has boosted their popularity at both adult and youth levels of sport (Akenhead & Nassis, 2016; Saw et al., 2015; Taylor et al., 2012). Furthermore, wellness questionnaires can incorporate a wide variety of questions surrounding an athlete's sleep, stress levels, mood, fatigue, muscle soreness and appetite dependent upon the preferences of the practitioner in question (McLean et al., 2010; Noon et al., 2015; Thorpe et al., 2015). This ability to tailor wellness questionnaires in line with the practitioner's requirements has also extended to practitioners utilising different scoring systems. For example, McLean and colleagues' (2010) wellness questionnaire (Figure 2.6) utilises a behaviour-based scoring system, where specific feelings/behaviours are converted to numerical scores (e.g. restless sleep = 2, less interested in others/activities than usual = 3). On the other hand, Laurent and colleagues' (2011) Perceived Recovery Status scale (PRS) essentially uses a 0-10 reversed RPE scale (Figure 2.7).

	1	2	3	4	5	Score
FATIGUE	Always tired	More tired than normal	Normal	Fresh	Very fresh	
MUSCLE SORENESS	Very sore	Increase in soreness / tightness	Normal	Feeling good	Feeling great	
SLEEP QUALITY	Insomnia	Restless sleep	Difficulty falling asleep	Good	Very restful	
STRESS	Highly stressed	Feeling stressed	Normal	Relaxed	Very relaxed	
MOOD	Highly annoyed / irritable / down	Snappy with team-mates, family and friends	Less interested in others / activities	Generally good mood	Very positive mood	

Figure 2.6: Subjective wellness questionnaire, first published by McLean et al. (2010), utilising a behaviour-based scoring system,

PERCEIVED RECOVERY SCALE	
Very well recovered / Highly energetic (10)	
Well recovered / Somewhat energetic (8)	
Moderately recovered (6)	
Adequately recovered (5)	
Somewhat recovered (4)	
Not well recovered / Somewhat tired (2)	
Very poorly recovered / Extremely tired (0)	

Figure 2.7: Perceived Recovery Status scale, first proposed by Laurent et al. (2011), using a reversed RPE scoring system.

However, despite the growing popularity of wellness questionnaires, the literature surrounding the relationship they hold with training load is still in its infancy and their relationship with sleep is almost unexplored (Saw et al., 2017).

2.7.2.1 Relationship with measures of training dose and training recovery

The initial driver for the use of subjective wellness questionnaires within sport was the analysis of their changes in response to a weekly training schedule. An example of this analysis is depicted in Figure 2.8 using data from Gallo and colleagues (2017), but similar results have been observed in adult rugby league (McLean et al., 2010) and youth rugby union (Roe, Till et al., 2016). All three studies detailed a short-term reduction in wellness, which recovered back to baseline levels within 72 hours of match play. However, as with longitudinal studies of s-IgA measures, the usefulness of such observational analysis is limited as it only shows readers what happens, without providing any statistical explanation as to why it happens. For example, it is logical to deduce that the reduction in wellness is due to the training load imposed by a competitive fixture (Montgomery & Hopkins, 2013) but, amongst other factors, the disappointment at losing a fixture or poor sleep in the aftermath of the match could also influence the changes observed (Abbott, Browlee et al., 2018; Skein et al., 2013). Consequently, recent research has attempted to understand the direct relationship between training load and subjective wellness measures, so practitioners can better understand their athlete's response to training.

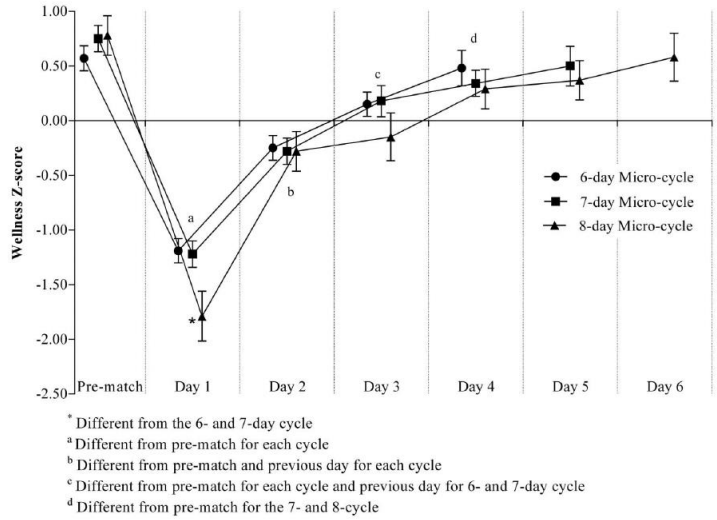


Figure 2.8: Wellness changes following match play in Australian Rules football players. Figure adapted from Gallo et al. (2017).

2.7.2.1.1 Training load

Given the trends shown in response to match play exposure and the small number of studies evaluating the influence of training load on wellness questionnaires (all of which have taken place in adult athletes), the relationship between the two measures is surprisingly contentious (Buchheit et al., 2013; Gallo et al., 2017; Montgomery & Hopkins, 2013; Thorpe et al., 2015). For example, in elite adult Australian Rules football players, Buchheit and colleagues (2013) observed small changes (exact effect sizes not reported) in all individual subscales of the McLean et al. (2010) questionnaire depicted in Figure 2.6. However, in the same cohort, using the same questionnaire and the same s-RPE measure of training load, Gallo and colleagues (2017) observed no changes in the overall score of the questionnaire in response to the previous day's workload.

It is possible that this discrepancy in findings is due to the training loads present within the two studies. Buchheit and colleagues (2013), who found small changes in all individual subscales, reported weekly training loads of 10,000 AU, whereas Gallo and colleagues (2017), who found no overall change in the questionnaire, only reported a weekly training load of approximately 1,750 AU. Given that excessively high training loads are believed to

affect mood and stress prior to the overtraining syndrome (Meeusen et al., 2013), it is possible that the fatigue, muscle soreness and sleep quality subscales may have been affected by lower training loads observed in Gallo and colleagues' (2017) study, but these lower training loads did not influence the mood and stress subscales. The lack of association with these subscales may have led to a masking effect blunting the overall wellness response. Unfortunately, no subscale analysis was provided by Gallo and colleagues (2017) to confirm this theory. Furthermore, it doesn't explain why Buchheit and colleagues' (2013) reported positive associations between training load and mood/stress – and this is not discussed within their study.

In other studies considering the relationship between training load and individual subscales, greater scoring ranges have been used but the results have been equally conflicting. For example, Thorpe and colleagues (2015) utilised a 1-7 scoring range for their subscales and identified a large relationship between high speed running distance and fatigue (r = -0.51; ±0.11, p < 0.001), but no relationship was observed with muscle soreness (r = -0.04; ±0.15, p = 0.71) or sleep quality (r = -0.10; ±0.15, p = 0.37) subscales in elite adult soccer players. Conversely, Montgomery and Hopkins (2013) used a similar 0-10 range as Laurent and colleagues' (2011) PRS scale (Figure 2.7) and observed 'clear and small' increases in muscle soreness in response to s-RPE training load, with an additive small effect on muscle soreness occurring post-match play (exact effect sizes not reported).

Taken together, the four studies currently attempting to evaluate the relationship between training load and wellness measures provide little consensus. This may be due to the method by which the measures are developed and adapted according to each individual practitioners' requirements. Although lauded as a contributing factor to the popularity of subjective wellness measures, this adaptability may also negatively influence the scientific rigour and reliability of the questionnaires (Saw et al., 2017). In an attempt to improve the

scientific rigour by which wellness questionnaires are devised, researchers have developed the PRS scale (Laurent et al., 2011). In two laboratory-based validation studies (Laurent et al., 2011; Sikorski et al., 2013), the PRS has shown moderate negative correlations with sprint performance (r = -0.63, p < 0.01) and significant reductions in response to resistance training protocols (Pre PRS 8.6 ± 2.3 AU, Post PRS 4.2 ± 1.9 AU; p < 0.05). However, no study has yet evaluated the scale within a field-based study. Comparing this laboratory validated questionnaire to the previously unvalidated wellness questionnaires commonly used within sport may therefore provide a more scientifically rigorous angle by which the relationship between training load and wellness can be considered.

2.7.2.1.2 Sleep

With limited research considering the relationship between traditional aspects of the athlete monitoring cycle (i.e. training load and fatigue/wellness measures), it is unsurprising that no research has directly evaluated the relationship between sleep and short subjective wellness questionnaires as proposed within section 2.4.1. Indeed, perhaps due to the negative influence training load can have on an athlete's sleep quality (Sargent et al., 2014; Thornton et al., 2017), this measure of sleep has more commonly been used within wellness questionnaires (McLean et al., 2010). However, despite not yet translating to the sport-specific wellness questionnaire literature, the influence of sleep on longer format wellness measures has previously been considered and provides support for the use of sleep as an input to the monitoring process (Lastella et al., 2014; Oginska & Pokorski, 2006; Pilcher et al., 1997).

The first of these studies took place in university students where self-reported sleep logs and the Profile of Mood States (POMS; McNair et al., 1971) were used to compare the effect of sleep duration and sleep quality on measures of wellness (Pilcher et al., 1997). The authors observed stronger relationships with sleep quality than sleep duration for

tension/anxiety (r = -0.52, p < 0.01 *vs* r = -0.05, p > 0.05), depression/dejection (r = -0.52, p < 0.01 *vs* r = 0.12, p > 0.05), anger/hostility (r = -0.32, p > 0.05 *vs* r = -0.17, p > 0.05), vigour (r = 0.24, p > 0.05 *vs* r = -0.15, p > 0.05), fatigue (r = -0.57, p < 0.001 *vs* r = -0.23, p > 0.05) and confusion/bewilderment (r = -0.41, p < 0.05 *vs* r = -0.07, p > 0.05). Subsequently, the significant negative relationships observed between sleep quality and fatigue (r = -0.28, p = 0.004), and sleep quality and tension/anxiety (r = -0.21, p = 0.030) were replicated when compared with self-reported pre-marathon sleep characteristics (Lastella et al., 2014). The strong correlations observed with tension/anxiety, depression/dejection and fatigue suggest that sleep quality could influence the mood and fatigue subscales of the McLean and colleagues' (2010) wellness questionnaire used within sport if this relationship was evaluated.

Interestingly, although confirming Pilcher and colleagues' (1997) observations regarding the relationship between sleep quality and wellness measures, Lastella and colleagues' (2014) results contradicted those previously found with sleep duration. In their study, Lastella, Lovell and Sargent (2014) reported significant small correlations between fatigue (r = -0.23, p = 0.023), tension (r = -0.20, p = 0.044) and sleep duration. These results are supplemented by Oginska and Pokorski's (2006) observations that the amount of sleep obtained as a ratio of that needed was significantly related to fatigue symptoms (r = -0.36, p < 0.0001) and mood complaints (r = -0.30, p < 0.0001) in academic youths. In the same study, Oginska and Pokorski (2006) indicated that absolute sleep duration had no relationship with fatigue symptoms or mood complaints as previously indicated by Pilcher, Ginter and Sadowsky's (1997) study. Together, these results indicate that while absolute sleep duration may not be related to wellness measures, variation from that which is needed or habitual to the athlete may influence an athlete's wellness. Consequently, despite conflicting evidence, there is scope to explore the use of sleep duration within the athlete monitoring cycle.

Given both sleep duration and sleep quality have shown relationships with wellness measures at different times, it may also be worthwhile considering a sleep index variable where both measured are considered in tandem. Such a variable has not yet been considered in the literature, but it is logical to assume that nine hours of “good” sleep would provide greater recovery than six hours of “good” sleep, or that six hours of “very restful” sleep may provide greater recovery than nine hours of “restless sleep”. Consequently, a sleep index variable (e.g. sleep duration multiplied by sleep quality) may provide a simple measure by which both the influence of sleep duration and quality on wellness measures can be evaluated using a single value and deserves further attention.

2.7.2.2 Relationship with illness

Like studies evaluating the relationship between training load and wellness, the literature considering the relationship that wellness questionnaires hold with illness is scarce and limited to two studies (Thornton et al., 2016; Watson et al., 2017). In both cases, wellness questionnaires were included in analysis alongside the training load imposed upon the athlete, but the approach used to evaluate the influence of wellness questionnaires on illness incidence differed between the studies.

Watson and colleagues (2017) used a correlation-based univariate poisson regression model to compare training load and wellness measures on the day of illness and the day preceding illness in female collegiate soccer players. No wellness measures were deemed to be significant with fatigue showing the strongest relationship (ES = -0.25, p = 0.11). However, it could be argued that by solely evaluating the previous day’s wellness measures, the lack of relationship should have been expected given wellness should rise and fall alongside a well-programmed super compensation curve. Consequently, wellness measures are potentially of more interest when they do not respond as expected by the supercompensation curve.

Support for this theory is provided by Thornton and colleagues' (2016) prediction-based random forest approach to predicting illness in elite adult rugby league players. In their study, the authors found that alongside an increase in internal training load, a decrease in wellness measures of less than 7.25 arbitrary units (AU) increased the accuracy of their illness prediction model. However, the decision tree model was only able to obtain 46% accuracy, which is remarkably similar to the 42-48% values previously reported within the s-IgA literature (Fahlman & Engels, 2005; Neville et al., 2008). Furthermore, observing a small drop in wellness as a predictor of illness in response to increased training load appears counterintuitive. It could be argued that if the body already feels fatigued because a latent virus is already within the body (Schwellnus et al., 2016), wellness measures could be expected to show greater reductions in response to a similar training load. However, further research is necessary to confirm or disprove this theory.

2.7.2.3 Summary of subjective wellness questionnaire literature

Subjective wellness questionnaires have become increasingly popular in recent years, but the scientific evidence supporting their use as measures of an athlete's response to training can be questioned (Saw et al., 2017). It seems likely that training load has a negative influence on perceptions of fatigue and muscle soreness (Buchheit et al., 2013; Montgomery & Hopkins, 2013; Thorpe et al., 2015), but its relationship with mood and stress is less clear (Buchheit et al., 2013; Gallo et al., 2017). Similarly, although research within longer wellness questionnaires such as the POMS indicates that sleep may be related to the individual wellness subscales of tension, vigour and fatigue (Lastella et al., 2014; Oginska & Pokorski, 2006; Pilcher et al., 1997), no studies have yet considered this relationship using the short subjective wellness questionnaires common within sport. Consequently, more research is required to evaluate the relationships between these short wellness questionnaires and measures of the training dose and recovery experienced by athletes. This research should also consider whether the use of overall wellness scores is appropriate or whether this results in a masking effect where the effect

of some subscales is lost when others show either opposing relationships or no relationships at all (Buchheit et al., 2013; Saw et al., 2016). It may also wish to consider whether the relationships observed differ between questionnaires promoted based on practitioners' requirements (McLean et al., 2010; Thorpe et al., 2015) and those which have been tested in laboratory-based studies prior to usage in field-based settings (Laurent et al., 2011).

Alongside a lack of certainty surrounding their validity as measures of the athlete response, support for the use of wellness measures within the prediction of illness is limited to Thornton and colleagues (2016) study in adult rugby league players (Watson and colleagues' (2017) study is not considered a prediction study as it does not validate the model on data it has not previously seen – see section 2.9.3). One possible reason for this is a current inability of studies to distinguish between an expected reduction in wellness (i.e. one that happens following a single hard training session) and an unexpected reduction in wellness (i.e. one that may happen following a single easy training session). If the expected change in wellness can be inferred from statistical analysis, this may provide a method by which wellness measures of interest can be identified and used to predict illness risk more accurately.

As could possibly be expected given the overall dearth of evidence supporting the use of wellness questionnaires within sport, there is no research considering the relationships they may hold with training load, sleep or illness incidence in youth athletes. Given the growing popularity of these questionnaires within youth sport (Noon et al., 2015; Roe, Darrall-Jones, Till et al., 2017) and the unique academic, maturational and social stressors encountered by youth athletes (see sections 1.1.1 and 1.1.2), which provide numerous opportunities for the response to training to be modified, it is pivotal that this gap in the literature is filled.

2.7.3 Practical considerations when measuring fatigue/wellness in youth athletes

As with the training dose and recovery measures selected, it is important to consider the time and monetary cost alongside the ease of use when identifying an appropriate method of measuring fatigue and wellness in youth athletes (Bergeron et al., 2015; Saw et al., 2017). When considering these criteria, using subjective wellness questionnaires, which can be incorporated alongside s-RPE training loads and self-reported sleep measures within a single morning questionnaire, is a logical choice. However, the relationship with the outcome measure of choice, in this case illness, should also be considered.

Despite the convenience of using short subjective wellness questionnaires, the research surrounding their validity as measure of the athlete response or as predictors of illness incidence is not strong in adult athletes and has not been considered in youth athletes (see section 2.7.2). One potential reason for this is the flexibility of the scales used by different researchers and practitioners (McLean et al., 2010; Montgomery & Hopkins, 2013; Thorpe et al., 2015). Whilst such flexibility in questions and scales used is undoubtedly beneficial from a practical perspective, it has recently been argued that making these changes without appropriate prior research could hinder the scientific validity of wellness questionnaires (Saw et al., 2017). Consequently, there is scope for comparative studies evaluating the relationships between training load, sleep and practitioner-developed wellness questionnaires (McLean et al., 2010) and laboratory-validated wellness questionnaires (Laurent et al., 2011).

Given the time and cost benefits of using subjective wellness questionnaires rather than objective s-IgA measures to evaluate an athlete's response to training, it may also be worthwhile comparing the relationships the two measures hold with illness. The ability of s-IgA as a predictor of illness incidence is now established at 42-48% (Fahlman & Engels,

2005; Neville et al., 2008). If the predictive ability of wellness questionnaires, alongside training load and sleep measures, with regards to illness incidence can be elucidated, practitioners can make informed decisions as to whether the additional cost of objective wellness measurement via s-IgA is worthwhile. Consequently, a study considering the relationships between training load, sleep, objective and subjective wellness measures, and their ability to predict illness in the same youth athlete cohort would be beneficial.

2.8 Preparedness to play measures

Preparedness to play measures are used to evaluate whether an athlete is physically ready for a further training stimulus to be applied. Unlike the other aspects of the athlete monitoring cycle considered so far, preparedness to play measures are usually only evaluated objectively (Gabbett et al., 2017), via neuromuscular fatigue measures. Examples of neuromuscular fatigue measures include CMJ's, plyometric press ups and six second maximal cycling power tests (McLean et al., 2012; Roe, Darrall-Jones, Till, Phibbs et al., 2016). Given the cost of the equipment associated with six second maximal cycling power tests, and the anecdotal knowledge that some participants within youth sport are unable to complete a body weight press up successfully, only CMJs will be considered in this section. Their relationship with the training dose (training load) and training recovery (sleep) experienced by the athlete will be discussed. However, it is not possible to evaluate the relationship between CMJ and illness incidence as no studies have yet considered it.

2.8.1 Countermovement jump

As a simple test of lower body maximal neuromuscular performance, which can be performed quickly and with relatively little fatigue cost, the CMJ is the most commonly used measure of neuromuscular fatigue (and thus preparedness to play) in sport (Claudino et al., 2017). With increasingly advanced technology available, studies of CMJ

metrics have been conducted using jump mats (Oliver et al., 2015; Thorpe et al., 2015), Optojump technology (Malone et al., 2015) and force plates (McLean et al., 2010; Roe, Darrall-Jones, Till et al., 2017). Furthermore, technological developments have allowed multiple metrics to be calculated including, but not limited to: jump height, peak power, relative peak power, relative power, mean power, peak velocity, peak force, mean force, rate of force development, flight time/eccentric time and flight time/contraction time (Claudino et al., 2017). With such a wide variety of technologies and metrics available, there is a plethora of research considering the use of CMJ as a measure of neuromuscular fatigue in response to training interventions (Claudino et al., 2017). However, there is significantly less literature directly evaluating the relationship between CMJ and training load or sleep (Malone et al., 2015; Rowell et al., 2017; Thorpe et al., 2017).

2.8.1.1 Relationship with measures of training dose and training recovery

As with subjective wellness questionnaires, the use of CMJ as part of the athlete monitoring cycle can be traced back to McLean and colleagues' (2010) study, where the authors showed that CMJ flight time, but not relative power was significantly lower one (ES = -1.67, $p < 0.001$) and four (ES = -1.12, $p < 0.05$) days post-match when compared against baseline pre-season values in elite adult rugby league players (Figure 2.9). More recently, reductions in CMJ metrics post-match play have been confirmed in youth rugby union players with a significant ($p < 0.05$) post-match reduction in CMJ height observed following three matches over a seven-week period (Oliver et al., 2015). Unfortunately though, neither study identified the micro cycle recovery curves for these CMJ variables so it is unclear how they fluctuate over a typical training week.

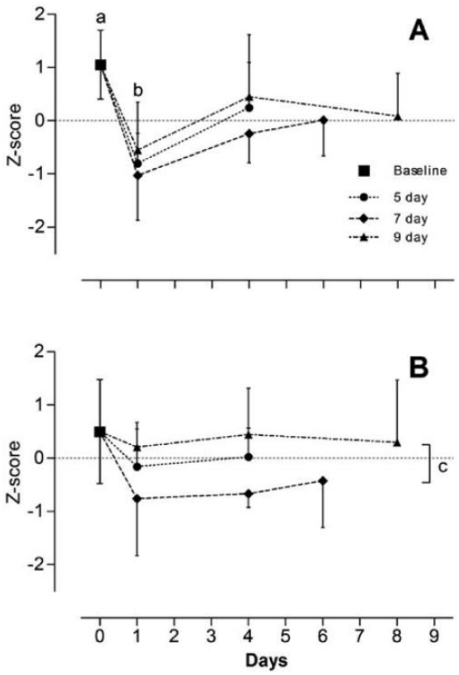


Figure 2.9: Depiction of CMJ flight time (A) and CMJ relative power (B) trends following match play in elite adult Rugby League players. Figure adapted from McLean et al. (2010).

In addition to changes pre- and post-match play. some CMJ measures have shown significant reductions following accumulated periods of training. In the same study that identified pre- to post-match changes in youth rugby union players, Oliver and colleagues (2015) identified significant reductions in pre-match CMJ height from baseline at weeks four (-6.8 ± 7.1%) and seven (-14.6 ± 5.9%), suggesting it may provide information with regards to their accumulated neuromuscular fatigue status. Similarly, Roe and colleagues (2016) observed *likely* to *almost certainly* reduced CMJ mean power from weeks five to eleven (-10.0 ± 4.3% to -14.7 ± 6.9%) of their eleven week preseason study in youth rugby union players. However, neither CMJ flight time (reduced in weeks 2, 4-6 and 9-10) nor CMJ mean force (only reduced at week 5) fully repeated this trend, highlighting the difficulties in interpreting CMJ data with such a vast array of metrics. Furthermore, despite all three studies identifying differences in CMJ metrics in response to accumulated training load or match play, they did not directly evaluate the relationship between training load

and CMJ measures. Consequently, as with the initial wellness questionnaire publications, their usefulness in practice is limited.

Recently, two studies in adult soccer (Rowell et al., 2017; Thorpe et al., 2015) and one in youth soccer (Malone et al., 2015) have evaluated the relationship between training load and CMJ performance, providing conflicting results. Using traditional correlation coefficients, Thorpe and colleagues (2015) identified a significant positive relationship between high speed running distance and CMJ height (r = 0.23; ±0.19, p = 0.04), which contrasts with the non-significant negative association observed between the same two variables (r = -0.23, p = 0.27) by Malone and colleagues (2015). It is possible that this difference in results is due to the different statistical methods used. Thorpe and colleagues (2015) analysed their data using partial correlations, which accounted for the trend in each participant's responses. This method of analysis is much more advanced than the Pearson correlation coefficients employed by Malone and colleagues (2015), which would have required data to be averaged by individual or incorrectly treated as independent observations. Although the more advanced statistics used by Thorpe and colleagues (2015) may explain the difference in results with Malone and colleagues (2015), they don't explain the opposing relationship observed by Rowell and colleagues (2017) in the same elite adult soccer players cohort. Rowell and colleagues (2017) also accounted for individual trends in the CMJ response to training load but, to provide a more practical understanding of the results, they split training load into low (<500 AU), medium (500-1000 AU) and high (>1000 AU) groups based on the PlayerLoad score derived from three individual matches. When compared to low training load groups, both the medium (-12 ± 11%, moderate) and high (-18 ± 11%, large) groups experienced a substantially greater reduction in CMJ height. This reduction in CMJ height was maintained 18 hours post-match where *likely* small reductions were still present in both the medium (-7 ± 7%) and high (-9 ± 7%) groups, but trivial differences between groups were observed after 42 hours indicating that the lower body neuromuscular fatigue measured via CMJ

performance may dissipate within two days. Thorpe and colleagues (2015) suggested that the surprising positive association between high-speed running and CMJ height they observed may have been due to a high-speed running priming effect, which enhanced CMJ performance the following day. However, they also indicated that the athletes in their study's motivation to complete CMJ performance varied dependent on the previous day's workload so the results of Rowell and colleagues (2017) may provide a better representation of the relationship between training load and CMJ height. These findings are much more consistent with the generally accepted theory that increased training load is associated with greater neuromuscular fatigue (Banister, 1991). Furthermore, they are congruent with Claudino and colleagues' (2017) meta-analysis, which indicated that CMJ height was able to detect changes in fatigue (effect size (ES) = -0.27; ±0.21, p = 0.01).

As with wellness questionnaires, there is no research evaluating the relationship between sleep and CMJ when used as part of the athlete monitoring cycle. However, two studies by Mah and colleagues (2011, 2019) have provided insight into the potential positive effect of sleep extension and negative effect of sleep restriction on neuromuscular performance. In the first of these studies, the group observed a significant improvement in basketball specific (282 foot) sprint performance (16.20 ± 0.61 seconds *vs* 15.50 ± 0.54 seconds, $p < 0.001$) when sleep time was extended from 7.8 ± 1.1 hours to 10.4 ± 1.1 hours (Mah et al., 2011). This research has recently been extended to show that maximal CMJ height is significantly reduced (44 ± 9 cm *vs* 42 ± 10 cm, p = 0.02, hedges g ES = 0.21) following three days of sleep restriction (4.0 ± 0.2 hours *vs* 7.4 ± 0.5 hours) in adult male cyclists (Mah et al., 2019). Although neither study considered the influence of day to day deviations in sleep, they do indicate that fluctuations in sleep may affect neuromuscular performance. Consequently, there is merit in conducting a study which evaluates whether day to day fluctuations in sleep affect CMJ height, thus providing further information as to its suitability within athlete monitoring cycle.

2.8.2 Practical considerations when measuring preparedness to play in youth athletes

As has been suggested throughout the selection of measures for use within the integrated athlete monitoring cycle, it is important to consider the time and monetary cost of the preparedness to play measures used (Bergeron et al., 2015; Saw et al., 2017). In this situation, the monetary cost of the equipment is likely to be the most important factor. Previous studies have used force plates (Roe, Darrall-Jones, Till & Jones., 2016; Rowell et al., 2017), Optojump (Malone et al., 2015) and jump mats (Oliver et al., 2015; Thorpe et al., 2015). Based on approximate costings, it is likely that a force plate would prove too expensive for most school sport scholarship schemes, but the purchase of an Optojump or jump mat could potentially be justified. Of these two pieces of equipment, the flexibility of the Optojump to evaluate a wider variety of jump related measures should they be required for performance rather than monitoring purposes would make it a more flexible purchase on a limited budget. Consequently, it will be used to evaluated CMJ height as a preparedness to play measure in this thesis.

Despite the widespread use of CMJ performance as a preparedness to play measure in the athlete monitoring cycle (Taylor et al., 2012), the evidence supporting its use in the cycle is weak. Of the three studies directly considering the relationship between CMJ performance and training load, only one observed the negative association that could be expected based on traditional fitness-fatigue training models (Banister, 1991; Rowell et al., 2017). It is possible that this is due to the statistical model considered in one of the studies (Malone et al., 2015), but a lack of control for the recovery experienced by the athletes could also be a factor given both sleep extension and sleep restriction have been shown to influence CMJ height (Mah et al., 2011; 2019). Consequently, by accounting for both the training dose (via training load) and training recovery (via sleep), it may be

possible to establish the appropriateness of using CMJ within the athlete monitoring cycle conclusively.

Alongside these uncertainties regarding the relationship between training load, sleep and CMJ performance, there is limited research within youth athletes (Malone et al., 2015; Oliver et al., 2015; Roe, Darrall-Jones, Till & Jones., 2016). Despite this, both Oliver and colleagues (2015) and Roe and colleagues (2016) identified CMJ as a potential marker of accumulated fatigue indicating that it is worthy of further research. By re-evaluating the relationship between CMJ and training load/sleep using a similar statistical model to Rowell and colleagues (2017), it is possible that the changes previously shown in adult soccer players may be replicated in a youth athlete population.

With regards to the key aim within this thesis of predicting the adverse outcome of illness, there is no research evaluating the efficacy of CMJ as a predictor. This is perhaps unsurprising given that until recently there was no obvious link between changes in neuromuscular performance and illness risk. However, the negative influence of psychological stress on physical performance has recently been identified (see section 2.2.3; Stults-Kolehmainen et al., 2014) and potentially provides an avenue by which CMJ may be able to help predict illness. Although Stults-Kolehmainen and colleagues (2014) identified no obvious difference in the recovery profiles of squat jump height between low and high stress groups, the low stress group's pre-protocol squat jump height was much greater than the high stress group (45.6 ± 11.9 cm *vs* 41.7 ± 12.1 cm). It is possible that these differences in squat jump height are influenced by underlying stress levels, either from a neuromuscular or motivation perspective. Consequently, within the athlete monitoring cycle, CMJ height falling below the level expected may be a sign that life stressors are shifting the stress-recovery balance of the athlete and they may be at risk of illness. Future research may therefore wish to evaluate changes in CMJ alongside

changes in subjective wellness questionnaires in response to the training process to evaluate illness risk.

2.9 Statistical considerations

A central theme of this literature review has been to highlight statistical anomalies in the literature with reference to measures of the training dose and response present within the athlete monitoring cycle. The anomalies identified include the poor reliability of subjective wellness measures (section 2.7.2.1.1), potentially suboptimal statistical approaches to the analysis of CMJ data (section 2.8.1.1) and question marks surrounding the true predictive ability of s-IgA with regards to illness incidence (section 2.7.1.2). The aim of this section is to provide further detail with regards to these concerns and identify how this thesis will overcome them.

2.9.1 Reliability and usefulness of athlete monitoring cycle measures

In order to be confident that changes in a test's performance are "real" and not due to its daily variation, it is important to quantify the variation in performance that can be expected between two completions. This is termed the between-day reliability and is given by calculating the typical error (TE) as a coefficient of variation (CV; Hopkins, 2000). Good between-day reliability refers to a protocol which has acceptably small variation between test completions, and is usually assessed against the arbitrary threshold of 5-10% CV (Cormack et al., 2008; Roe, Darrall-Jones, Till, Phibbs, et al., 2016). However, alongside good between-day reliability, it is important that the test is sensitive enough to detect its smallest worthwhile change (SWC). This has been termed its "usefulness" and is assessed by converting the TE into a factor of the SWC and comparing the ratio between the two variables (Hopkins, 2000). If the TE:SWC ratio is less than 1 (i.e. the SWC is greater than the TE), the test is considered to have good usefulness. However, if the TE:SWC ratio is greater than 1 (i.e. the SWC is less than TE), the test's usefulness is said

to be marginal (Hopkins, 2004). This understanding of the reliability and usefulness of the test can then be used to assess its ability to detect real changes in performance over a specified time period. In this thesis the wellness/fatigue and preparedness to play measures could be considered daily tests completed by the athletes. It is therefore important that their reliability and usefulness is calculated so it can be accounted for within future decision-making processes.

Of the training response measures identified as useful and cost-effective for daily use in school sports scholarship schemes within this literature review, subjective wellness questionnaires, incorporating measures such as mood, stress and fatigue, have received the most attention within the literature (Gastin et al., 2013; Roe, Darrall-Jones, Till, Phibbs et al., 2016; Thorpe et al., 2015). The published TE of these questionnaires varies dependent on the sport involved, ranging from 7.1% to 24.1% in rugby union (7.1%; Roe, Darrall-Jones, Till, Phibbs et al., 2016), Australian Rules football (24.1%; Gastin et al., 2013) and soccer (9-13%; Thorpe et al., 2015), which is understandable given the unique demands of each sport. However, although there is a body of research considering the reliability within individual sports, no study has considered the TE of these wellness questionnaires in youth sport athletes from a variety of sports. Furthermore, only Roe and colleagues (2016) have considered the usefulness of these questionnaires, concluding that they have marginal usefulness in adolescent rugby union players. The addition of this information in youth athletes from a variety of sports could be valuable for school sports scholarship schemes and collegiate/university programmes where coaches may wish to monitor all athletes with one wellness questionnaire to save processing time rather than individualising it for each sport (Murray, 2017; Saw et al., 2017; Taylor et al., 2016). In contrast to these global wellness questionnaires, there is no published literature surrounding the between-day reliability and usefulness of the PRS, which is likely due to its validation only taking place in laboratory settings so far (Laurent et al., 2011; Sikorski et al., 2013). It is therefore important that the between-day reliability and usefulness of the

PRS in youth athletes across multiple sports is evaluated prior to assessing its relationship with measures of the training dose and recovery experienced by athletes.

The reliability and usefulness of CMJs have been considered extensively using force plate based methods (Cormack et al., 2008; Roe, Darrall-Jones, Till, Phibbs et al., 2016). For example, TE's ranging from 5.2 to 6.8% have been reported for jump height and from 2.9 to 3.6% for flight time (Cormack et al., 2008; McLean et al., 2010; Roe, Darrall-Jones, Till, Phibbs et al., 2016). However, force plates are relatively expensive and the research surrounding the less expensive Optojump system is limited (Glatthorn et al., 2011). In their study, Glatthorn and colleagues (2011) evaluated the TE for jump height as measured by the Optojump system to be 2.2%. However, this study took place in a group of older, less well-trained individuals and so it is important to confirm the reliability and usefulness of CMJ as measured by the Optojump system in youth athletes across multiple sports.

2.9.2 Practically interpretable statistical analyses

Within sports science research, the use of *p*-values (and more recently magnitude based inferences) alongside ES or correlation coefficients to analyse data statistically is well established. Within the athlete monitoring literature, this is best shown by the research considering the influence of sleep on wellness, which utilised correlation coefficients and *p*-values (Lastella et al., 2014; Oginska & Pokorski, 2006; Pilcher et al., 1997), but is also prevalent within the training load and wellness research as Buchheit and colleagues (2013) analysed their data using correlation coefficients and magnitude based inferences. The use of these standardised ES at a group mean level is undoubtedly important so that researchers can make comparisons between studies in the literature, however within the athlete monitoring cycle, which is based on an individual's needs, a standardised ES is of little benefit to practitioners.

In recent years, as researchers have become more skilled at interpreting the raw coefficients of statistical models, it has become more common to provide percentage or unit changes in addition to standardised ES within athlete monitoring research. For example, Thorpe and colleagues' (2015) analysis using partial correlations identified a large negative relationship between high-speed running and a fatigue wellness measure (r = -0.51 ± 0.11). Alongside this, the coefficients from the model indicated that an increase in high-speed running of 400 metres was required for a one unit reduction in the measure. By providing this data, practitioners can consider the likelihood of a 400 metre increase in high-speed running occurring and plan for when an increase in fatigue may occur. Similarly, when using linear mixed models for their analysis, Rowell and colleagues (2017) provided the percentage differences in CMJ height that could be expected by the medium (-12 ± 11%) and high (-18 ± 11%) training load groups relative to the low training load group, alongside the moderate and large ES reported. These results again allowed practitioners to obtain a real world understanding of the changes expected for usage within the athlete monitoring cycle.

Despite the benefits of the statistical models employed by Thorpe *et al.* (2015) and Rowell and colleagues (2017), a more useful and flexible method has been considered within the literature (Montgomery & Hopkins, 2013). Montgomery and Hopkins (2013) utilised the same linear mixed model procedure as Rowell and colleagues (2017), but considered the influence of training load as a continuous covariate rather than discretely grouping it into low, medium and high groups. By standardising the training load to two within participant standard deviations, the authors were able to establish a 'clear and small' effect of s-RPE training load on muscle soreness in elite adult Australian Rules football players, which equated to approximately 0.41 units of the scale. This method is particularly exciting because it allows for an individual's variation in training load to be accounted for within the athlete monitoring cycle. For example, a two standard deviation change in training load for athlete 1 may be equivalent to 250 AU, whereas for athlete 2 the figure could be double,

or even treble that of athlete 1. By establishing the observed change in training load as a fraction of a two standard deviation change, it would then be possible to calculate the expected change in soreness at an individual athlete level so this can be compared to the observed result.

It is this consideration of the expected change in wellness in response to training load and sleep measures that could provide the key to understanding when illness incidences may occur. Recall from Figure 2.2 that performance capacity/wellness is expected to fluctuate negatively in response to training load, before returning to a positive state following appropriate recovery. Within current statistical models, these changes must be included and treated equally to establish whether, for example, low wellness scores are related to increased risk of illness. However, if it is known that the individual was subjected to a high training load the day before a low wellness score, this negative training response (i.e. the low wellness score) could be identified as an expected change and, provided appropriate recovery is provided, should not result in illness incidence. By including the low wellness score blindly (i.e. disregarding the fact that it was expected and would likely not be acted upon in practice), the predictive accuracy of the model would be unrealistically reduced. Using Montgomery and Hopkins' (2013) analysis it should be possible to establish the change in training response measures expected at an individual level in following variations in the training load and sleep experienced by the athlete. Subsequently, any unexpected changes (e.g. wellness scores above or below the expected score ± the TE of the measure) can be highlighted and evaluated as predictors of illness incidence. However, as Montgomery and Hopkins (2013) method has only been used within single scale questionnaires, it will be important to confirm relationships between measures of the athlete monitoring cycle exist using the analysis of Thorpe *et al.* (2015) and Rowell and colleagues (2017) before progressing to this more practically interpretable statistical analysis.

2.9.3 Prediction vs association

When analysing a dataset and interpreting its results, practitioners attempt to achieve one of two key goals:

- To identify the association between the inputs (or independent variables) and outputs (or dependent variables) of a model;
- To predict outputs using a model based on a set of inputs

The statistical analysis described within this section so far has focussed on identifying the association between the inputs and outputs of a model. Associations between variables are analysed using a data modelling or correlation-based approach (e.g. via linear mixed models or regressions). This form of analysis is optimised to maximise how well the model fits the dataset given, which enables the relationship between the variables to be evaluated (Breiman, 2001b). However, it does not assess the model against previously unseen data and is therefore unable to establish the true predictive ability of a set of model inputs. It is possible to use the coefficients from these correlation-based approaches to predict future events, but in order to understand the true predictive ability of a set of inputs, it may be more beneficial to shift to a machine learning or prediction-based approach (e.g. via decision trees or random forests). Prediction-based approaches are optimised by evaluating the predictive accuracy of the model on unseen data (Breiman, 2001b). This method of optimisation allows the overall predictive ability of the model and the importance of each individual input to this predictive ability to be evaluated.

The importance of this switch from correlation-based approaches, which can be used to predict future events, to prediction-based approaches, which are optimised against these unseen future events, within athlete monitoring has recently been highlighted by the debate surrounding the acute:chronic workload ratio (ACWR) as a method of predicting

soft tissue injury incidence (Fanchini et al., 2018; Hulin et al., 2016; Williams et al., 2016). The ACWR received significant interest after it was claimed that the ratio could 'predict' non-contact soft tissue injuries (Hulin et al., 2016). Numerous follow up studies adopting a similar correlation-based approach (Hulin et al., 2016; Malone et al., 2018; Murray et al., 2017) confirmed this conclusion, and several opinion pieces were published depicting how the method could be used in practice (Blanch & Gabbett, 2016; Gabbett, 2016; Gabbett et al., 2017). Despite this body of correlation-based evidence supporting the 'predictive' capabilities of the ACWR with regards to soft tissue injury incidence, two follow up studies using machine learning approaches against data previously unseen by the model found the true predictive ability of the AWCR to be poor (Fanchini et al., 2018; McCall et al., 2018). It has subsequently been accepted that given the correlation-based analysis employed, the ACWR should have been described as a risk factor for, rather than a predictor of, non-contact soft tissue injuries (Hulin & Gabbett, 2019).

An understanding of the differentiation between data modelling or correlation-based and machine learning or prediction-based approaches is important in this thesis for the same reasons as the ACWR debate. Section 2.7.1.2 identified the correlation-based research, showing relationships between changes in s-IgA measures and illness incidence (Fahlman & Engels, 2005; Neville et al., 2008). However, the true predictive ability of these relationships was questioned as they were not evaluated using prediction-based approaches. Consequently, the studies within this thesis attempting to identify the true predictive ability of variables (e.g. between s-IgA or wellness measures and illness incidence) will use predication-based machine learning approaches validated on data previously unseen by the model rather than traditional correlation-based approaches.

2.10 Summary

In summary, this literature review has highlighted the importance of the athlete monitoring cycle to researchers and practitioners working in applied sport environments. The athlete monitoring cycle is used to establish an athlete's position along the supercompensation curve, which is important to ensure appropriate load and recovery is applied. However, despite the importance of recovery to this position along the supercompensation curve, it is not usually considered within the athlete monitoring cycle (Gabbett et al., 2017). Consequently, it is possible that an integrated athlete monitoring cycle incorporating an athlete's training recovery (Figure 2.5) would be a more appropriate model to use, but researchers are yet to consider this model within the literature.

Without appropriate load and recovery, performance will be reduced and there is an increased risk of adverse outcomes to the training process. Perhaps the most under researched adverse outcome within youth sport is illness. Illness is particularly interesting within youth sport and school sports scholarship schemes because both physical and psychological stressors affect the immune system by the same HPA axis. As youth athletes will not fully develop their stress coping skills until adulthood and are subjected to a unique set of academic, maturational and social stressors (particularly within the school sports scholarship scheme environment), it is possible that the underlying life stress levels they experience will widely vary. However, this is not usually considered within athlete monitoring models.

To date, relationships between measures of the athlete monitoring cycle have been limited to correlations between the training dose (i.e. the training load) and the training response (i.e. fatigue/wellness measures and preparedness to play measures). Such an approach is limited because it does not account for the varying levels of recovery experienced by different athletes. The athlete monitoring cycle literature is further limited

with regards to this thesis as the majority has taken place within adult athletes. It is possible that part of this lack of literature in youth athletes is due to the time or monetary cost of the equipment that can be used (e.g. GPS devices) so it would be prudent to focus on those measures which are more easily affordable. Consequently, in line with the proposed integrated athlete monitoring cycle, the s-RPE training load method will be considered as a measure of the training dose, self-reported sleep measures will be considered as the training recovery, subjective wellness questionnaires used as fatigue/wellness measures, and CMJ height will be utilised as preparedness to play measures.

The use of mainly subjective measures may provide an additional advantage within the prediction of illness incidence because an individual's cognitive appraisal of their current situation influences how their HPA axis responds to psychological stressors. For example, despite experiencing the same external levels of stress, an athlete who perceives they are stressed will experience a more negative immune response than one who does not believe they are stressed (Gunnar & Quevedo, 2007). Consequently, when evaluating the ability of the integrated athlete monitoring cycle measures to predict illness incidence, the objective immune measure of s-IgA will also be considered.

By evaluating the relationships between the training dose, recovery and response, it will be possible to calculate the expected change in training response measures when the training dose and recovery experienced by an athlete fluctuates, but their underlying life stress remains consistent. If the reliability of the training response measure is accounted for, a range of values that an athlete could be expected to provide can be calculated. It is possible that any values below this expected range could indicate that an athlete's life stress has increased and is negatively affecting the athlete's response to training, potentially placing them at greater risk of illness incidence. However, an integrated athlete monitoring cycle model of this type has not yet been considered by researchers.

In order to create this integrated athlete monitoring cycle model and truly understand its predictive ability with regards to illness incidence, a different statistical approach will be required. Within the literature review, limitations within current statistical approaches were discussed, included the practical application of findings and the incorrect lauding of measures as ‘predictive’. This thesis will aim to fill these gaps in the literature by providing practical interpretable relationships between the training dose, recovery and response measures. Subsequently, the relationships identified between the measures within the integrated athlete monitoring cycle will be used to evaluate its true predictive ability with regards to illness incidence in youth athletes using a machine learning based approach.

Chapter 3 General Methods

3.1 Introduction

This chapter will provide an overview of the commonly used methods and concepts within this thesis. Firstly, it will provide an overview of the studies completed. Secondly, details regarding the institution from which the participants were recruited, the method of participant recruitment and the procedures involved in the collection of data for the integrated athlete monitoring cycle will be provided. Finally, the statistical analyses aimed at providing more practically interpretable results than currently present within the literature will be outlined. The methodologies specific to individual studies will be outlined in the relevant chapters.

3.2 Overview of studies

Five studies were completed in this thesis. Each progressed from the findings of the previous study to move towards the end goal of evaluating the true predictive ability of an integrated athlete monitoring cycle with regards to illness incidence in youth athletes. The studies contributed to the end goal in three distinct ways. Study 1 (Chapter 4) detailed the reliability of the fatigue/wellness and preparedness to play measures used within this thesis. These values were intended for use within study 5, where they could help provide a range of values an athlete would be expected to provide based on their individual circumstances. Studies 2-4 (chapters 5-7) identified the most appropriate training response measures to use within the integrated athlete monitoring cycle in youth athletes and evaluated their relationship with the training dose and recovery experienced by the athlete. Finally, it was hoped that study 5 (chapter 8) would evaluate the true predictive ability of the integrated athlete monitoring cycle model with regards to illness incidence in youth athletes. Unfortunately, due to technical issues with the web-based application outside of the author's control (see section 3.4), it was not possible to achieve this aim. Consequently, a fully worked example of the integratedathlete monitoring cycle model is provided within the future directions section of the summary discussion (section 9.9). In

place of its original aim, the statistical analysis of study 5 was modified to understand the true predictive ability and relative importance of s-IgA measures with regards to illness incidence, and to outline the longitudinal change in objective and subjective fatigue/wellness measures over an academic year in youth athletes.

Accounting for this change in study 5's aim, Table 3.1 provides a broad outline of the aims, participants recruited, research design and data collected for each study. Prior to commencing data collection for each study, ethical approval was received from the university ethics committee. All ethical applications are provided in Appendix 1. Data collection started in February 2015 and was completed in May 2017.

Table 3.1: Overview of studies within this thesis.

Study title	Aims	Participants	Research Design	Data collected
Between-day reliability and usefulness of fatigue/wellness and preparedness to play measures in youth athletes	Evaluate the between-day reliability and usefulness of fatigue/wellness and preparedness to play measures in youth athletes across multiple sports	52 youth athletes	Within-participant between-day reliability study	Wellness questionnaire and CMJ on two occasions separated by 5-7 days.
Establishing the relationships between measures of the integrated athlete monitoring cycle in youth athletes using previously employed statistical analyses	Evaluate the relationships between measures of the integrated athlete monitoring cycle in youth athletes using statistical analyses previously employed in elite adult sport studies	52 youth athletes	7-week observational prospective cohort study	Wellness questionnaire and maximal CMJ performance collected four days per week.
Analysing the relationships between measures of the integrated athlete monitoring cycle in youth athletes using more practically interpretable statistics	Evaluate the relationships between measures of the integrated athlete monitoring cycle in youth athletes using statistical analyses providing more practically interpretable results	48 youth athletes	13-week observational prospective cohort study	Wellness questionnaire collected every day.
Exploring the use of sleep as a measure of training recovery within the integrated athlete monitoring cycle	Evaluate the use of different sleep indices as measures of training recovery within the integrated athlete monitoring cycle	48 youth athletes	13-week observational prospective cohort study	Wellness questionnaire collected every day.
Understanding the link between objective and subjective, fatigue/wellness measures and illness incidence in youth athletes	Calculate the true predictive ability and relative importance of s-IgA measures with regards to illness incidence in youth athletes Outline the longitudinal changes in objective and subjective fatigue/wellness measures over an academic year in youth athletes	23 youth athletes	36-week observational prospective cohort study	Wellness questionnaire collected every day, s-IgA concentration and secretion rate collected on 15 occasions over the duration of the study separated by 2-4 weeks.

N.B.: PRS = Perceived Recovery Status scale, CMJ = countermovement jump

3.3 Participant recruitment

3.3.1 Institution

All studies within this thesis took place at the same institution, a local independent school in the UK. The school educates children and youths aged 4-18 years and typically employs a 33-week academic year, which is split into 6 terms. Terms 1 and 2 take place before Christmas; terms 3 and 4 typically occur between Christmas and Easter; and terms 5 and 6 are placed after Easter. Each of these term pairings is split by a one-week half term break, but the break between terms 2-3 (Christmas) and 4-5 (Easter) is longer, ranging from 2-4 weeks. Due to the structure of the academic sporting year, with academic examinations taking prominence in term 6 (described below), only terms 1 to 5 were used in this thesis.

As outlined in the introduction (section 1.1.1), the institution is one of thousands of independent schools within the UK and across the world, who have a sports scholarship scheme to help provide them with an identity and marketing materials outside of their academic achievements (Radtke & Coalter, 2007). The scholarships are given to talented athletes aged 16-18 years and waive some or all of the tuition fees that would normally be paid for academic tuition at the school. At this school, athletes in the sports athletics, basketball, cricket, football, hockey, netball, rugby and swimming are eligible for scholarships.

3.3.2 Participant's schedules

As part of their scholarships, students are expected to participate in their sport for the school over the course of the academic year. Typically, a student would be expected to participate in two technical training sessions, two strength and conditioning sessions and one match per week at school. This schedule is generally expected in terms 1-5 dependent on the sport's progress in team competitions. In addition to this, many students

play their sport at club, academy, county or national level outside of school, which can result in the students experiencing a high training load alongside their 8.30am to 4pm full time school commitments (Phibbs et al., 2018). The differences in these training loads between representative (e.g. academy, county or national level) and non-representative (e.g. club or school level) was identified alongside this thesis by Scantlebury and colleagues (2019). In this study, it was clear that representative athletes completed considerably more load outside school, particularly in term 3 (ES = 0.75-0.78), than non-representative athletes. This increased load was also present in terms 2 (ES = 0.36-0.43) and 4 (ES = 0.44-0.63), providing significant scope for additional stress to be placed on these athletes, either through the training dose itself, through reduced training recovery or through increased life stress as participants may have fallen behind with their academic studies due to the high training doses experienced.

Over the duration of the academic year, there are multiple coursework deadlines and examinations. However, three time periods could be considered most stressful from an academic perspective: the second week back after the Christmas break (mock exam week); the final two weeks before Easter (final coursework deadlines); and the whole of term 6 (final academic examinations). Although adhering to any of these coursework and examination deadlines can be difficult given the length of the school day and the sporting endeavours most students pursue following the school day, the final coursework deadline weeks can be particularly stressful as they usually fall at a similar time to the finals of cup competitions. Given the integrated athlete monitoring cycle's inclusion of life stress as a moderating factor within an athlete's response to training, it would have been beneficial to include term 6 within the analyses. Unfortunately, this was not possible due the competitive season ending prior to this term and participant's being provided study leave by the school to focus on their academic examinations.

3.3.3 Recruitment of participants

Over the duration of this thesis, 65 participants were recruited from the local independent school described above. The participants were part of the school's sports scholarship scheme and aged 16-18 years. All sports, except athletics, were represented in this thesis. Initially, the director of sport was contacted to discuss the proposed research projects. Following his consent, the lead coach for each individual sport and the school's sports facilities manager (as gate keepers for the school's athletes and facilities respectively) were contacted and their consent for the study was obtained. Finally, students on the sport scholarship scheme were approached to ascertain their willingness to participate in the research. Prior to data collection, potential participants were made aware of the risks and benefits of partaking in the study and provided written informed consent (examples of all participant information sheets and consent forms are provided in Appendix 2).

3.4 Collection of integrated athlete monitoring cycle data

All five studies within this thesis collect data related to the integrated athlete monitoring cycle proposed in Figure 1.2. Data collection occurred over two academic years and involved the use of a Google Drive spreadsheet (Google Forms, Google, CA, USA) in year one, and a custom-built web application (Sports-train, Nice, France) in year two. Screenshots of the questionnaires as seen by the participants are provided in Appendix 3. Unfortunately, the custom-built web application used to collect data in year two proved to be unreliable with regards to training loads, resulting in a vast amount of missing data, which resulted in the aim of study 5 being changed as described in section 3.2.

3.4.1 Integrated athlete monitoring cycle questionnaire

Participants provided details on their self-reported training dose, recovery and response using a single questionnaire. The questionnaire was completed before 11am every day, prior to the participant's first training session. The online nature of the questionnaire allowed participants to complete it in isolation, and if a participant had not completed the questionnaire by 10.30am on weekdays, they were verbally reminded. However, it was not possible to provide verbal reminders on weekends.

As part of their usual athlete monitoring programme, all participants were familiar to the questionnaire prior to the studies taking place. This familiarisation involved a three month period, where participants filled out the questionnaire and were able to ask any questions with regards to how they should respond. This time period also allowed the researchers to question any responses with the individual participants to ensure their understanding. In addition to this, in both years, a one hour familiarisation session was provided with regards to the technology used. This occurred on a sport by sport basis to maximise that participant's comfort with the technology and covered the Google Drive system in year one and the Sports-train system in year two.

3.4.1.1 Training dose

Participants provided details regarding the previous day's training dose via the s-RPE method. Three questions were asked for each individual session a participant reported. These questions outlined the type of training session (e.g. school – technical training, school – strength and conditioning, club – match, other), the duration of the session (in minutes), and its intensity (as an RPE measured via the Borg category-ratio 10 scale (Foster et al., 2001)). The chosen RPE descriptor was converted to its numerical equivalent and multiplied by the session duration to provide the s-RPE (Foster et al., 2001). In total, a participant could report four sessions per day, which were summated to

provide the daily load. The use of the s-RPE method in this manner has twice been validated in youth sport cohorts (Phibbs et al., 2017; Scantlebury et al., 2018).

3.4.1.2 Training recovery

As a measure of the training recovery experienced by the athlete, participants were asked to record their sleep duration for the previous night, in hours, via the estimated time in bed method adapted from Cohen and colleagues (2009). More specifically, the sleep duration question was termed: *"In hours, how much sleep did you get last night, based on the time you last turned off the lights and started trying to sleep, to the time you got out of bed this morning?".* The use of self-reported sleep has previously been validated against actigraphy in athletic populations (Caia et al., 2018; Kölling et al., 2016). Without access to actigraphy or polysomnography, it was not possible to confirm this validation in this cohort as part of this thesis.

3.4.1.3 Training response

The questionnaire also included two subjective fatigue/wellness questionnaires to measure the athlete's training response on the day of completion. The first of these was McLean and colleagues' (2010) previously published wellness questionnaire (DWB). The DWB has been used within the literature on multiple occasions (Buchheit et al., 2013; Gallo et al., 2017; McLean et al., 2012) and provides an example of a practitioner developed fatigue/wellness questionnaire. The questionnaire asks participants to describe their fatigue, muscle soreness, sleep quality, stress and mood and converts the responses to a 1-5 scoring system. The score from all five subscales is added to provide the overall DWB score. Alongside DWB, the PRS was included as a fatigue/wellness questionnaire developed within a laboratory setting (Laurent et al., 2011). The PRS is a single 0-10 scale allowing a participant to provide details on their perceptions of recovery.

3.4.1.4 Illness incidence

Finally, participants were asked to state whether they believed they were suffering from illness or injury. For illness data, they were asked to state the duration they believed they had been suffering and for injury data, they were asked to provide a short, written description of the ailment.

3.5 Statistical considerations

This section will outline the key statistical considerations within this thesis. Firstly, the analysis of repeated measures data will be considered. This section will highlight the value of linear mixed models when analysing this type of data and will show how they can be used to provide practically interpretable results. Following this, null hypothesis significance testing (NHST) and magnitude-based inferences (MBI) will be discussed as methods of providing statistical interpretation of the results. Finally, the statistical power of the studies will be considered.

3.5.1 Analysis of repeated measures data

Before analysing any dataset, it is important that the key assumptions of the test to be utilised are met or appropriately accounted for. These assumptions are used to produce the residual (error) variance, which in turn provides the basis from which the results are interpreted statistically. Using traditional statistical analysis methods, the datasets within this thesis would be obliged to adhere to three key assumptions: normality of residuals; a linear relationship between independent and dependent variables; and independence between data points. For the models in chapters 5-8, the data analysed satisfied the first two assumptions. The assumption of residual normality was assessed using the Shapiro-Wilks test. Using raw data, the dependent variables in chapters 5-8 were not normally distributed and so log transformation (in the case of CMJ and s-IgA measures) or percentage conversion (DWB and PRS) were undertaken to ensure normality and non-

uniformity of error (Hopkins, Marshall, Batterham, & Hanin, 2009). The impact of these transformations was evaluated via visual inspection of the Q-Q plots. It should be noted that although percentage conversion ensured normality of residuals within this thesis, this is due to a large number of the dependent variables falling between 20 and 80%. In other studies, where there is a wider spread of percentages (i.e. 0-100%), this will result in a sigmoidal relationship, which would be better analysed using other statistical methods, such as generalised linear mixed models with a beta distribution. A linear relationship between independent and dependent variables was also assumed as it is logical that a greater training dose or reduced training recovery would result in lower training response scores the following day.

The assumption of independence is more difficult to satisfy given the longitudinal analysis employed within this thesis. The assumption of independence dictates that there should be no connection between the data points within the dataset. However, within athlete monitoring data, multiple measures are obtained from each participant resulting in a clear connection between each participant's data points. This connection violates the assumption of independence, which vastly inflates the regularity of significant results from an expected frequency of 5% to occur with as much as 75% regularity (Scariano & Davenport, 1987). Consequently, two methods have been developed to analyse longitudinal data without violating the assumption of independence: repeated measures analysis of variance (ANOVA) and linear mixed models.

The differing approaches between the two models, and their suitability for the longitudinal analysis conducted within thesis, are described below. For ease of understanding, the methods will be evaluated alongside an applied example. In this hypothetical example, imagine a longitudinal study was conducted assessing the influence of resistance training on maximal strength, measured via the isometric mid-thigh pull (IMTP). Ten athletes were split into two groups (HIGH and LOW), based on the amount of resistance training they

performed each week. HIGH completed three resistance training sessions per week, LOW completed one resistance training session per week. The athletes were tested for their maximal strength every month for a period of six months, resulting in a total of six measures recorded for each participant. We will use the terms “GROUP” to distinguish between the HIGH and LOW resistance training participants and the term “TIME” to identify the test month (1-6). Table 3.2 outlines the strength progression of the participants over the six-month testing period.

Table 3.2: Strength testing data for ten participants completing the IMTP (kg) on six occasions over a six month testing period.

		TIME					
Participant	**GROUP**	**1**	**2**	**3**	**4**	**5**	**6**
1	LOW	120	133	135	133	140	137
2	LOW	121	126	127	121	120	125
3	LOW	118	113	118	120	113	110
4	LOW	119	122	127	120	130	135
5	LOW	122	128	120	130	129	130
6	HIGH	122	135	150	160	170	185
7	HIGH	120	145	140	150	165	180
8	HIGH	119	147	152	155	160	175
9	HIGH	118	135	140	150	155	160
10	HIGH	122	138	141	145	150	155
Average	LOW	120	124.4	125.4	124.8	126.4	127.4
Average	HIGH	120.2	140	144.6	152	160	171

N.B.: HIGH = high frequency resistance training group; LOW = low frequency resistance training group.

3.5.1.1 Repeated Measures ANOVA

A repeated measures ANOVA is an extension of the traditional ANOVA approach, in which TIME is added as a repeated measures within-subject factor and the assumption of sphericity is proposed. The assumption of sphericity states that the variance of the differences between all possible pairs of within-subject factors should be equal. In simple terms, this means that when the difference between all test pairs (e.g. test 1-test 2, test 1-test 3, test 2-test 3) is calculated, the variance in these change scores must always be

equal. Using tests 1, 2 and 3 from the applied example, Table 3.3 provides an example of the change score variance.

Table 3.3: Sample of the differences between test scores (change scores) for participants and the variances of the differences.

	Raw Score			Change Scores		
Participant	**1**	**2**	**3**	**2-1**	**3-1**	**3-2**
1	120	133	135	-13	-15	-2
2	121	126	127	-5	-6	-1
3	118	113	118	5	0	-5
4	119	122	127	-3	-8	-5
5	122	128	120	-6	2	8
6	122	135	150	-13	-28	-15
7	120	145	140	-25	-20	5
8	119	147	152	-28	-33	-5
9	118	135	140	-17	-22	-5
10	122	138	141	-16	-19	-3
Variance				102.5	136.3	38.8

Unfortunately, as shown in Table 3.3, the variances within the applied example are not equal, resulting in a violation of the assumption of sphericity. This is a common problem within athlete monitoring cycle data, where individual differences in the response to the training dose and recovery experienced by athletes will occur due to their differing physical characteristics and training histories. Furthermore, the sphericity of the data can only be calculated when the number of observations provided by each participant is equal. Consequently, if one participant (e.g. participant 4) missed one testing point (e.g. test 2), either all of participant 4's data or all of the test point 2 data would have to be removed

from the analysis. Similarly, if participant 4 missed test 2 and participant 7 missed test 3, either both participants or both test points would have to be removed from the analysis. Within longitudinal athlete monitoring studies where participants are required to provide data every day over multiple weeks, it is almost certain that certain participants will miss at least one time point (due to injury, illness or other reasons). This potential loss in statistical power, inability to calculate the sphericity of the data and lack of flexibility for individual responses renders the assumption of sphericity and, by extension, repeated measures ANOVA unsuitable for longitudinal analyses such as those conducted in chapters 5-8 of this thesis.

3.5.1.2 Linear Mixed Models

With a more flexible error structure, linear mixed models are much better equipped to analyse the longitudinal data present in this thesis. Linear mixed models use random effects to partition the residual variance into between-participant and within-participant components. This changes the method by which the residual variance is calculated relative to a repeated measures ANOVA and ensures that correlated measures can be appropriately accounted for. Furthermore, the correlated measures are accounted for using trend lines, so a complete set of observations is not required for linear mixed model analysis to take place.

Within statistical models, a coefficient can be estimated as either a fixed or a random effect. A fixed effect calculates the mean of a set of data, for example the GROUP fixed effect will establish the mean IMTP of the HIGH and LOW groups respectively. A random effect, however, estimates the variation from the mean, based on one or more separate cluster variables. For example, although the mean IMTP for the HIGH and LOW groups can be calculated via the GROUP fixed effect (from either a repeated measures ANOVA or a linear mixed model), this value is taken from six correlated observations from each participant within the study. If we add participant as a random effect, these measures can

be clustered together and a trend line for each participant can be drawn. The difference between these trend lines and the group mean line can be used to provide the between-participant variation, which provides an indication of the individual variation in IMTP strength gains with regards to the amount of resistance training completed per week.

When a single random effect is added to the model, it is a random intercept linear mixed model. A random intercept linear mixed model allows the intercept of the trend line (i.e. where it crosses the y-axis) to vary for each individual, but states that all individual trend lines must maintain the same gradient as the group mean trend line. This is appropriate in some situations, but in the applied example it fails to account for the different rates of strength improvement/decrement shown by the individual participants. It is therefore more accurate to consider a random slopes linear mixed model where the interaction between participant and a continuous covariate is used to evaluate the change in gradient between the participant's line and the group mean trend line. The use of this model within the applied example allows the analysis to account for the variation in strength improvements/decrements occurring between individuals over time.

It is important to note that each time a random effect is added, it results in a further partitioning of the residual term. Consequently, a repeated measures ANOVA contains one residual term (the residual variance), a random intercept mixed model has two residual terms (now partitioned into the between participant variance and the within participant variance), and a random slopes mixed model has three residual terms (the between participant variance, the between participant variance in the effect of the independent variable on the dependent variable, and the within participant variance).

3.5.1.3 An illustrative example

To provide a greater understanding of the difference between a repeated measures ANOVA, comprised solely of fixed effects, and a linear mixed model, which utilises both

fixed and random effects, this section will work through the applied example considering a repeated measures ANOVA and both types of linear mixed model. Figure 3.1 provides a visual representation of the data in Table 3.2. With such a large amount of data in one graph, it is difficult to assess the trend unique to each individual. Therefore, for the purposes of this section, only two participants from each group will be considered and magnified so these individual trends can be seen more clearly (Figure 3.2).

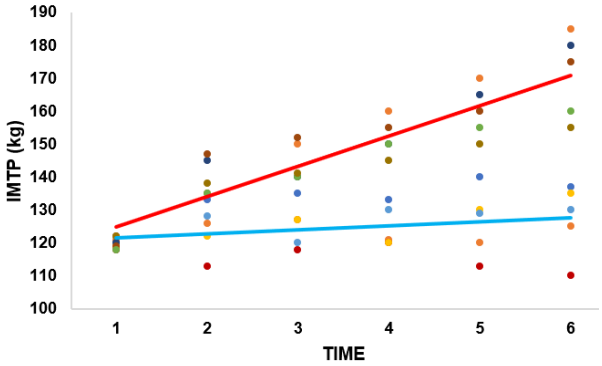


Figure 3.1: Visual representation of the data used for the worked analysis. The red line represents the group mean trend line for HIGH, the blue line is the group mean trend line for LOW. Data taken from Table 3.2.

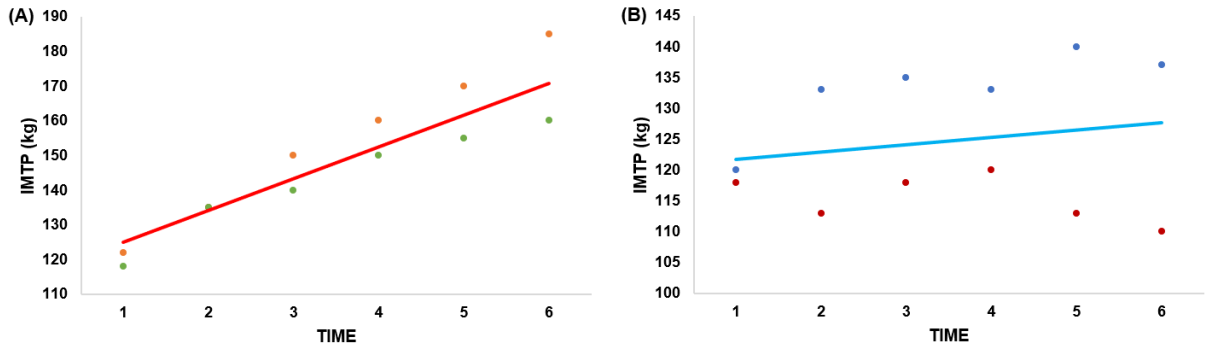


Figure 3.2: Visual representation of two participants from the HIGH resistance training group (A) and two participants from the LOW resistance training group (B). The red (HIGH) and blue (LOW) lines represent the group mean trend lines, coloured dots represent connected data points for individual participants.

A repeated measures ANOVA is a fixed effect only model. Fixed effects are used to calculate the mean of a set of data. For example, the fixed effect for GROUP provides the mean IMTP value for the HIGH and LOW groups respectively. As a consequence of the model assuming independence between data points, there is only one residual variance term. A repeated measures ANOVA could be fit to the applied example using Equation 3.1:

Equation 3.1: Formula for repeated measures ANOVA.

$$IMTP = \beta_0 Intercept + \beta_1 GROUP + \beta_2 TIME + \beta_3 GROUP * TIME + \varepsilon$$

Where β refers to the estimated coefficients, GROUP and TIME refer to the high/low training groups and the testing time point, and ε refers to the distance between each individual data point and the group trend line (i.e. the residual variance).

Within this model, the residual variance is calculated by assessing the distance from the individual point to the group mean line (Figure 3.3). However, it is clear in Figure 3.3 that there is a trend for one participant to respond better than the group mean and the other to respond worse than the group mean. It is therefore unreasonable to assume that all data

points are independent. Consequently, a model with an error structure capable of accounting for this correlation is required.

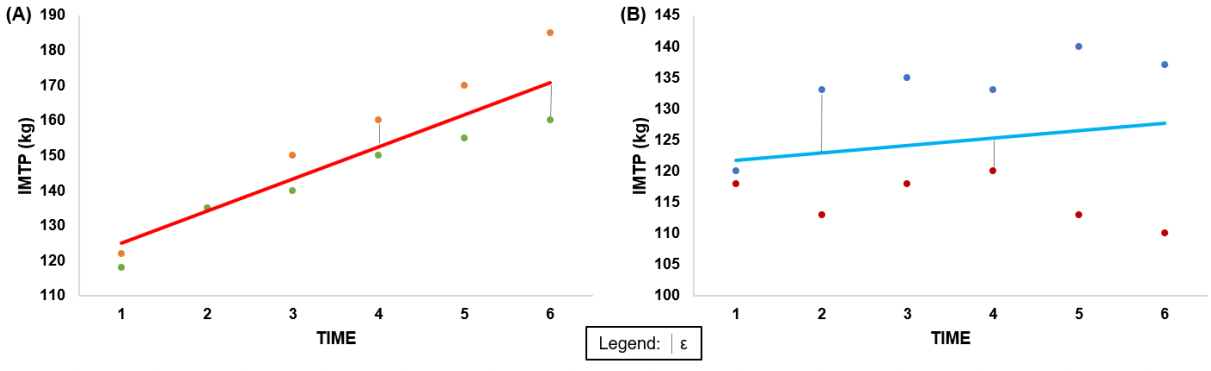


Figure 3.3: Visual representation of repeated measures ANOVA for the worked example.

Linear mixed models account for the correlation between participants' observations by partitioning the residual variance into between-participant and within-participant variance. This is achieved using random effects, which account for the correlation between observations by evaluating them as clusters. Unlike fixed effects, which identify the mean for a group, random effects consider the variation shown by the trendlines of the clusters. For example, the six repeated testing measures obtained for each participant in the example study will all be clustered around the participant in question, so participant can be added as a random effect. When added as a random effect, an individual trend line will be calculated for each athlete and compared to the group mean trend line (Figure 3.4 and Figure 3.5). The variation in the individual participants' line relative to the group trend line is evaluated as the between participant variance. Any other variance in the model is calculated as the within-participant variance.

The simpler of the two types of linear mixed models is the random intercept model. This model allows the intercept of the trend line to vary for each participant, on the condition that its gradient remains the same as the group mean trend line. The addition of this random effect necessitates the addition of a second error term to allow the partitioning of

the residual variance into the between- and within-participant variance. Equation 3.2 shows the subsequent formula for the random intercept linear mixed model.

Equation 3.2: Formula for random intercept linear mixed model.

$$IMTP = \beta_0 Intercept + \beta_1 GROUP + \beta_2 TIME + \beta_3 GROUP * TIME + u_i + \varepsilon_{ij}$$

Where β refers to the estimated coefficient, GROUP and TIME refer to the high/low training groups and the testing time point respectively, u_i refers to the distance between the individual trend line and the group trend line (i.e. the between participant variation in IMTP strength) and ε_{ij} refers to the distance between each individual data point and the individual's trend line (i.e. the within participant variation in IMTP strength).

Notice the subscripts i and j now follow the u and ε signals respectively (u_i and ε_{ij}). The 'i' refers to the participant in question and the 'j' refers to any individual data point. These terms are key as they allow the residual term to change according to the participant and data point considered, unlike a repeated measures ANOVA, where residual terms vary only by data point. Figure 3.4 shows the random intercept linear mixed model relevant to the example data. It provides a visual representation of the error terms. As a random intercept model, the u_i (between-participant variance in IMTP strength) is taken as the spread of individual trend lines, which must follow the same gradient as the group mean trend line. Conversely, the ε_{ij} (within-participant variance in IMTP strength) refers to the distance of each individual data point from the individual's specific trend line. Figure 3.4A shows that this is clearly a more suitable method of accounting for the clustering caused by repeated observations from the same participant. However, in Figure 3.4B both participants in the LOW training group are forced to fit unsuitable individual trend lines due to the restrictions imposed on them by the random intercept model.

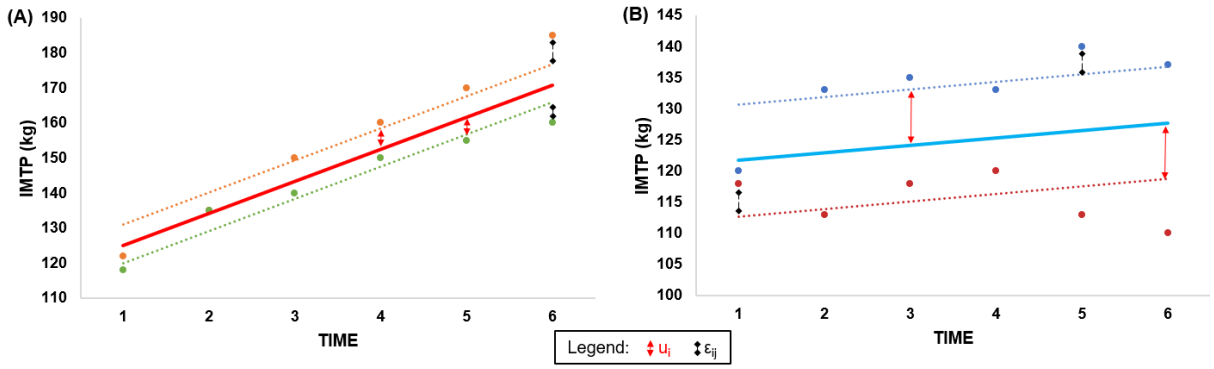


Figure 3.4: Visual representation of random intercept linear mixed model for the worked example

The poor fitting of the individual trend lines in the random intercept linear mixed model is caused by the gradient of the individual trend line remaining the same as the group mean trend line. To counteract this issue, it is possible to utilise a random slopes linear mixed model. A random slopes linear mixed model allows the gradient of each individual trend line to vary so that the best possible fit for each participant can be achieved. This is achieved by adding an interaction to the between-participant random effect, and thus adding a third error term. The resulting formula for the random slopes linear mixed model is shown in Equation 3.3.

Equation 3.3: Formula for random slopes linear mixed model.

$$IMTP = \beta_0 Intercept + \beta_1 Group + \beta_2 Time + \beta_3 Group * Time + u_{1i} + u_{2i} Time + \varepsilon_{ij}$$

Where β refers to the estimated coefficient, GROUP and TIME refer to the high/low training groups and the testing time point respectively, u_{1i} refers to the distance between the individual trend line and the group trend line (i.e. the between participant variation in IMTP strength), u_{2i}Time denotes the difference in slope between the individual best fit gradient and the mean best fit gradient for each unit of time (i.e. the between participant variation in the influence of time on IMTP strength), and ε_{ij} refers to the distance between each individual data point and the individual's trend line (i.e. the within participant variation

in IMTP strength). Note: TIME must be converted to a continuous covariate within the model to be used as an interaction term in this manner (see section 3.5.1.4).

Figure 3.5 provides a graphical representation of the individual trend lines and residual terms in a random slopes linear mixed model. By allowing the trend lines' gradients to vary between individuals they now fit much better than either the repeated measures ANOVA (Figure 3.3) or the random intercept linear mixed model (Figure 3.4). Consequently, the estimated coefficients will be more accurate than in the other models where the residual measure is much larger due to the poor fit of the model relative to the dataset.

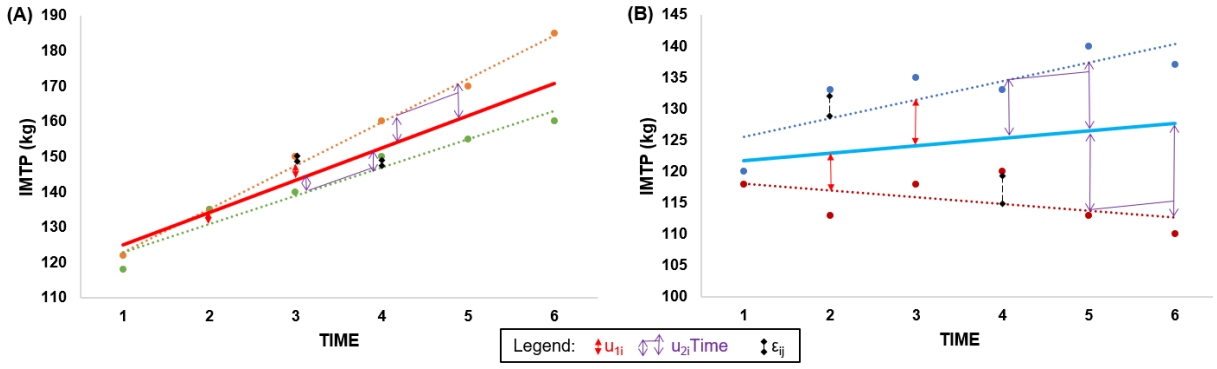


Figure 3.5: Visual representation of random slopes linear mixed model for the worked example.

3.5.1.4 Covariates within linear mixed models

When covariates are included within statistical analyses, they can be used as either control variables (e.g. it would have been possible to control for total volume load across each time point within this example) or as important independent variables (e.g. where the total volume load, rather than the time between tests is the more important variable). In this thesis, particularly in chapters 6 and 7, there is an emphasis on understanding the relationships the training dose and recovery hold with measures of the training response.

This section will show how the two covariates can be incorporated into the linear mixed models by using total volume load rather than TIME within the example.

Covariates are normally evaluated using correlation coefficients. Unfortunately, it is extremely difficult to obtain these values using linear mixed models with complicated random effects structures like those employed in this thesis (Roy, 2006). Furthermore, correlation coefficients provide little information with regards to how the relationship can be considered in practice. It is possible to circumvent this problem by converting the continuous variable into discrete categories (e.g. z-scores) and comparing them to each other in a similar manner to that indicated above with GROUP and TIME. This method has been used in chapter 5 and mimics the analysis previously conducted by Rowell and colleagues (2017), but still does not provide practically interpretable individualised data. In addition to this, it is not appropriate when attempting to model the relationship these variables may have with outcome measures (Carey et al., 2018).

In an attempt to provide more practically interpretable information, it has been suggested that covariates are analysed by evaluating the ES of a two standard deviation difference in the covariate (Hopkins et al., 2009). The authors argue that a two standard deviation difference maintains congruence with the usual Cohen's *d* ES thresholds and allows covariates to be assessed in a practically usable manner (Hopkins et al., 2009). In order to perform such an analysis, a linear relationship is assumed between the covariate and the dependent variable. The means of the covariate one standard deviation below the mean and one standard deviation above the mean are then compared and the difference is used to provide a Cohen's *d* ES for the covariate. Figure 3.6 depicts this process. In Figure 3.6, the TIME group x-axis has been replaced by a standardised continuous covariate (total volume load) x-axis, which is mean centred by participant and standardised by the group standard deviation. Mean centring allows the within-participant differences to be considered by this variable. It has also previously been advocated that

the participant's mean value should be included as a fixed between-participant effect (Bell et al., 2019). This variable was not added in this thesis as the between-participant differences were considered within the random effects of the models.

A two standard deviation increase in the covariate total volume load can be calculated using the ESTIMATE statement in SAS University Edition (SAS Institute, Cary, NY) via Equation 3.4. Alternatively, because a linear relationship is assumed between the covariate and the dependent variable, any 2 unit increase in the covariate can be used to obtain the same result.

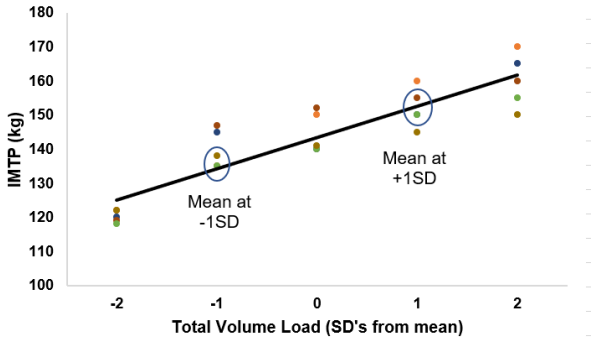


Figure 3.6: Visual representation of two standard deviation difference in total volume load on IMTP strength performance

Equation 3.4: Calculation of 2SD increase in total volume load when used as a continuous covariate

$$2SD\ increase\ in\ total\ volume\ load = Mean\ at + 1SD\ -\ Mean\ at - 1SD$$

Where SD is the standard deviation calculated for the covariate at a group level.

3.5.1.5 Using random effects to gain greater insight

Using a two standard deviation difference in the covariates is particularly beneficial within this thesis because it allows the random effects and random effect structure to be used to gain greater insights into the results. The random effects can be used to understand how

the mean relationships between training dose, training recovery and training response measures vary between participants and can be used to account for the covariance between two covariates.

3.5.1.5.1 Individual responses

The key benefit of random effects with regards to this thesis is their ability to quantify the variation in the influence of training dose and recovery measures on the training response between participants. In practice, these random effects allow each participant's individual coefficients to be obtained but from a research perspective the individual responses (Hopkins, 2015; McLaren et al., 2016) and practically interpretable results are more informative. In order to calculate the individual responses, the random effect is square rooted to provide its SD and doubled to ensure congruence with the 2 SD change in the covariate evaluated (Hopkins, 2015). It is then divided by the observed between participant standard deviation in line with the Cohen's *d* ES principle (Cohen, 1988). This calculation is shown by Equation 3.5.

Equation 3.5: Calculation of individual responses.

$$Individual\ responses\ = \frac{2 \times Random\ effect\ SD}{Observed\ between\ participant\ SD}$$

3.5.1.5.2 Practically interpretable relationships

Although the individual responses provide a standardised quantification of the variation in the relationship present, which can be compared against other studies, they do not provide an understanding of the practically interpretable relationships. One method by which this could be achieved is by taking the mean relationship's raw coefficient and adding/subtracting the raw standard deviation coefficient taken from the random effects. This addition and subtraction would provide a range of changes which would be expected

by a typical athlete. In this regard, a typical athlete is defined as one whose response to the covariate lies within one standard deviation of the mean response (either above or below). Understanding this range of possible changes in raw units provides a practical interpretation of the relationships and allows researchers and practitioners to evaluate the relationships in 'real life' rather than statistical terms.

3.5.1.5.3 Accounting for covariances

Alongside allowing individual responses and practically interpretable relationships to be calculated, the use of random slopes linear mixed models also allows for the covariance between two covariates to be calculated. The covariance refers to the change that can be expected between two measures within a model due to the relationship they hold and can be specified (e.g. compound symmetry, which is essentially the assumption of sphericity) or unspecified (e.g. the unstructured covariance structure, which calculates the best covariance for the model) dependent on the requirements of the model. This ability to account for the covariance is particularly important within athlete monitoring data analysis as high training loads have previously been shown to influence perceptions of sleep and poor sleep has shown associations with increased perceptions of physical exertion (Davenne, 2009; Fullagar, Skorski et al., 2015). Controlling for this relationship within the random effects of the model allows it to provide more accurate results, which are not influenced by this relationship. The analysis for chapter 5 groups the training dose and recovery measures into discrete z-score categories and so is unable to compute the covariance between the two measures. However, in chapters 6 and 7 where the training dose and recovery measures are considered as continuous covariates, the covariance is computed using an 'unstructured' covariance matrix.

3.5.2 Statistical and practical significance of results

Within the current sports science literature, there are three key methods of assessing the statistical significance of data: NHST, ES and MBI. This section details the theory behind the three approaches to statistical inference and discusses the advantages and disadvantages associated with each method.

3.5.2.1 Null hypothesis significance testing

NHST is the most traditional method of statistical significance testing. A central tenet of the approach is that before a statistically significant outcome can be accepted, the opposing theory must be shown to be untrue (Fisher, 1959). This is termed the 'null hypothesis' and gives NHST its name. In practice, this theory suggests that if we wish to prove that there is a statistically significant difference between two groups, we must first disprove the null hypothesis (i.e. there is no meaningful difference between the groups).

The null hypothesis assumes that a value will be subjected to random variability based on its distributional properties. This variability can be quantified by a test statistic, which is paired with a one or two-tailed *p*-value to provide an indication of how likely it is that the value would occur if the null hypothesis was correct. The *p*-value therefore provides the probability that a value at least as 'extreme' as that tested is likely to occur under the assumption that the null hypothesis is true (Szucs & Ioannidis, 2017) or, more simply, it provides the likelihood of the value occurring if there is no meaningful difference between the groups. In order to interpret the *p*-value, a level of statistical significance (α) must be set. This is usually set at 95% (or 0.95 in probability terms), resulting in a *p*-value threshold of 0.05 (probabilities work from 0 to 1, so 1-0.95=0.05). In order for the null hypothesis to be rejected, a *p*-value less than 0.05 must therefore be achieved, indicating that there is less than a 5% chance of the value occurring if there is no meaningful difference between the two groups. In this situation, it should be stated that the null

hypothesis of no meaningful difference between the two groups is rejected and further analysis should take place to establish whether there is a meaningful difference between the two groups. In the opposite situation, it should be noted that the *p*-value does not provide the probability that the null hypothesis is true (Wasserstein & Lazar, 2016).

Unfortunately, the use of *p*-values has changed over years of scientific publications to the extent that they are now used to indicate whether there is a difference between the two groups (Szucs & Ioannidis, 2017). This is a subtly different question to the original null hypothesis (that there is no meaningful difference between the groups) used within the method proposed by Fisher (1959). Such use of *p*-values is not only incorrect (Wasserstein & Lazar, 2016), but promotes inappropriate dichotomous decision making equivalent to buying a lottery ticket if you have a 5% chance of winning the jackpot, but not if you have a 4.9% chance (Stovitz et al., 2017). Such dichotomous decision making can also result in publication bias where non-significant results are not published because they don't meet the $p < 0.05$ threshold despite providing worthwhile results (Batterham & Hopkins, 2015).

Alongside these issues relating to publication bias, the dichotomous decision making associated with an arbitrary threshold ($p < 0.05$) fails to account for the uncertainty inherent within all effects (Batterham & Hopkins, 2006). Such uncertainty is magnified when using measurements with high variability or small sample sizes, increasing the likelihood of observing non-significant results due to the wide confidence intervals present in the ES. These wider confidence intervals are more likely to cross the zero ES threshold, which automatically results in a non-significant *p*-value because there is a chance that the effect could be zero (Goodman, 2008). Measurement variability and sample size issues of this nature are particularly prominent in applied sports science, limiting the use of *p*-values in this domain (Buchheit, 2016). Furthermore, *p*-values provide little indication of the magnitude, direction or importance of the effect in question, which limits their practical

applications (Wasserstein & Lazar, 2016). In sporting situations, stating that there is a significant difference is of limited use if the difference is not meaningful. For example, a 1kg increase in IMTP strength could be considered a significant difference if there is a large enough sample size and small enough confidence interval, however if it is known that the minimum improvement in strength required to enhance performance is 5kg, the 1kg increase is statistically significant, but not practically meaningful or significant. The combination of all the above factors ensures that the use of *p*-values alone is not suitable for research within applied sports environments.

3.5.2.2 Effect sizes

In an attempt to provide more detail with regards to the extent of the difference between two groups, ES measures have been developed (Cohen, 1988). The ES provides the magnitude of the difference between two groups by expressing it as a fraction of the variability between the participants within those groups (Winter et al., 2014). This variability is usually expressed using the pooled standard deviation, with the resulting value termed either the standardised ES or Cohen's *d* ES (Cohen, 1988). The pooled standard deviation can be calculated using Equation 3.6. However, it is also possible to obtain it directly from the random effects of a linear mixed model, by square rooting and summing the variances for the participant, participant*covariate (if applicable) and residual terms. An example of this for the linear mixed models used in chapters 6 and 7 is shown in Equation 3.7.

Equation 3.6: Traditional calculation of pooled standard deviation for Cohen's d effect sizes.

$$SD_{Pooled} = \sqrt{\frac{Group1SD^2 + Group2SD^2}{2}}$$

Where SD_{Pooled} is the pooled standard deviation and Group1SD and Group2SD refer to the standard deviations of all data points in groups 1 and 2 respectively.

Equation 3.7: Calculation of observed between participant standard deviation from random effect variances in a linear mixed model for Cohen's *d* effect sizes. Example covariates of training load and sleep duration are taken from chapter 6 of this thesis.

$$Observed\ between\ participant\ SD = \sqrt{BPV} + \sqrt{BPV\ training\ load} + \sqrt{BPV\ sleep\ duration} + \sqrt{Residual\ variance}$$

Where SD is a standard deviation and BPV refers to the between participant variance.

The use of ES allows practitioners to interpret the magnitude and direction of the effect in question rather than solely stating that there is a difference. The magnitudes in this thesis are evaluated using the thresholds: $d \leq 0.19$ *trivial*, $0.20 \leq d \leq 0.59$ *small*, $0.6 \leq d \leq 1.19$ *large*, $d \geq 1.20$ *very large*, as it has been argued these values are mathematically similar to the correlation coefficients used in previous studies in this area (Hopkins et al., 2009; Thorpe et al., 2015, 2017).

A further advantage of ES's is that they are standardised against the variability within the study in question, so they can be compared to other studies and used within meta analyses (Sullivan & Feinn, 2012). However, despite their usefulness in showing the magnitude and direction of an effect, ES's are flawed in that they only provide a point estimate and so provide little understanding of the uncertainty in the effect.

3.5.2.3 Confidence Intervals

To truly understand the size of an effect and its range of possible values, it is important to consider the confidence intervals surrounding the effect. In the vast majority of scientific studies, it is not possible to analyse the entirety of the population in question, so the study sample is taken as a sample of the general population. Consequently, there is inherent

uncertainty in the ES point estimate, which represents the 'best guess' of the value of the effect if the whole population was analysed (Cumming, 2012). The uncertainty in the point estimate of the ES can be quantified using confidence intervals (Page, 2014).

Confidence intervals are used to identify how likely it is that the point estimate would be observed if the test was completed an infinite number of times. Usually, confidence intervals are set at 90, 95 or 99%, with an increasing level of confidence resulting in a wider confidence interval. Based on these thresholds, there is a 10, 5 and 1% chance that the true value of the ES will lie outside the confidence interval. The choice of confidence level represents how certain the results are, with higher percentages normally used when performing multiple comparisons to minimise the likelihood of significant results occurring by chance (Batterham & Hopkins, 2006). In addition to the confidence level, the sample size can also influence the confidence intervals as smaller sample sizes result in wider confidence intervals. However, the confidence intervals can be considered robust if the sample size is greater than ten (Cumming, 2014). Equation 3.8 shows the formula for the calculation of 90% confidence intervals used in this thesis. 90% confidence intervals are used as the majority of sample sizes used in this study are approximately powerful enough to provide results for this level of confidence (see section 3.5.3). However, it should be noted that using 90% rather than 95% confidence intervals doubles the risk of Type 1 errors occurring to 10% from 5%, ensuring there is a greater potential for false positives to occur (Bulpitt, 1987).

Equation 3.8: Calculation of 90% confidence intervals.

$$90\%\ Confidence\ intervals = Mean\ \pm\ t_{90(n-1)} \times \frac{SD}{\sqrt{n}}$$

Where Mean is the mean difference between two groups, $t_{90(n-1)}$ refers to the t-statistic under the conditions of 90% confidence limits and *n-1* degrees of freedom, *n* is the

sample size and SD is the standard deviation of the mean differences between the groups.

The use of ES and confidence intervals alongside *p*-values provides considerably more information than dichotomous NHST alone. Such information allows practitioners to understand the size of the effect and the confidence in the ES stated. However, these results still provide little indication with regards to the meaningfulness of the effect. For example, if an average IMTP strength increase of 7±3 kg is observed over the duration of the example study, this will provide a statistically significant result via NHST and will show a clear ES. However, if the minimum improvement in strength required to elicit performance enhancement remains at 5 kg, the average increase in strength must be compared to this figure to evaluate whether the improvement in strength shown over the study is meaningful in practice. This discrepancy between a statistically meaningful result and a practically meaningful result is the key flaw in the use of NHST, ES and confidence intervals and provides the key rationale for the use of MBI's in association with ES's (Batterham & Hopkins, 2006).

3.5.2.4 Magnitude-based inferences

In recent years, the use of MBI's within sports science research has become extremely popular (Buchheit, 2016). MBI's provide an alternative to NHST by comparing the ES and confidence intervals to the smallest practically meaningful change (otherwise termed the smallest worthwhile change; SWC). There are three methods by which the SWC can be selected: 'anchor-based', 'expert opinion' or 'distribution-based'. An anchor-based approach uses previous research findings to form the SWC, whereas an expert opinion approach occurs when a consensus is gained from a group of experts. An anchor-based approach is therefore more objective than the expert opinion approach, however when neither of these is available, or when comparison with the literature is required, the distribution-based approach is used. This method uses a standardised difference for the

SWC. This is usually 0.2 multiplied by the observed between participant SD in line with Cohen's *d* methodology and is the method that will be used in this thesis (Cohen, 1988; George & Batterham, 2015).

To obtain an MBI, the ES and confidence intervals are interpreted as a t-distributed continuous probability distribution, which is plotted against the SWC. The comparisons to the SWC are divided by the standard error obtained from the confidence intervals as the method of standardisation required for a t-distributed curve to be obtained. The likelihood that the effect is greater or smaller than the SWC is identified by evaluating the likelihood that the t-distributed curve falls outside the SWC. The amount of the t-distributed curve that lies within the SWC range is considered the likelihood that the effect is *trivial* and is calculated by subtracting the probability that the effect falls outside the SWC from one. These probabilities are then converted to percentages for ease of understanding. Equations provide the formula by which the percentage chance of a positive, negative and trivial change is calculated.

Equation 3.9: Calculation of positive MBI percentage

$$Positive\ MBI\% = 100\ \times (1 - Tdist\left(\frac{Effect - Positive\ SWC}{Standard\ Error}, DF, one - tailed\right))$$

Equation 3.10: Calculation of negative MBI percentage

$$Negative\ MBI\% = 100\ \times (1 - Tdist\left(\frac{Effect - Negative\ SWC}{Standard\ Error}, DF, one - tailed\right))$$

Equation 3.11: Calculation of trivial MBI percentage

$$Positive\ MBI\% = 100\ \times (1 - Positive\ MBI - Negative\ MBI)$$

Where MBI refers to magnitude based inference, Tdist refers to the student's t-distribution and provides a probability based on the equation in brackets, SWC refers to smallest worthwhile change and DF is the degrees of freedom.

Figure 3.7 provides a visual representation of this process for the average 7±3 kg improvement in IMTP strength described above against an SWC of 5 kg. The likelihood of the effect being greater or less than the SWC can also be described using the thresholds: <0.5% *almost certainly/most likely not*; 0.5-5% *very unlikely*; 5-25% *unlikely*; 25-75% *possibly*; 75-95% *likely*; 95-99.5% *very likely*; >99.5% *almost certainly/most likely*. In the event that there is a greater than 5% chance that both the positive and negative SWC are crossed, the effect is described as *unclear* (Hopkins et al., 2009). This usually occurs when there are large confidence intervals, so it is suggested a decision on the beneficial or harmful nature of the effect is delayed until further data is obtained.

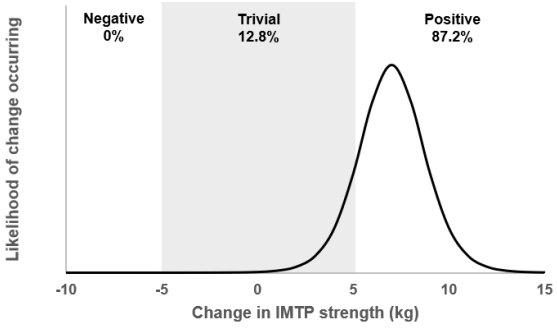


Figure 3.7: Visual representation of MBI calculation for IMTP strength increase of 7±3 kg against an SWC of 5 kg. Y-axis values are removed for ease of understanding. For reference, MBI descriptors would be: almost certainly not negative change (0%), possibly trivial change (12.8%) and likely positive change (87.2%) in strength.

As the popularity of MBI's has increased, there has been significant debate surrounding whether the method is statistically sound (Hopkins & Batterham, 2016, 2018; Sainani, 2018; Welsh & Knight, 2015). The debate has mainly centred around whether MBI analysis is considered frequentist or Bayesian and the subsequent implication for the probabilistic statements used, and the error rates experienced. In their most recent rebuttal, Hopkins and Batterham (2018) described MBI as a 'legitimate form of Bayesian

inference with a minimally informative dispersed uniform prior'. As a Bayesian method of analysis, the use of the probabilistic statements such as *likely*, *very likely* and *possibly* obtained from confidence intervals is well established (Burton, 1994; Burton et al., 1998). However, it should be noted that the authors had previously described MBI as "the ideal frequentist-Bayesian hybrid" (Batterham & Hopkins, 2015). Whether it is possible for the statistical assumptions to be changed in such a manner or this change is due to unclear communication by the authors initially is beyond the knowledge of the author of this thesis, but it is important to note the change to provide an unbiased representation of the method.

The error rate critique is again unclear when compared to traditional NHST. The error rates for MBI are much higher than NHST when sample sizes increase; for example, Type-1 error rates of ~15-70% for MBI and ~5-40% for NHST are shown for a sample size of 50+50 (Hopkins & Batterham, 2016; Sainani, 2018). However, such a comparison is unrealistic as it compares the error rates of two statistical methods with different approaches to achieving statistical/practical significance. In this regard, it is important to distinguish between the NHST philosophy of proving that the difference between two groups is not zero and the MBI philosophy of proving that the difference between two groups is practically meaningful. Indeed, in the rebuttal to Sainani (2018) it was argued that *trivial* effects, which are considered significant via NHST are not considered Type-1 errors via traditional definitions. However, based on current usage of NHST whereby a significant effect is deemed meaningful regardless of the size of the effect, these results should arguably be labelled as Type-1 errors (Hopkins & Batterham, 2018). Such an explanation may also help explain why NHST Type-1 error rates can be much higher than traditionally taught (Szucs & Ioannidis, 2017).

3.5.2.5 Interpretation of statistical analyses within this thesis

It is clear from the sections above that both NHST and MBI can be subjected to extensive criticism dependent on which method the practitioner has a greater affinity to. It is

understandable and healthy for such debate to occur, and it is possible that NHST is superior to MBI in some situations, whereas MBI is superior in others. Throughout this thesis, it is argued that MBIs are more appropriate than NHST due to the nature of the applied sporting environment within which the data was collected.

The nature of sport dictates that solely stating there is a difference between two groups is not beneficial and that the best insight is gleaned by identifying whether this difference is meaningful in practice. MBI's provide researchers and practitioners with the ability to evaluate the likelihood that the change is greater than an SWC of their choice, providing incredible flexibility with regards to its use. Furthermore, the use of percentage probabilities with regards to the outcome variable is extremely useful and avoids a dichotomous decision-making process. For the purposes of this thesis, practical significance will be set as a *likely* or ≥75% chance of a relationship or difference occurring, but further thresholds will be set to describe the significance as *very likely* or *almost certainly/most likely*. The use of these thresholds allows for the reader to interpret the strength of the evidence relative to their needs. For example, if there is an 80% chance of an important athlete experiencing self-reported illness symptoms following participation in a rugby session due to their previous training and sleep exposure, practitioners may decide that is not worth risking them in a training session before a big cup final. However, in a cup final which is the last match of the season before a two-week break from training, it may be decided that this risk is worth taking. These decisions based on the balance of probabilities are not possible when using NHST.

3.5.3 Statistical power

In order to be fully confident in the precision of the results obtained from any study, it is important that the study is designed with adequate statistical power. In the case of magnitude-based inferences, the precision is adequate when the measurement of

uncertainty of the effect (i.e. the confidence interval) does not exceed the positive and negative important effects when the value of the sample statistic is zero (Hopkins, 2006). In layman terms, this states that when the value of a standardised statistic is zero, the confidence intervals must not pass -0.2 and 0.2 respectively (as this would result in the results being classified as unclear). To estimate the sample size required for adequate precision, and thus statistical power, the within-participant standard deviation (typical error as a coefficient of variation), between-participant standard deviation and smallest worthwhile change are required (Hopkins, 2006). The values used within this thesis were calculated in the reliability study (chapter 4) and at the beginning of their respective studies for $DWB_{no\text{-}sleep}$ (chapter 7) and s-IgA (chapter 8). The reliability values were input into a pre-built Microsoft Excel spreadsheet to identify the sample sizes required (Hopkins, 2006).

Chapters 5 to 8 utilised a repeated measures study design. Consequently, for adequate statistical power, a sample size of 29 was required for CMJ measures, 66 for DWB, 49 for PRS, and 40 for $DWB_{no\text{-}sleep}$. In chapter 8, a sample size of 279 was required for s-IgA concentration and 309 for s-IgA secretion rate. These sample sizes are extremely difficult to obtain within sports teams, resulting in some aspects of the statistical analysis in all chapters being underpowered. The implications of this lack of statistical power will be discussed in the relevant chapters. However, it is important to note that the studies within this thesis have significantly larger sample sizes than the currently available literature (Buchheit et al., 2013; Fahlman & Engels, 2005; Mortatti et al., 2012; Thorpe et al., 2017), either in terms of total participant numbers (for chapters 5, 6 and 7) or the total number of observations per participant (chapter 8). Consequently, despite lacking some statistical power, they can still be considered more powerful than previous studies in the area.

Chapter 4 STUDY 1

Between-day reliability and usefulness of fatigue/wellness and preparedness to play measures in youth athletes

Sawczuk, T., Jones, B., Scantlebury, S., Weakley, J., Read, D., Costello, N., Darrall-Jones, J., Stokes, K., & Till, K. (2018) Between-day reliability and usefulness of a fitness testing battery in youth sport athletes: Reference data for practitioners. *Measurement in Physical Education and Exercise Science.* 22(1), 11-18.

4.1 Introduction

As identified within section 2.9.1 in the literature review, the reliability and usefulness of any test is important when considering its use in practice. Within the integrated athlete monitoring cycle, the fatigue/wellness measures of DWB and PRS, and the preparedness to play measure of CMJ height can be considered as tests of the training response, which are completed by athletes on a daily basis.

Of the these measures, the DWB has received the most attention within the literature with TE's ranging from 7.1% to 24.1% in the individual sports of rugby union (Roe, Darrall-Jones, Till, Phibbs et al., 2016), Australian football (Gastin et al., 2013) and soccer (Thorpe et al., 2015), However, no study has considered the TE of a DWB in youth athletes across multiple sports. Furthermore, only Roe and colleagues (2016) have considered the usefulness of these questionnaires, concluding that they have marginal usefulness in youth rugby union players. In contrast to DWB, there is no published literature surrounding the between-day reliability and usefulness of the PRS. It is therefore important that the between-day reliability and usefulness of the PRS in youth athletes across multiple sports is evaluated prior to assessing its relationship with inputs to the training process.

Although the reliability and usefulness of CMJ have been considered extensively using force plates (Cormack et al., 2008; Roe, Darrall-Jones, Till, Phibbs et al., 2016), there is limited research evaluating these properties in the less expensive Optojump system used within this thesis (Glatthorn et al., 2011). In their study, Glatthorn and colleagues (2011) calculated the TE as 2.2% for CMJ height when measured by the Optojump system. However, this study took place in a group of older, less well-trained individuals and so it is important to confirm the reliability and usefulness of CMJ height as measured by the Optojump system in youth athletes across multiple sports.

4.1.1 Aim

The aim of the study was to evaluate the between-day reliability and usefulness of fatigue/wellness and preparedness to play measures in youth athletes across multiple sports.

4.1.2 Objectives

- To evaluate the between-day reliability and usefulness of DWB, PRS and CMJ height in youth athletes.

4.2 Methods

4.2.1 Participants

Fifty-two youth athletes aged 16-18 (age 17.3 ± 0.6 years, height 173.0 ± 18.2 cm, body mass 73.7 ± 12.6 kg) were recruited from a local UK independent school to participate in this study. Participants competed in basketball (n=1), cricket (n=5), football (n=10), hockey (n=8), netball (n=9), rugby (n=17) and swimming (n=2). The athletes were members of the school's sport scholarship scheme and were club/school (n=30), academy (n=6), county/regional (n=12) or international (n=3) standard in their respective sports. Participants were recruited according to the procedures outlined in the general methods (section 3.3).

4.2.2 Design

To complete this within-participant between-day reliability study, an observational study design was employed. Fatigue/wellness and preparedness to play measures were collected on four weekdays per week for a period of seven weeks. Upon completion of data collection, two or three completions per participant of each fatigue/wellness and preparedness to play measure were selected for analysis based on pre-determined

criteria. All data were collected in term 5 of the academic year (the first-half term after Easter), between April and May 2016.

4.2.3 Procedures

4.2.3.1 Fatigue/wellness measures

Participants completed a daily wellness questionnaire, including DWB and PRS, on four weekdays for a seven-week period. The wellness questionnaire was completed online via Google Docs (Google Forms, Google, CA, USA) before 11am. On training days, the questionnaire was completed before the first training session of the day. The wellness questionnaire also included details on the previous day's training load and sleep duration, which were used to identify appropriate data for analysis. Further details on the wellness questionnaire are provided in section 3.4.1 and Appendix 3A.

4.2.3.2 Preparedness to play measures

Prior to CMJ performance, a standardised dynamic warm up including leg swings, lunges and squats was completed. The CMJ was performed using the Optojump system (Microgate, Bolzano, Italy). CMJ height was reported in centimetres. Participants began with their legs fully extended and their feet at a self-selected width, with their hands on their hips. They were then instructed to squat down and jump as high as they could in a fluid, countermovement motion. The depth of the countermovement was self-selected. Participants were instructed to keep their legs extended in flight and to land with straight legs. Two warm up jumps were completed, before three maximal efforts were executed with a 3-minute rest provided in between each repetition. These technical specifications for CMJ performance were the same as a previously published study (Roe, Darrall-Jones, Till, Phibbs et al., 2016).

4.2.3.3 Data selection criteria

As the data collection period took place during the in-season period of the academic sport season and included a number of participants who also competed at club level, there was little control over the physical activity levels encountered by participants. However, given the training response measures will be considered with regards to their relationships with the training dose and recovery experienced, it was important that these measures were considered within the selection of observations. Consequently, DWB, PRS and CMJ height data from the seven-week collection period were selected for analysis according to the following criteria (listed in order of importance):

- Selected data points were preceded by a day of rest (i.e. self-reported daily training load of 0 AU)
- Selected data points were 5-7 days apart.
- Where possible, selected data points were chosen on the same weekday
- When multiple comparison options were available, the two or three data points meeting the above criteria with the smallest difference in self-reported sleep duration were chosen.

4.2.3.4 Statistical analyses

Prior to analysis, DWB and PRS scores were converted to percentages to better fit a normal distribution via Equation 4.1. Similarly, CMJ height was log transformed to reduce bias as a result of non-uniformity of error. Subsequently, the TE was calculated as a CV via Equation 4.2, using a pre-made Microsoft Excel spreadsheet (Hopkins, 2015b).

Equation 4.1: Calculation of 0-100 (percentage) score for DWB and PRS.

$$0 - 100\ Score = 100\left(\frac{Observed\ score - \ Minimum\ possible\ score}{Maximum\ possible\ score - Minimum\ possible\ score}\right)$$

Equation 4.2: Calculation of TE for fatigue/wellness and preparedness to play measures.

$$TE = \frac{S_{diff}}{\sqrt{2}}$$

Where S_{diff} is the standard deviation of the difference score between observations (Hopkins, 2000). When three data points were selected for an individual, the S_{diff} was calculated for data point 2 minus 1 and data point 3 minus 2. These results were averaged to provide the overall TE (Hopkins, 2015b).

As detailed in the introduction, values as high as 10% have been considered appropriate thresholds for the reliability of fatigue/wellness and preparedness to play measures (Cormack et al., 2008). However, for the purposes of this study, a stricter CV of 5% was identified as the threshold for good reliability in line with a similar study (Roe, Darrall-Jones, Till, Phibbs et al., 2016) and more recent recommendations (Hopkins et al., 2009). The SWC was calculated as 0.2 multiplied by the between-subject standard deviation (SD) and expressed as a percentage of the mean in order to compare with the CV. The usefulness of the test was classified according to Hopkins' (2000) criteria: Good (CV < SWC; TE:SWC ratio < 1), OK (CV ~ SWC; TE:SWC ratio ~ 1), or marginal (CV > SWC; TE:SWC ratio > 1). Results are presented as mean ± SD or TE (lower confidence interval, upper confidence interval).

4.3 Results

4.3.1 Fulfilment of selection criteria

In total, 138 observations were selected for analysis, for each of DWB, PRS and CMJ height, resulting in 52 pairs of observations for data point 2 minus 1, and 34 pairs of observations for data point 3 minus 2. All data points fell within the stated range of 5-7 days (median = 7 days, range = 5-7 days). The median figure of 7 days is indicative of the

stated aim to compare the same day on consecutive weeks where possible. The difference in self-reported sleep duration between two data points was 0.1 ± 1.1 hours, thus satisfying the aim of minimising differences in sleep length between data points.

4.3.2 Reliability and usefulness of measures

Table 4.1 provides the means, SDs, TE and SWC for DWB, PRS and CMJ height. The TE:SWC ratios were 1.9, 1.7 and 0.7 for DWB, PRS and CMJ height respectively. Consequently, DWB and PRS were classified as having 'marginal' usefulness, whereas CMJ height was classified as having 'good' usefulness.

Table 4.1: Summary of day 1, 2 and 3 values (mean ± SD), TE as a CV (90% CIs in brackets) and SWC as percentages (Hopkins, 2000).

Measure	Day 1	Day 2	Day 3	TE as CV (%)	SWC (%)
DWB	61.8 ±15.6	61.2 ±15.9	62.1 ±13.9	11.7 (9.8 – 14.7)	6.2
PRS	72.7 ±16.4	71.8 ±17.4	68.8 ±17.1	8.5 (6.5 – 12.4)	4.9
CMJ	34.4 ±5.9	34.4 ±6.4	33.6 ±6.2	2.8 (2.4 – 3.3)	3.9

N.B: DWB = wellness questionnaire; PRS = Perceived Recovery Scale; CMJ = countermovement jump height

4.4 Discussion

The aim of this study was to evaluate the between-day reliability and usefulness of daily fatigue/wellness (DWB, PRS) and preparedness to play (CMJ height) measures in youth athletes across multiple sports. The results show both subjective wellness questionnaires (DWB and PRS) to have poor between-day reliability and 'marginal' usefulness. Conversely, the lower body neuromuscular recovery measure of CMJ height displayed good between-day reliability and usefulness.

4.4.1 Reliability of fatigue/wellness and preparedness to play measures

Both DWB (TE = 11.7%) and PRS (TE = 8.5%) were shown to have poor between-day reliability based on the predetermined 5% threshold. The TE of 11.7% for DWB falls within the range of 7.1-24.1% previously shown using similar wellness questionnaires (Gastin et al., 2013; Montgomery & Hopkins, 2013; Roe, Darrall-Jones, Till, Phibbs et al., 2016). To the author's knowledge, there are no previous studies considering the between-day reliability of PRS in a practical environment. In contrast to the subjective wellness questionnaires, CMJ height, as measured using the Optojump system, demonstrated good reliability. The 2.8% TE in this study is similar to the 2.2% shown in an older, less well-trained age group (Glatthorn et al., 2011), and is much lower than values reported in previous force plate-based studies (Cormack et al., 2008; Roe, Darrall-Jones, Till, Phibbs et al., 2016). It is suggested that this difference is because force plates calculate jump height differently to the Optojump system. Force plates calculate jump height using the velocity of the centre of mass at take-off, whereas the Optojump system calculates flight time using the breaking of an infrared beam. Neither previous force plate study provided their equation for jump height calculation (Cormack et al., 2008; Roe, Darrall-Jones, Till, Phibbs et al., 2016) but both provided between-day reliability values for the flight time of the jump and the 2.8% between-day reliability value observed in this study is comparable with the 3.3% (Cormack et al., 2008) and 2.6% (Roe, Darrall-Jones, Till, Phibbs et al., 2016) measurements previously quoted.

It is important that practitioners consider the between-day reliability of fatigue/wellness and preparedness to play measures when evaluating an athlete's response to training because it provides an understanding of the potential error in the measures when they are completed under the same conditions. The results of this study show that an athlete's response could vary by up to 11.7% for DWB, 8.5% for PRS and 2.8% for CMJ height due to the error inherent within the test. In practice, this is indicative of a maximum 3 unit

variation in either direction for DWB (11.7% of the maximum score of 25 equals 2.925 units, rounded up as the questionnaire is measured in whole units), and a 1 unit shift for PRS (8.5% of the maximum score of 10 units, rounded up). However, because the TE is measured as a percentage, the actual variation will differ dependent on the score achieved (e.g. 11.7% of a score of 14 is only 2 units of variation). Table 4.2 shows the range of possible values that could be observed based on the reliability of the measures assessed, when the true value is known.

Table 4.2: Example of the range of values of DWB, PRS and CMJ height, which may be observed when the true value and TE are known.

	True value (Raw TE)		**Potential observed values**	
Scale (TE)	**Day 1**	**Day 2**	**Day 1**	**Day 2**
DWB (11.7%)	17 (2)	15 (2)	15-19	13-17
PRS (8.5%)	6 (1)	4 (1)	5-7	3-5
CMJ height (2.8%)	33.4 (1)	31.2 (0.9)	32.4-34.4	30.3-31.1

NB: Raw TE is calculated from the day 1 or 2 value. E.g. Day 1 value for DWB is 17. Raw TE is 17 multiplied by 0.117 (11.7%), which is 1.989. Round this up to obtain the smallest possible difference outside the TE, which is 2. CMJ height is rounded to the nearest 0.1cm as this is the smallest unit shown by the Optojump system.

Table 4.2 provides an understanding of the influence a high TE can have on the observed values of the wellness and recovery measures. This inherent variability can have a dramatic effect on the changes observed. For example, although the true change between day 1 and day 2 values for DWB is -2 (17 minus 15), the observed change can vary from -6 (19 to 13) to +2 (15 to 17). In the case of PRS, the true change is -2, but potential observed changes vary from 0 to -4, and for CMJ height the true change is -2.2, but the differences that could be observed range from -1.3 to -3.1. However, although the between-day reliability of a measure provides detail on the wide range of possible

changes between two days, it provides little understanding as to how these relate to the SWC. To consider this, the usefulness of the measure must be considered.

4.4.2 Usefulness of fatigue/wellness and preparedness to play measures

The usefulness of a measure compares the SWC to the TE to assess whether the SWC can be determined above and beyond the typical variation of the test. If the SWC is greater than the TE, the test has good usefulness because its inherent variability will not cause a true change of zero to be observed as greater than the SWC (Hopkins, 2000). Both subjective fatigue/wellness questionnaires measured in this study (DWB and PRS) displayed marginal usefulness, indicating that they could not differentiate between the SWC and a trivial effect when a true change of zero was observed. However, CMJ height was described as having good usefulness suggesting that it was able detect real changes in the SWC.

The marginal usefulness of DWB mirrors findings in the only other previous study to consider its reliability and usefulness (Roe, Darrall-Jones, Till, Phibbs et al., 2016). No other study has considered these characteristics in PRS. Although the reliability and usefulness statistics suggest that the wellness questionnaires should not be used, it is important to note that the SWC used was calculated as though the wellness questionnaires were standalone tests (i.e. as though the outcome of the questionnaire was the only important result). In sporting contexts though, this is not the case as wellness questionnaires are used to help maximise performance and understand the likelihood of an athlete suffering from injury, illness or overtraining (Gabbett et al., 2017). To date, only one study has considered the potential predictive ability of wellness questionnaires with regards to injury, illness or overtraining using practically interpretable units (Thornton et al., 2016). Thornton and colleagues (2016) found that a difference in daily wellness scores lower than 7.25 AU was a predictor of self-reported illness in elite adult rugby league

players, when a drop of less than 2.05 SD in the ‘how you feel’ rating z-score, which asked athletes to rate how they felt from 1-10, was also present. Unfortunately, these findings do not provide a lower limit on the sensitivity required by the questionnaires but do indicate that smaller changes are more important than large variations suggesting the usefulness of DWB and PRS may be insufficient.

The CMJ height showed good usefulness when measured against this study’s TE:SWC ratio < 1 criteria. No other study has considered the usefulness of the CMJ using the Optojump system, but the usefulness of both CMJ height and flight time were questioned when assessed using a force plate (Roe, Darrall-Jones, Till, Phibbs et al., 2016). We previously noted that the method by which CMJ height was attained differs between force plates and the Optojump system, which could explain the difference between the two statistics. However, despite the good usefulness shown by CMJ, similar reservations are present as those with the wellness questionnaires. Although the test is able to detect changes from the distribution based SWC (0.2 x between-participant standard deviation), it is not yet clear whether these changes actually contribute to an outcome measure of the training process. The results should therefore be treated with caution when using CMJ height as a monitoring measure but confirm that it has good usefulness as a fitness testing parameter. Future research should now attempt to identify the SWC of fatigue/wellness and preparedness to play measures necessary for questionnaire or jump performance to be responsive to performance changes or injury, illness and overtraining risk.

4.4.3 Limitations

This is the first study to evaluate the between-day reliability and usefulness of the fatigue/wellness and preparedness to play measures in youth athletes across multiple sports. It is therefore a worthy addition to the literature. However, the results are subject to

several limitations. The first of these is the study design used. Although all possible efforts were taken to standardise the physical activity and recovery experienced by participants in the 24 hours prior to the fatigue/wellness questionnaires selected, the days before this were disregarded. It is not yet known whether wellness questionnaires are affected by more than the previous day's training loads and so it is possible that the training loads two or three days prior to the selected questionnaires affected responses, similar to the impact of physical activity on delayed onset muscle soreness (Cheung et al., 2003). However, within this ecologically valid setting where it wasn't possible to control exposure to training during the in-season period, all reasonable controls were made to ensure conditions were as standardised as possible. A similarly ecologically valid consideration was the use of multiple sports within the calculations, which the author suggests is a strength of the study but acknowledges it could also be considered a weakness given the varying physical demands between sports (Chandler et al., 2014; Read et al., 2017). Unfortunately, due to the sample size, it was not possible to calculate the reliability and usefulness differences between sports to compare whether it is more appropriate to use DWB, PRS or CMJ height in different sports. Finally, as previously discussed, the use of the SWC as a performance measure rather than relative to an outcome measure (e.g. injury, illness or overtraining) is a limitation within the calculation of these statistics. However, with insufficient research available to confirm the SWC with regards to enhanced performance, injury, illness or overtraining, this study provides an initial understanding of how useful the wellness and recovery measures may be in youth athletes.

A final limitation is the possibility that using the TE as a measure of reliability is not appropriate when measuring fatigue/wellness scales' reliability. The TE as been used as it is appropriate for assessing the reliability of continuous data and DWB and PRS have both been converted to percentages in order to allow them to be considered in this manner. However, it should be noted that, at their most fundamental level, both questionnaires are still ordinal measures (i.e. they can only hold values from 1-5 in single

unit intervals or 0-10 in one or two unit intervals respectively). Consequently, future analyses may wish to evaluate the reliability using a different measure, such as the median absolute deviation, which is less influenced by outlying values than the TE.

4.5 Conclusions

In conclusion, the results of this study provide reference reliability data for the fatigue/wellness measures of DWB and PRS, and the preparedness to play measure of CMJ height. The results show TE's of 11.7% for DWB and 8.5% for PRS, indicating that both measures had poor between-day reliability. CMJ height's TE of 2.8% was indicative of good between-day reliability. Similarly, the between-day usefulness of the fatigue/wellness measures was poor, whereas CMJ showed good usefulness. It should be noted though that the usefulness of these measures was calculated based on a distributional assumption (i.e. 0.2 multiplied by the between-subject SD) rather than based on the change in training response measure required to increase the risk of adverse outcome (e.g. injury, illness and overtraining) incidence, which limits their applicability to practice.

The reliability values from this study will be considered later in this thesis as part of the integrated athlete monitoring cycle model aiming to predict illness incidence. It is only when the predictive ability of this integrated athlete monitoring cycle model is evaluated and the smallest worthwhile change in training response measures relative to an increased risk of illness is identified that the usefulness of the measures in the integrated athlete monitoring cycle can be properly evaluated. To this end, it is pivotal that future research now considers the relationships between measures of the integrated athlete monitoring cycle in order that they can be used within the integrated athlete monitoring cycle model to predict adverse training outcomes.

Chapter 5 STUDY 2

Establishing the relationships between measures of the integrated athlete monitoring cycle in youth athletes using previously employed statistical analyses

Sawczuk, T., Jones, B., Scantlebury, S., Till, K. (2018) Relationships between training load, sleep duration and daily well-being and recovery measures in youth athletes, *Pediatric Exercise Science,* 30(3), p345-352.

5.1 Introduction

Having calculated the TE of the training response measures for use within the integrated athlete monitoring cycle model, it is now important to establish the relationships these measures have with other aspects of the athlete monitoring cycle. Within this study, training load (as a measure of the training dose), sleep duration (as a measure of the training recovery), DWB and PRS (as measures of fatigue/wellness) and CMJ height (as a measure of preparedness to play) will be considered. Unfortunately, the research evaluating the relationships between these measures is limited in youth athletes. Indeed, the only relationship considered within youth sport is the non-significant relationship between CMJ height and training load (r = -0.153, p = 0.419) in elite youth soccer players (Malone et al., 2015). In the literature review (section 2.8.1.1), it was suggested that the lack of association between training load and jump height observed by Malone and colleagues (2015) may have been a result of the simple Pearson correlation coefficients utilised for analysis. One method to assess this hypothesis is to evaluate the relationships using different statistical analyses, which have previously been considered within the literature.

Two studies have evaluated the relationships between measures of the athlete monitoring cycle using more advanced statistical methods than Malone and colleagues (2015). Both took place in adult soccer. These are the studies of Thorpe and colleagues (2015), who employed partial correlations and Rowell and colleagues (2017), who used a linear mixed model with three groups of training load. Using high-speed running as their measure of training load, Thorpe and colleagues (2015) observed a large negative relationship with a custom made fatigue scale (r = -0.51; ±0.12, p < 0.001), and a small positive relationship with CMJ height (r = 0.23; ±0.19, p = 0.04) in elite adult soccer players. The relationships with sleep quality (r = -0.04; ±0.15, p = 0.71) and muscle soreness (r = -0.10; ±0.15, p = 0.37) were non-significant. Unlike Thorpe and colleagues (2015), and this thesis, Rowell

and colleagues (2017) used PlayerLoad as their measure of training load. The group observed substantial differences in CMJ height immediately post-match play in high training load (-18 ± 11%, large) and medium training load (-12 ± 11%, moderate) groups *vs* low training load groups. By evaluating the relationship between measures of the athlete monitoring cycle in youth athletes using both these statistical methods, which have previously shown relationships in elite adult soccer players, it will be possible to establish whether the differences between the studies are due to the statistical analyses employed or population differences between youth and adult athletes.

5.1.1 Aim

The aim of this study was to evaluate the relationships between measures of the integrated athlete monitoring cycle in youth athletes using statistical analyses previously employed in elite adult sport studies (Rowell et al., 2017; Thorpe et al., 2017).

5.1.2 Objectives

- Evaluate the relationships training load (as a training dose measure) and sleep duration (as a training recovery measure) have with DWB, PRS (as fatigue/wellness measures) and CMJ height (as a preparedness to play measure)using partial correlations (Thorpe et al., 2015).
- Evaluate the relationships training load (as a training dose measure) and sleep duration (as a training recovery measure) have with DWB, PRS (as fatigue/wellness measures) and CMJ height (as a preparedness to play measure)using linear mixed models splitting training load and sleep duration into three discrete groups for analysis (Rowell et al., 2017).

5.2 Methods

5.2.1 Participants

Fifty-two youth athletes aged 16-18 years (age 17.3 ± 0.6 years, height 173.0 ± 18.2 cm, body mass 73.7 ± 12.6 kg) were recruited for this study from a local independent school in the UK. The athletes were part of the school's sport scholarship scheme and competed in basketball (n=1), cricket (n=5), football (n=10), hockey (n=8), netball (n=9), rugby (n=17), swimming (n=2). All athletes had previously competed at academy level or above and were now club/school (n=31), academy (n=6), county/regional (n=12) or international (n=3) standard in their respective sports. Participants were recruited according to the procedures outlined in the general methods (section 3.3).

5.2.2 Design

For this prospective cohort study, a longitudinal, observational study design was used. A bespoke online wellness questionnaire, including DWB, PRS and details on the previous day's self-reported training load and sleep duration, was completed four weekdays per week for a period of seven weeks. Alongside the questionnaire, participants performed three maximal CMJ's each day prior to their first session of the day. As participants were required to perform three maximal CMJ's in the presence of the researcher, four days per week was the maximum number that could be conducted in this study.

In total, 825 observations were analysed, with a median of 16 out of 27 complete datasets (incorporating training load, sleep duration, DWB, PRS and CMJ height data) per participant. Neither Thorpe and colleagues (2015) nor Rowell and colleagues (2017) provided details as to the size of their final dataset, but the number of observations used in this study is significantly greater than the maximum possible for either study (170 and 54 respectively). All data were collected in term 5 of the academic year, which was seven weeks long, between April and May 2016.

5.2.3 Procedures

5.2.3.1 Data collection

Participants completed a bespoke daily wellness questionnaire, including DWB and PRS, on four weekdays for a seven-week period. The wellness questionnaire was emailed to participants at 6am and completed online via Google Docs (Google Forms, Google, CA, USA). On training days, the questionnaire was completed before the first training session of the day. If necessary, verbal reminders were provided at 10.30am to remind athletes to complete the questionnaire by 11am. The wellness questionnaire also included details on the previous day's training load (evaluated via the s-RPE method) and self-reported sleep duration (in hours). Further details are provided in section 3.4.1 and Appendix 3A. In study 1, the TE was established as 11.7% for DWB and 8.5% for PRS. The SWC's were 6.2% and 4.9% respectively.

Prior to CMJ performance, a standardised dynamic warm up including leg swings, lunges and squats was completed. The CMJ was performed using the Optojump system (Microgate, Bolzano, Italy). CMJ height was reported in centimetres. Participants began with their legs fully extended and their feet at a self-selected width, with their hands on their hips. They were instructed to squat down and jump as high as they could in a fluid, countermovement motion. The depth of the countermovement was self-selected. Participants were instructed to keep their legs extended in flight and to land with straight legs. Two warm up jumps were completed, before three maximal efforts were executed with a 3-minute rest provided in between each repetition. The technical specifications for CMJ performance were the same as a previously published study (Roe, Darrall-Jones, Till, Phibbs et al., 2016). In study 1, the TE for CMJ height was 2.8%, with a SWC of 3.9%.

5.2.3.2 Statistical analyses

Prior to analysis, the assumptions of residual normality, heteroskedasticity and linear relationship between dependent and independent variables were evaluated as outlined in section 3.5.1. CMJ jump height was log transformed to reduce bias as a result of non-uniformity of error. DWB and PRS scores were converted to percentages. The relationships between training load, sleep duration, DWB, PRS and CMJ height were evaluated using previously published statistical methods (Rowell et al., 2017; Thorpe et al., 2015).

5.2.3.2.1 Partial correlations

Partial correlations were used to assess the linear relationship between training load, sleep duration, DWB, PRS and CMJ height, in line with the approach of Thorpe and colleagues (2015). Athlete, Sport, week, weekday, training load and sleep duration were included in all correlations. Athlete and Sport referred to the ID of the athlete and the sport they played. Week referred to the week of the study (1-7), weekday referred to the day of the week (Monday to Thursday). Used in this manner, partial correlations allowed the relationship between training load and sleep duration to be accounted for within the analysis.

5.2.3.2.2 Linear mixed models

The data were also analysed using linear mixed models as described by Rowell and colleagues (2017). In these models, the training load and sleep duration measures were separated into three groups according to each athlete's individual z-scores for the day in question: low (training load or sleep duration < -1z); moderate (-1z < training load or sleep duration <1z); and high (training load or sleep duration >1z). It was therefore possible for an athlete to be classified as having high training load, but low sleep duration on one day, but moderate training load and high sleep duration on another day, or any combination of

the three groupings. Training load, sleep duration, sport, week and weekday were added to the model as fixed effects, athlete was added as a random effect. Pairwise comparisons showed the magnitude of difference between the groups, with the moderate group used as the reference for visualisation purposes. Data were analysed using SAS University Edition (SAS Institute, Cary, NC).

Results were analysed for practical significance via MBI's using a pre-made Microsoft Excel spreadsheet (Hopkins, 2006a). Further details surrounding the MBI approach (section 3.5.2.4) and the ES used (section 3.5.2.2) are provided in the general methods. Thresholds for correlations (*r*) were set as: 0.1 *small*; 0.3 *moderate*; 0.5 *large*; 0.7 *very large*; 0.9 *almost perfect* (Hopkins et al., 2009). ES and correlation coefficients are reported ES and *r*; ± 90% confidence intervals.

5.3 Results

5.3.1 Partial correlations

The mean training load was 251 ± 301 AU; the mean self-reported sleep duration was 7.3 ± 1.3 hours. Table 5.1 shows the partial correlations between the fatigue/wellness measures of DWB and PRS, the preparedness to play measure of CMJ height, and training load and sleep duration. It shows a small positive correlation between DWB and sleep duration (r = 0.28; ±0.05) and a small negative relationship between training load and PRS (r = -0.23; ±0.05). All other effects were trivial or did not reach the pre-determined threshold for meaningful inference.

Table 5.1: Partial correlation coefficients, directions, magnitudes and descriptors for the effect of training load and sleep duration on DWB, PRS and CMJ height. Data are presented as *r*; ±90% CIs.

	Correlation Coefficient	**Magnitude**	**Descriptor**
DWB			
Training Load	-0.05; ±0.06	Trivial	*Likely*
Sleep Duration	0.28; ±0.05	Small	*Most Likely*
PRS			
Training Load	-0.23; ±0.05	Small	*Most Likely*
Sleep Duration	0.12; ±0.06	Small	*Possibly*
CMJ height			
Training Load	-0.09; ±0.06	Trivial	*Possibly*
Sleep Duration	0.01; ±0.06	Trivial	*Very Likely*

5.3.2 Linear mixed models

Table 5.2 provides descriptive characteristics for the training load and sleep length zones utilised within the linear mixed models. Figure 5.1 and Figure 5.2 visualise the pairwise comparisons for the effect of differing quantities of training load and sleep duration on DWB and PRS. The CMJ was not plotted in this way due to its trivial relationship with training load and sleep duration (Table 5.1). DWB showed a negative trend with training load, but as the differences between groupings were trivial (*likely* for low *vs* moderate, *very likely* for high *vs* moderate), this was not deemed practically meaningful. A *likely* small positive difference between low training load and moderate training load is shown for PRS (*d* = 0.29; ±0.17), along with a *very likely* small difference for high training load (*d* = -0.36; ±0.11) relative to moderate. There was a *very likely* small negative difference

between low and moderate sleep durations for DWB (*d* = -0.33; ±0.11), but this change was not observed when comparing moderate to high sleep durations. The PRS showed no practically meaningful relationship or trend with sleep duration.

Table 5.2: Descriptive statistics for training load and sleep duration groups as independent variables (IV) based on individual z-scores (z).

	Low (IV <-1z)	**Moderate (-1z< IV <1z)**	**High (IV >1z)**
Training Load (AU)			
n	73	628	124
Minimum	0	0	300
Maximum	380	1235	2450
Median	0	180	627.5
Interquartile Range	0	300	397.5
Sleep Duration (hours)			
n	88	709	28
Minimum	3	5	9
Maximum	10	11	13
Median	6	7	10
Interquartile Range	2	1	1

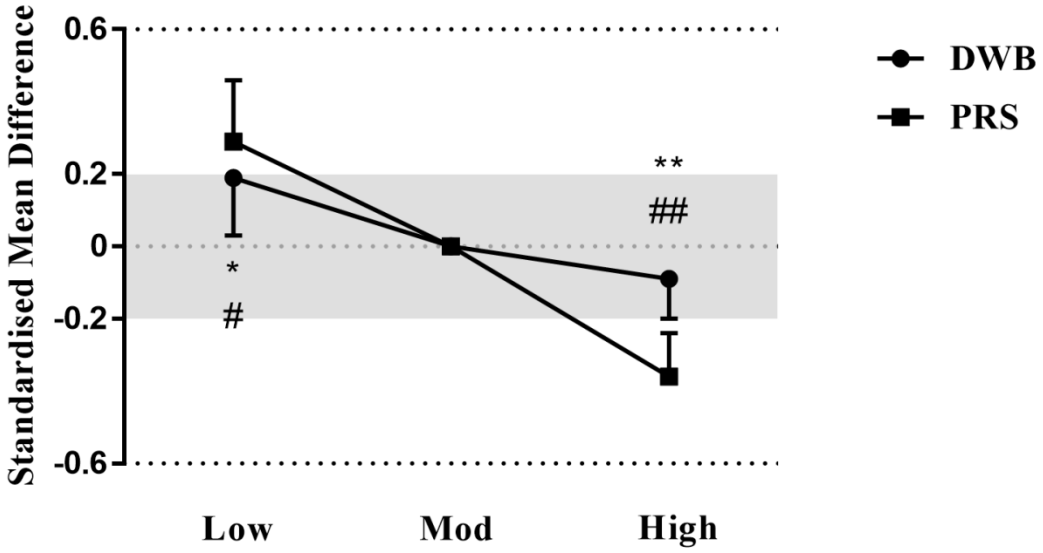


Figure 5.1: Visual representation of pairwise comparisons for the differing effect of high, moderate and low training loads on DWB and PRS. Data are presented as mean difference relative to moderate training load ± 90% confidence intervals. Shaded area represents SWC. Asterisks and hashtags denote likelihood that the difference in effect is greater than the smallest worthwhile change: * likely; ** very likely for DWB; # likely; ## very likely for PRS.

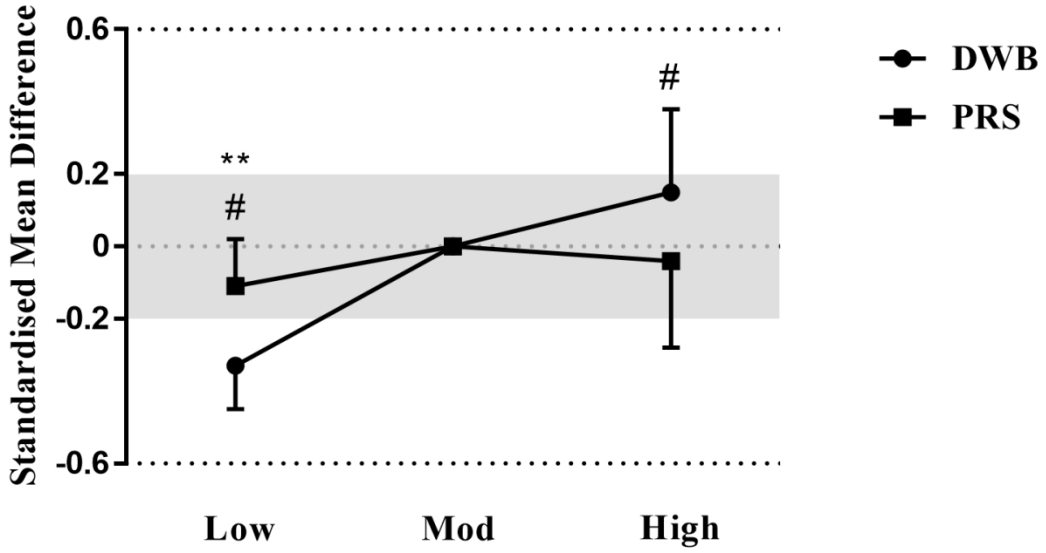


Figure 5.2: Visual representation of pairwise comparisons for the differing effect of high, moderate and low sleep durations on DWB and PRS. Data are presented as mean difference relative to moderate sleep length ± 90% confidence intervals. Shaded area represents smallest worthwhile change. Asterisks and hashtags denote likelihood that the difference in effect is greater than the smallest worthwhile change: ** very likely for DWB; # likely for PRS.

5.4 Discussion

The aim of this study was to evaluate the relationships between measures of the integrated athlete monitoring cycle in youth athletes using statistical analyses previously employed in elite adult sport studies (Rowell et al., 2017; Thorpe et al., 2017). The results indicated that although partial correlation analysis identified no linear relationship between DWB and training loads, a small relationship with sleep duration was identified (r = 0.28; ±0.05). Further linear mixed model analysis suggested that this relationship was a function of the low sleep durations which were associated with reduced DWB, rather than the high sleep durations, which were not similarly associated with increased DWB. Conversely, partial correlations identified a small correlation between PRS and training load (r = -0.23; ±0.05), which was replicated within the linear mixed model analysis for both high and low training loads. There was no meaningful relationship between PRS and sleep duration.

CMJ height was not meaningfully related to training load or sleep duration in this youth athlete cohort.

5.4.1 DWB

The key observation from this study is the inability of either statistical model to identify a relationship between DWB and training load. These results conflict with research in elite adult team sport athletes indicating that training load has a small to large association with DWB measures (Buchheit et al., 2013; Montgomery & Hopkins, 2013; Thorpe et al., 2015). It is possible that these contradictory results are due to differing influences of physical and psychological stressors between the two population groups. Although both cohorts encounter physical stress, the physical demands of adult sport are substantially greater than those of youth sport (Chandler et al., 2014; Cormack et al., 2014; Read, Weaving et al., 2017; Roberts et al., 2008). For example, in rugby union the total distance covered by backs in match play increases from under 16's (3884 ± 700m) to under 18's (4489 ± 1299m), under 20's (5889 ± 719m) and senior professionals (6127 ± 724m). This reduced physical stress, alongside increased psychological stress in youth athletes, given the social, academic and maturational stressors they are subjected to (Mountjoy et al., 2008), provides a potential avenue by which training load is not as important to a youth athlete's wellness as these other factors. This theory is further supported by the coping skills of youth athletes not fully developing until they reach adulthood (Compas et al., 2014), but more research is needed to confirm the relationship these life stressors may have on the DWB responses provided by youth athletes.

The association between sleep duration, particularly at low levels, and DWB at the expense of training load is unique to this study. Perhaps because sleep quality has been included as a subscale within DWB or because increases in training load are associated with reduced sleep duration (r = -0.31; ±0.19) during intensified periods of training (Thornton et al., 2017), no previous study has considered the relationship between sleep

and DWB. The small negative relationship between sleep and DWB observed here contradicts previous suggestions that absolute sleep duration is not related to fatigue or mood measures (Oginska & Pokorski, 2006; Pilcher et al., 1997), but is congruent with Oginska and Pokorski's (2006) observation that significant negative relationships are present between a youth's failure to meet their sleep requirements and the fatigue (r = -0.36, p < 0.0001) and mood (r = -0.30, p < 0.0001) symptoms experienced. The National Sleep Foundation has recommended that adolescents obtain 8-10 hours of sleep per night (Hirshkowitz et al., 2015), but this recommendation does not account for the additional requirements of any athletic individual relative to the general population (Davenne, 2009), so the requirement in the cohort studied here could be even higher. Despite this, the average sleep duration in this study was 7.3 ± 1.3 hours, so it is clear that the athletes in this study were experiencing insufficient sleep relative to their requirements, which may explain why a relationship was observed between DWB and sleep duration.

5.4.2 PRS

The results of this study indicate that there is a small linear relationship between PRS and training load, but PRS is not associated with sleep duration. This is the first study to consider the PRS in a practical setting and progresses the literature from previous laboratory based studies (Laurent et al., 2011; Sikorski et al., 2013). The results indicate that the PRS has a similar, but weaker relationship with training load when compared to the fatigue subscale previously used by Thorpe and colleagues (2015). In this study in elite adult soccer players, a large relationship was observed between the fatigue subscale and total high-speed running (r = -0.51; ±0.11, p < 0.001). Given the same statistical approach was used in both studies, it is logical to hypothesize that the difference between the small relationship identified in this study and the large relationship observed by Thorpe and colleagues (2015) is a function of differing training intensities between the two cohorts. Unfortunately, it is not possible to confirm this theory as GPS devices were not

used to measure high-speed running distances in this study and previous publications in adult and youth sports have used multiple different definitions for speed zones limiting readers' ability to compare the two cohorts using previously published data (Abbott, Brickley et al., 2018; Read, Weaving et al., 2017; Roberts et al., 2008; Thorpe et al., 2015).

The PRS shows a consistent linear relationship with training load whereby both high and low training loads fall outside the smallest worthwhile change of the moderate training load group (Figure 5.1). To this end, it is more responsive to training load than DWB, which may be due to it not considering as many factors (e.g. mood, muscle soreness or stress) within its measurement. The PRS solely asks "*how recovered do you feel?*" on a 0-10 scale and may therefore be a more effective and simple method of monitoring the training response and prescribing training than DWB.

Although described as having a small ES, the relationship between PRS and sleep duration did not reach the pre-determined threshold for practical significance. This lack of a clear, practically meaningful association between the two variables could indicate that the PRS is primarily affected by perceptions of physical and mental fatigue rather than the psychological disturbances caused by changes in sleep duration (Oginska & Pokorski, 2006) or the other stressors associated with this cohort (Mountjoy et al., 2008). However, further research with a greater number of observations is required to obtain a clear understanding of how practically meaningful this relationship is.

5.4.3 CMJ height

The finding that CMJ height was not related to training load conflicts with the literature showing training load to result in a decrease in CMJ height in elite adult athletes (Rowell et al., 2017; Thorpe et al., 2017), but agrees with that in elite youth soccer players (Malone et al., 2015). We previously suggested that the difference in results between

these three studies was due to the statistical analysis employed, but this hypothesis has now been disproved. It has previously been argued that youth athletes train at a lower intensity than adult athletes (Chandler et al., 2014; Cormack et al., 2014; Read, Weaving et al., 2017; Roberts et al., 2008). This difference in the physical demands between cohorts could result in lower neuromuscular fatigue and a reduced need for a neuromuscular fatigue test such as CMJ height in youth athletes. The agreement of the results of this study with a previous study in a similar cohort using the same equipment (Malone et al., 2015) provides further evidence within the literature that training load (within the ranges presented in this study) does not affect CMJ performance in this population.

The lack of association between CMJ height and sleep duration contradicts previous literature suggesting that sleep deprivation and extension can have positive and negative effects on neuromuscular performance respectively (Mah et al., 2011; Skein et al., 2013). However, given the training stimulus in this study may not have been intense enough to reduce neuromuscular function and the sleep durations observed in this study were reasonably uniform in nature (709/825 observations fell into the moderate group), it is understandable that there was no meaningful difference in neuromuscular recovery attributable to the duration of sleep experienced. In addition to this, the wide variability in the effect of training load on CMJ height (r = 0.09; ±0.06) suggests there was inherent variation in the motivation shown between and within participants over the duration of this study, which may have resulted in participants not always providing their best effort (Thorpe et al., 2015). Regardless, these results indicate that CMJ height is not responsive to training load or sleep duration in this population.

5.4.4 Limitations

Using more advanced statistical analysis than previously employed within the youth athlete literature and with a sample size greater than any previous study, this study's

results provide significant additions to the literature. However, they are subject to limitations. The primary data collection limitation of the study is that it took place on four weekdays, which skews the distribution of sleep in favour of low sleep durations as evidenced by the number of observations in the low sleep group (n=88) *vs.* those in the high sleep group (n=22). Similarly, but perhaps less impactful within this study, 628/825 observations were placed in the moderate training load group. Future studies should attempt to collect data over all seven weekdays so that a more complete understanding of its relationships with fatigue/wellness and preparedness to play measures can be obtained.

The aim of this study was to repeat the methods of previously published studies and confirm the relationships between measures of the athlete monitoring cycle in youth athletes. The study was successful in identifying the relationships present for the overall DWB score, but a greater understanding of the relationships present could be gathered if individual subscale analysis was employed to identify the relationships between training load, sleep duration and specific subscales. It has recently been suggested that overall wellness scores may suffer from a masking effect whereby the relationships that training load holds with individual subscales are overpowered by relationships that training load holds with other subscales in the same or opposing directions (Saw et al., 2016). For example, the small negative relationship between training load and muscle soreness observed by Buchheit and colleagues (2015) would have been cancelled out by the small positive association training load held with mood if the two measures were added together to produce an overall scale. It would therefore be beneficial to provide individual subscale analysis in future studies.

From a training load perspective, for the purposes of this study all training loads were grouped together to provide a daily training load. It has previously been suggested that there may be an additive effect of match stress (Montgomery & Hopkins, 2013), and there

are likely to be different responses to aerobic and resistance exercise so a future study may wish to isolate different types of training and assess their effect on fatigue/wellness and preparedness to play measures to enhance understanding in the area. The use of self-reported sleep duration could also be criticised as it provides little understanding relating to the quality of the sleep. Sleep duration was chosen for this study because sleep quality is collected as part of fatigue/wellness questionnaires (McLean et al., 2010; Thorpe et al., 2017), but future research may wish to consider removing it from DWB and using it as an input to the monitoring process alongside sleep duration, given its known impact on fatigue/wellness measures (Pilcher et al., 1997).

Although the statistical analyses utilised within this study were appropriate to identify changes in the DWB, PRS and CMJ height relative to previously published literature, they provide limited insight into the practically interpretable relationship between measures of the athlete monitoring cycle. Analysing a larger data set using all seven days, as described earlier could allow for more advanced statistical analyses to be conducted controlling for the covariance between training load and sleep duration and predicting individual coefficients within the model. Furthermore, it would be useful to establish whether the relationships between measures of the athlete monitoring cycle are meaningful in relation to adverse outcome incidence risk or prediction.

Finally, the statistical power of the study should be considered. In section 3.5.3, sample sizes of 66 (DWB), 49 (PRS) and 29 (CMJ) were identified as necessary for adequate statistical power. It should therefore be noted that the sample size of 52 was too small for DWB, but adequate for both PRS and CMJ. Despite this issue of power, which tempers confidence in the results provided for DWB, the sample size used was greater than both studies the analyses were compared to (Rowell et al., 2017; Thorpe et al., 2015). The reported results therefore provide a worthy addition to the literature.

5.5 Conclusions

This study is the first to consider the relationship fatigue/wellness and preparedness to play measures hold with training load and sleep duration in youth athletes using statistical analyses previously employed within elite adult sport research (Rowell et al., 2017; Thorpe et al., 2015). Altogether, the results of this study provide support for the use of DWB and PRS, but not CMJ height, within the integrated athlete monitoring cycle in youth athletes. The PRS showed a greater association with training load than either DWB or CMJ height but may only provide an understanding of how physically or mentally recovered the athlete feels. The DWB on the other hand was not related to training load but, by asking a greater range of questions, may provide a greater understanding of the athlete's overall wellness and is associated with low sleep durations. Consequently, the use of both questionnaires may provide a more complete understanding of the youth athlete's training response. These conclusions provide valuable information for practitioners working within applied youth sport environments, but the results provide little understanding as to the practically interpretable changes in fatigue/wellness measures that may occur in response to fluctuations in training load and sleep duration. Such information is pivotal to the creation of an integrated athlete monitoring cycle model aimed at predicting adverse outcomes to the training process and should be considered in future research.

Chapter 6 STUDY 3

Analysing the relationships between measures of the athlete monitoring cycle in youth athletes using more practically interpretable statistics

Sawczuk, T., Jones, B., Scantlebury, S., Till, K. (2018) The influence of training load, exposure to match play and sleep duration on daily wellbeing measures in youth athletes. *Journal of Sports Sciences*, 36(21), p2431-2437.

6.1 Introduction

Study 2 identified the presence of a *most likely* small negative relationship between training load and PRS (r = -0.23; ±0.05), and between sleep duration and DWB (r = 0.28; ±0.05). No practically meaningful relationship was observed between CMJ height and training load or sleep duration. However, despite confirming the potential for DWB and PRS to be used as fatigue/wellness measures in youth athletes, the data collection and analysis conducted was subject to numerous limitations (e.g. the data collection period was limited to four days per week and the statistical analyses did not provide practically interpretable results; for further details see section 5.4.4). Study 3 will build upon the limitations of study 2 to gain a greater understanding of the practically interpretable relationships between measures of the integrated athlete monitoring cycle in youth athletes.

Fundamentally, it was the data collection period, restricted to four weekdays per week, which limited the results obtained in study 2. Within the adult literature, it is common for wellness data to be collected a similar number of days per week as athletes are usually given 1-2 rest days per week (Gastin et al., 2013; Montgomery & Hopkins, 2013). However, by not collecting information from athletes seven days per week, practitioners may obtain a skewed view of the training load and sleep durations their athletes experience. This skewed view was shown in study 2 as the majority of training load (628/825) and sleep duration (709/825) observations fell within 1 z-score of the mean (Table 5.2). In study 3, using an online questionnaire emailed to participants every day, it will be possible to obtain wellness data seven days per week allowing practitioners to gain a more accurate representation of the weekly training load, sleep duration and fatigue/wellness fluctuations experienced by youth athletes.

Collecting data seven days per week will also lead to a larger dataset, which can handle more complicated statistical analyses, controlling for the covariance between training load and sleep duration. Controlling for this covariance with random effects will also allow the individual responses to training load and sleep duration to be evaluated, allowing for more practically interpretable results to be provided. Furthermore, the larger dataset will allow individual subscale analysis to be conducted to identify whether a masking effect was present with the results in study 2 (Saw et al., 2016). By evaluating the effect of training load as a covariate rather than within discrete groups, the inclusion of a dummy match variable can also be incorporated. Montgomery and Hopkins (2013) previously observed a ”clear and small” effect of match exposure on a muscle soreness scale, which added to the small effect of training load (exact ES not reported) in elite adult Australian Rules Football players. Consequently, accounting for this difference in the effect of training load on fatigue/wellness measures when training *vs.* when participating in match play may also be necessary to obtain an accurate understanding of the relationships between measures of the integrated athlete monitoring cycle in youth athletes.

6.1.1 Aim

The aim of this study was to evaluate the relationships between training load and match exposure (as measures of the training dose), sleep duration (as a training recovery measure), DWB and PRS (as fatigue/wellness measures) in youth athletes using statistical analyses providing more practically interpretable results than previously.

6.1.2 Objectives

- Evaluate the relationships training load, match exposure and sleep duration hold with DWB, its individual subscales (fatigue, muscle soreness, sleep quality, mood and stress) and PRS

6.2 Methods

6.2.1 Participants

Forty-eight youth athletes aged 16-18 years (age 17.3 ± 0.5 years, height 172.8 ± 18.3 cm, body mass 73.6 ± 12.8 kg) participated in this study. Participants were recruited from a local independent school in the UK, where they were members of the school's sport scholarship scheme. The sports cricket (n=5), football (n=10), hockey (n=10), netball (n=10) and rugby union (n=13) were represented by athletes competing at club/school (n=29), professional academy (n=6), county/regional (n=10) and international (n=3) standard in their respective sports. Participants were recruited according to the procedures outlined in the general methods (section 3.3).

6.2.2 Design

For this prospective cohort study, a longitudinal, observational study design was used. A bespoke online wellness questionnaire, including DWB, PRS and details on the previous day's self-reported training load and sleep duration, was completed every weekday for a period of seven weeks. This study is only the second to explicitly state that wellness questionnaires were completed seven days per week during the in-season period, following Thorpe and colleagues' (2015) study. Previously, Buchheit and colleagues (2013) collected wellness data seven days per week during a two-week pre-season period.

In total, 2727 observations were analysed for this study at a median response rate of 54/91 completions per person. Overall, 2181 training sessions, 292 matches and 991 rest days were included. Neither Thorpe and colleagues (2015) nor Buchheit and colleagues (2013) detailed their final dataset size, but the total number of observations considered within this analysis is substantially greater than the maximum possible for either study (170 and 252 observations respectively). All data were collected in terms 4 and 5 of the

academic year, and data collection continued through the half-term break. The data collection period was thirteen weeks long, taking place between February and May 2016. This data collection period is significantly longer than the 14 (Buchheit et al., 2013) and 17 (Thorpe et al., 2015) days previously considered.

6.2.3 Procedures

6.2.3.1 Data collection

Participants completed a bespoke daily wellness questionnaire, including DWB and PRS, seven days per week for a thirteen-week period. The wellness questionnaire was emailed to participants at 6am and completed online via Google Docs (Google Forms, Google, CA, USA). On training days, the questionnaire was completed before the first training session of the day. If necessary, verbal reminders were provided at 10.30am to remind athletes to complete the questionnaire by 11am. The wellness questionnaire also included details on the previous day's training load (evaluated via the s-RPE method) and self-reported sleep duration (in hours). Further details are provided in section 3.4.1 and Appendix 3A. In study 1, the TE was established as 11.7% for DWB and 8.5% for PRS. The SWC's were 6.2% and 4.9% respectively.

6.2.3.2 Statistical analyses

Prior to analysis, the assumptions of residual normality, heteroskedasticity and linear relationship between dependent and independent variables were evaluated as outlined in section 3.5.1. Consequently, DWB, its individual subscales (fatigue, muscle soreness, sleep quality, mood and stress) and PRS scores were converted to scores out of 100. To provide a greater understanding of the relationships between measures of the integrated athlete monitoring cycle at both an overall and subscale level, linear mixed models were employed for analysis. The overall DWB score, its individual subscales and PRS score were used as separate dependent variables. Sport (referring to the athlete's sport), week

(referring to the week of the study), and day (referring to the day of the week) were added as fixed factors and provided estimated means for the fatigue/wellness scores for each factor. Training load and sleep duration were mean centred by individual and added as time varying covariates. The effect of the covariates was calculated by assessing a 2 SD difference in the covariate (see section 3.5.1.4 for details). The additive effect of exposure to match play was calculated by a dummy covariate on any day where the participant reported they had taken part in a match. Athlete*training load*sleep duration was added as an unstructured random effect to allow for variation in the effect of the covariates on the dependent variables between individuals to be calculated. This random effect structure also accounted for the covariance between training load and sleep duration, given previous studies identifying a relationship between the two measures (Sargent et al., 2014; Thornton et al., 2017). Data were analysed using SAS University Edition (SAS Institute, Cary, NC).

Results were analysed for practical significance via MBI's using a pre-made Microsoft Excel spreadsheet (Hopkins, 2006a). Further details surrounding the MBI approach (section 3.5.2.4) and the ES used (section 3.5.2.2) are provided in the general methods. The individual responses to the covariates were evaluated using the random effect variance. The random effects were square rooted to provide the standard deviation, doubled to evaluate the effect for a 2 SD change (Hopkins, 2015a) and standardised by the observed standard deviation (Equation 3.7). Standardised random effects were compared against the same ES thresholds as the fixed effects but were not evaluated using the MBI method as their chi squared distribution does not allow for this type of analysis. The practically interpretable effect of a 2 SD change in training load and sleep duration on fatigue/wellness measures for a 'typical athlete' (i.e. one who's response falls within 1 SD of the mean response) was identified by adding and subtracting the standard deviation taken from the random effects to the mean coefficient of the covariate (see section 3.5.1.5.2). These values were evaluated using the raw units to assess qualitatively

how likely it was that a ‘typical athlete’ would experience a one unit change in the fatigue/wellness scale in response to a 2 SD change in the covariate. Normally distributed fixed effect ES are reported ES; ± 90% confidence intervals, chi square distributed random effects are reported ES; lower 90% confidence interval, upper 90% confidence interval.

6.3 Results

Across the thirteen week data collection period, the mean daily training load was 250 ± 317 AU and the mean sleep duration was 7.7 ± 1.5 hours. A 2 SD difference in training load equated to 556 ± 208 AU, whereas the difference for sleep duration was 2.6 ± 1.3 hours.

6.3.1 Statistical relationships

Figure 6.1 depicts the influence of training load, exposure to match play and sleep duration on the DWB overall score, its individual subscales and PRS. Training load showed a most likely small negative relationship with muscle soreness (*d* = -0.43; ±0.10) and PRS (*d* = -0.37; ±0.12). A likely small additive effect of match exposure was observed for both measures (muscle soreness *d* = -0.26; ±0.09, PRS *d* = -0.25; ±0.09). Sleep duration held a very likely moderate relationship with sleep quality (*d* = 0.80; ±0.14), and substantial small relationships with the DWB overall score (*d* = 0.45; ±0.09, most likely), fatigue (*d* = -0.42; ±0.12, most likely) and PRS (*d* = 0.25; ±0.09, likely). All other relationships were trivial or did not reach the pre-determined threshold for practical significance.

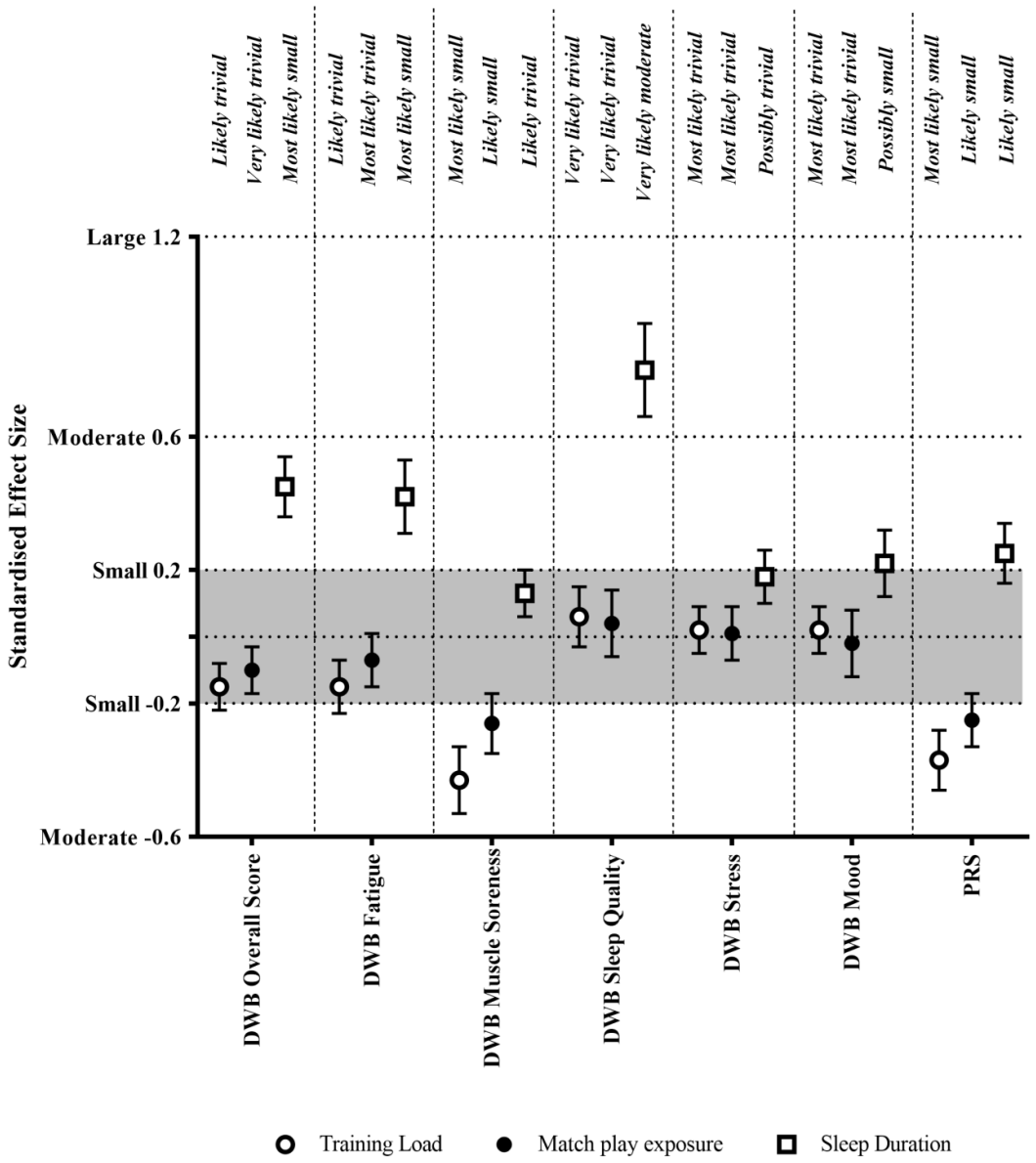


Figure 6.1: Statistical relationships between training load, exposure to match play and sleep duration with DWB, its individual subscales and PRS. Data are presented as effect sizes with 90% confidence intervals, shaded area denotes smallest worthwhile change.

Table 6.1 quantifies the individual responses to training load and sleep duration after accounting for the covariance between the two covariates. Most differences in the individual responses to training load and sleep duration were small, but trivial differences were observed between training load and the DWB overall score (*d* = 0.16; 0.11, 0.28), sleep duration and muscle soreness (*d* = 0.17; 0.12, 0.30), training load and stress (*d* = 0.14; 0.09, 0.37), and sleep duration and stress (*d* = 0.19; 0.14, 0.31).

Table 6.1: Individual responses to the relationships between training load, sleep duration, DWB, its individual subscales and PRS. ES are reported ES; lower 90% confidence interval, upper 90% confidence interval. Descriptor provides qualitative description of ES.

	Training Load		Sleep Duration	
Scale	**Effect Size**	**Descriptor**	**Effect Size**	**Descriptor**
DWB overall	0.16; 0.11, 0.28	Trivial	0.30; 0.24, 0.41	Small
Fatigue	0.20; 0.15, 0.34	Small	0.38; 0.31, 0.51	Small
Muscle soreness	0.27; 0.20, 0.42	Small	0.17; 0.12, 0.30	Trivial
Sleep quality	0.22; 0.16, 0.36	Small	0.45; 0.37, 0.61	Small
Mood	[a]		0.28; 0.22, 0.40	Small
Stress	0.14; 0.09, 0.37	Trivial	0.19; 0.14, 0.31	Trivial
PRS	0.23; 0.17, 0.37	Small	0.25; 0.19, 0.36	Small

[a] The linear mixed model was unable to compute the individual responses to the mood subscale due to a lack of variance within the measure (i.e. participants reported similar values most of the time). Usually this would result in removing the covariate from the random effect structure. By maintaining training load within the random effect structure, consistency was maintained between models and the covariance between training load and sleep duration with regards to mood could be accounted for in the sleep duration effect size.

6.3.2 Practically interpretable relationships

Table 6.2 details the practically interpretable relationships between measures of the integrated athlete monitoring cycle. Only the effect of training load with the additive effect of match play on PRS (-1.31, -1.55 to -1.07 units) was able to elicit a one unit change for a 'typical athlete'. However, the effect of sleep duration on the DWB overall score (1.30, 0.86 to 1.73 units) was close.

Table 6.2: Practically interpretable relationships between measures of the integrated athlete monitoring cycle. Values are presented in raw units as the mean response, with the range of responses for a 'typical athlete' in brackets.

	Training Load		
Scale	**Training day**	**Match day**	**Sleep duration**
DWB overall	-0.44 (-0.67 to -0.21)	-0.72 (-0.95 to -0.49)	1.30 (0.86 to 1.73)
Fatigue	-0.13 (-0.22 to -0.05)	-0.19 (-0.28 to -0.10)	0.35 (0.19 to 0.52)
Muscle soreness	-0.38 (-0.50 to -0.27)	-0.62 (-0.74 to -0.50)	0.11 (0.04 to 0.19)
Sleep quality	0.04 (-0.03 to 0.11)	0.06 (-0.01 to 0.13)	0.50 (0.36 to 0.64)
Mood	0.00 (incomputable)	0.00 (incomputable)	0.16 (0.06 to 0.25)
Stress	0.02 (-0.04 to 0.09)	0.03 (-0.03 to 0.09)	0.17 (0.08 to 0.26)
PRS	-0.79 (-1.03 to -0.55)	-1.31 (-1.55 to -1.07)	0.53 (0.27 to 0.79)

N.B.: Training day calculated using only training load, match day includes additive effect of match exposure. Model was unable to compute individual responses for relationship between training load and mood so range of values could not be provided.

6.4 Discussion

The aim of this study was to evaluate the relationships between training load and match exposure (training dose), sleep duration (training recovery), DWB, its individual subscales (fatigue/wellness) and PRS (fatigue/wellness) in youth athletes using statistical analyses providing more practically interpretable results than previously. Statistically, the results suggest small negative relationships are present between training load and the muscle soreness subscale and PRS. These relationships are augmented by a *likely* small negative additive effect of exposure to match play. Sleep duration held a moderate positive relationship with sleep quality and a small positive relationship with the DWB overall score, fatigue and PRS. Despite these statistical relationships, none of the relationships resulted in a one unit change in DWB or its individual subscales for a typical athlete. The influence of training load, with the additive effect of exposure to match play, did result in a one unit change in PRS for a typical athlete.

6.4.1 Statistical relationships

6.4.1.1 Training load and exposure to match play

The results of this study suggest that training load and exposure to match play are not related to the DWB overall score. There was, however, a most likely small negative relationship between training load and muscle soreness, which was augmented by exposure to match play. These results provide further support for the findings of study 2, which also suggested that the DWB overall score was not related to training load. Previous studies in elite adult sport have indicated that training load and match exposure have a small to large effect on wellness questionnaires and their individual subscales (Buchheit et al., 2013; Montgomery & Hopkins, 2013; Thorpe et al., 2015). In study 2, it was argued that the difference in results between these adult populations and the youth athlete cohort studied here could be due to differences in the relative physical and psychological stressors experienced (section 5.4.1). This study cannot confirm that theory,

but the results suggest that the masking effect suggested by Saw and colleagues (2016) does occur in DWB. To this end, although a small relationship was observed between training load and exposure to match play with muscle soreness, no meaningful relationship was observed with fatigue, sleep quality, mood or stress. Consequently, when the DWB overall score was evaluated, the four subscales showing no meaningful relationship with training load and match play exposure overpowered the single subscale holding a relationship with these measures of the training dose, resulting in a trivial overall relationship being reported for DWB. Moving forwards, all studies should provide full subscale analyses to ensure that any masking effect is shown and discussed rather than solely considering the overall score.

Alongside the small negative relationship between training load, exposure to match play and muscle soreness, a small negative relationship was present between training load, match play exposure and PRS. Interestingly though, this relationship was not present with the fatigue subscale of DWB. In line with the super compensation curve dictating that following a training stimulus, an athlete will experience a period of fatigue (Bompa & Haff, 2009), it was expected that both scales would be responsive to training load and exposure to match play. The lack of relationship between training load and the fatigue subscale is therefore surprising, but the small negative relationship between training load and PRS does agree with study two's observations. It is possible that the difference in the relationships shown is due to the weightings used (fatigue measure as a behaviour based category scale vs PRS as a category-ratio scale), but it could also be due to the anchoring words employed by the scales. Although the terminology used between the scales is very similar, the PRS, via its terms *"very poorly recovered/extremely tired"* to *"very well recovered/highly energetic",* possibly places a greater balance on how *recovered* an athlete feels, whereas the fatigue scale, via its terms *"very fresh"* to *"always tired"*, appears to consider how *tired* an athlete is. The participants in this study may have associated the term *recovery* with training load and physical recovery, whereas the term

tired may have been associated with perceptions of sleep and fatigue/sleepiness, which may explain the difference in results between the two scales. This would also explain why the fatigue scale has a greater relationship with sleep duration than the PRS in this population. Alternatively, it is possible that the difference in the two measures is due to the impact training load has on the subsequent sleep duration experienced. This study did not consider the interaction between the two measures, but it is likely that those participants who had higher training loads due to evening club training sessions slept less than those who did not due to increased travel time or the need to catch up with academic work. It is therefore possible that their perceptions of fatigue could have been caused by the indirect impact of the previous day's training load on their sleep duration. Future research may wish to consider this relationship and the impact it has on fatigue/wellness measures further.

As with the relationship between training load, exposure to match play and fatigue, it is perhaps surprising that no meaningful relationship was observed between training load, match play exposure and sleep quality. Leduc and colleagues (2019) recently identified reductions in self-reported sleep quality when total distance covered during pre-season training was high compared to low (d = -0.74; ±0.67) in elite adult rugby sevens players. Similarly, Thornton and colleagues (2017) reported self-reported sleep quality to be lower on a pre-season training camp compared to at home (d = 0.31; ±0.15). As with the lack of association between training load and CMJ height in this cohort (identified in study 2), the lack of relationship between training load and sleep quality could be due to the lower training intensities experienced by youth athletes (Read, Weaving et al., 2017; Roberts et al., 2008). Similarly, the lack of relationship between training load, match play exposure and mood or stress could be expected given these measures are usually affected prior to incidence of the overtraining syndrome (Meeusen et al., 2013), at higher training loads than the 1750 AU reported here.

6.4.1.2 Sleep duration

Sleep duration held a moderate positive relationship with sleep quality and a small positive relationship with the DWB overall score, fatigue and PRS. These relationships, with four out of the seven scales measured show the importance of sleep as a measure of training recovery within the integrated athlete monitoring cycle and highlight this as an under-researched area.

The moderate positive relationship identified between sleep duration and sleep quality is unsurprising in its presence as both measures are subjective indices of sleep, but its size is perhaps smaller than anticipated. A possible reason for this could be the difficulty in defining good sleep quality between individuals, compared to sleep duration, which can be estimated as an arbitrary duration. For example, for some individuals good sleep quality may occur with a longer sleep duration, which would provide a good correlation between the two variables, whereas for others it may be based on how many times they wake (consciously or subconsciously) during the night, which may have little relationship with the sleep duration they reported (Krystal & Edinger, 2008). This is supported by the relationship observed between self-reported sleep duration and actigraphy based total sleep time being very large (r = 0.85), whereas the relationship between subjective sleep quality and sleep efficiency was only small (r = 0.22-0.28) in a recent validation study (Caia et al., 2018). The moderate relationship observed between the two sleep variables in this study indicates that they do not provide the same information. Therefore, given sleep quality has previously shown relationships with the other wellbeing measures within DWB (Pilcher et al., 1997), there is scope for its consideration as a measure of training recovery within the integrated athlete monitoring cycle, rather than as part of a fatigue/wellness measure.

Study 2 was the first to consider sleep duration as a measure of training recovery within the integrated athlete monitoring cycle. In study 2, low sleep durations were identified as

having a particularly negative relationship with DWB when compared to moderate sleep durations (d = -0.33; ±0.11), but no meaningful relationship was observed with PRS. This study is unable to provide further support for the theory that low sleep durations have a greater impact on DWB than high sleep durations but does show that a practically meaningful linear relationship can be derived between sleep duration and both DWB and PRS. It is particularly interesting that sleep duration is related to the total score of both scales, as practically significant relationships are not present between training load and both scales. It could therefore be suggested that evaluating the training recovery of youth athletes is more important than any single individual stressor (e.g. training load). However, it remains to be seen whether lack of training recovery or an excessive training dose is predictive of true outcome measures of the training process when both are measured together. For example, previous studies have shown spikes in training loads (Putlur et al., 2004) and low sleep durations (Cohen et al., 2009; Prather et al., 2015) to be associated with illness risk, but no study has yet considered these variables together, in which situation one of the training dose imposed or the training recovery experienced may be more important than the other.

The small relationship between sleep duration and fatigue was expected given previous findings but the lack of relationship with mood and stress is less congruent with previous research (Oginska & Pokorski, 2006). Oginska and Pokorski (2006) found significant relationships between sleep duration, fatigue (r = -0.36, p < 0.0001) and mood (r = -0.30, p < 0.0001) when the amount of sleep needed by each individual was accounted for. As with study 2, the results of study 3 could reasonably be expected to confirm these findings and there is no obvious reason why they do not. However, sleep quality has also shown significant relationships with fatigue (r = -0.57, p < 0.001) and mood (r = -0.52, p < 0.01) variables in previous research, so it would be interesting to assess whether sleep quality holds stronger relationships with other measures of the fatigue/wellness training response

in youth athletes. If it did, the findings would support the use of sleep quality as a measure of training recovery rather than embedded within a fatigue/wellness measure.

The lack of relationship observed between sleep duration and muscle soreness could be explained by the 72 hours of soreness progression associated with delayed onset muscle soreness (Cheung et al., 2003). This study only considered the previous day's sleep duration as daily monitoring strategies usually evaluate the training response *vs.* the training dose of the previous day. However, over a 72 hour period, the restorative capabilities of one night's sleep are limited. It is possible that if the three day sleep duration for an athlete had been considered, a relationship may have been present, but it is unclear to this author how this would be modelled and interpreted in practice.

6.4.1.3 Individual responses

This study is the first to detail the between participant differences in the relationships between training load, sleep duration and fatigue/wellness measures. In total, sixteen of the twenty relationships evaluated showed small differences in the individual responses (Table 6.1). With no literature to compare to, it is not possible to state whether these differences deviate from normal variation in the response to wellness questionnaires, but it is interesting given the link between sleep duration and sleep quality that this relationship showed the greatest variance in individual responses (d = 0.45; 0.37, 0.61). Arguably the presence of such variation supports our previous hypothesis that the link between sleep duration and sleep quality is dependent on each participant's definition of sleep quality. However, it should also be noted that sleep duration and sleep quality had the largest relationship of all variables measured, so it is possible that the increased variation observed could be expected simply because the relationship between the two variables is larger than between the other measures considered.

6.4.2 Practically interpretable relationships

Table 6.2 details the practically interpretable relationships between training load, match exposure, sleep duration and fatigue/wellness measures for a typical athlete (i.e. one whose relationship is within 1 SD of the mean response). These results show the unit change in the fatigue/wellness measures in response to a 2 SD increase in training load, a 2 SD increase in training load which includes a match, and a 2 SD increase in sleep duration. Given the statistical relationships observed, it is surprising that only the relationship between training load and PRS with the additive effect of exposure to match play resulted in a one unit change for a typical athlete. However, this lack of responsiveness could be explained by previous research. Thorpe and colleagues (2015) previously identified a large statistical relationship between high-speed running and a fatigue scale (r = -0.51; ±0.11, p < 0.001), which was equivalent to a 400 m change in high-speed running being required for a one unit change in the scale. This 400 m change in high-speed running is only likely to happen between match days (typically 600 m or greater high-speed running) and training days (typically less than 350m high-speed running) during congested match play periods according to Buchheit (2019). Although direct comparison between the two studies is difficult due to the different thresholds used (Thorpe and colleagues' (2015) >14.4 km/hr *vs* Buchheit's (2019) >19.8 km/hr), these changes seem unlikely to occur in youth sport and school sports scholarship schemes where multiple training sessions or matches can take place every day due to school and club commitments (Phibbs et al., 2018b). Consequently, it is possible that there is insufficient variation in the training load present within youth athletes to elicit changes in wellness questionnaires and so unit changes in wellness questionnaires should not necessarily be expected. However, it is currently uncertain whether this lack of responsiveness to training load or sleep duration in raw units is important in practice. As has been highlighted repeatedly within this thesis, the fatigue/wellness measures themselves are not the important outcome measure within the athlete monitoring process,

illness, injury, overtraining and performance are. Therefore, further research is required to establish whether changes in wellness, and how they relate to the training dose and recovery experienced, are predictive of these adverse outcomes.

6.4.3 Limitations

Although the results of this study add to the literature, particularly through the sample size and time period of data collection which is much greater than the previous literature (Buchheit et al., 2013; Thorpe et al., 2017), alongside the advanced statistical methods used, they are not without their limitations. The first of these is the use of several different sports within the study, which increases the ecological validity of the study, but also increases the chance of a masking effect where meaningful effects in one sport (e.g. football) may be lost due to the trivial effects of another (e.g. cricket). Unfortunately, participant numbers prevented us from breaking the analysis down into sports to confirm this theory. It is possible that the differences between sports are accounted for by the small differences in the individual responses identified by the random effects though. One of the aims of this study was to use the random effects to provide practically interpretable relationships between measures of the integrated athlete monitoring cycle (i.e. evaluate what relationships could be present for a typical athlete), but it should also be noted that the random effects can be used to obtain individual coefficients for each athlete. These individual coefficients provide the relationship fatigue/wellness measures have with training load and sleep duration for each individual athlete and could be used in the future to provide a more individualised approach to monitoring via the integrated athlete monitoring.

This study was successful in identifying the presence of a masking effect within the DWB subscales, but the practically interpretable relationships identified also questioned the usability of these subscales alone within the integrated athlete monitoring cycle. Study 1

identified the poor reliability of the fatigue/wellness measures and how this can impact upon the observed scores (section 4.4.1). It is also possible that the 1-5 scoring system used for each subscale affects its usefulness as an individual measure in practice as it may be that too few options are available for athletes to provide accurate responses. However, Thorpe and colleagues (2015) previously showed that a 400 m difference in high-speed running is necessary for a one unit change in a seven point fatigue scale so this 1-5 scoring system may not necessarily be an issue. Future research should aim to consider how changes in these fatigue/wellness measures in response to the training dose and training recovery experienced relate to the prediction of adverse outcome measures, the primary of interest within this thesis being illness incidence.

Finally, it is important to consider the statistical power of this study. In section 3.5.3, sample sizes of 66 for DWB and 49 for PRS were identified as necessary for adequate statistical power. This study's sample size of 48 falls short of both these numbers (although only by one participant in the case of PRS) and so the results should be treated with caution. However, as was identified in the study design (section 6.2.2), the sample size within this study is considerably greater than two previous studies (Buchheit et al., 2013; Thorpe et al., 2015) and so the results are still useful additions to the literature.

6.5 Conclusions

In conclusion, the results of this study show training load to have a most likely small negative statistical relationship with muscle soreness and PRS. This relationship is boosted by an additional likely small negative effect of match exposure on both measures. Conversely, sleep duration held a very likely moderate relationship with sleep quality and likely small relationship with the DWB overall score, fatigue and PRS. These more frequent and, in some cases, stronger relationships provide more evidence that within youth athletes the training recovery experienced may be more important than the training

dose. However, this conclusion may be skewed by the moderate relationship between sleep duration and sleep quality, so future studies may wish to remove sleep quality from the fatigue/wellness measures and consider it as a measure of the training recovery.

The results also showed the DWB overall score to be associated with sleep duration but not training load. Despite this, the individual subscale of muscle soreness was related to training load suggesting that a masking effect may have occurred with the overall score. This does not mean that the subscales not showing a relationship with training load are not valuable because they were, with the exception of the mood and stress subscales, related to the training recovery experienced by the athlete and may still be important, either alone or as part of the overall DWB score, for the detection of future adverse outcomes (e.g. illness). Future studies should continue to provide individual subscale analyses to confirm whether masking effects occur within overall scales. The PRS was related to both the training dose (training load and additive match play exposure) and the training recovery encountered (sleep duration), suggesting that as a single measure to monitor the athlete's response to a training programme it may be superior to DWB and its individual subscales. However, like DWB, its relationship with adverse outcomes, such as illness, is yet to be elucidated.

Finally, despite the presence of statistical relationships between measures of the integrated athlete monitoring cycle, only the relationship between training load and PRS with the additive effect of match exposure resulted in a one unit change in the scales for a 'typical athlete'. Using these practically interpretable statistics alongside the statistical relationships casts doubt on the suitability of the scales for use within athlete monitoring, but until fatigue/wellness measure changes are related to the prediction of adverse outcomes, it is not possible to state with clarity that they are fit or unfit for purpose.

Chapter 7 STUDY 4

Exploring the use of sleep as a measure of training recovery within the integrated athlete monitoring cycle

Sawczuk, T., Jones, B., Scantlebury, S., Till, K. (2018) Influence of perceptions of sleep on well-being in youth athletes. *Journal of Strength and Conditioning Research*, epub ahead of print.

7.1 Introduction

One of the more notable findings from study 3 was the relationship between sleep duration and sleep quality, which was larger and more variable than any other relationship measured. A 2 SD increase in sleep duration held a *very likely* moderate relationship with sleep quality (d = 0.80; ±0.14), with small differences in the individual response present (d = 0.45; 0.37, 0.61). Although larger than all other associations measured, the size and variability present within this relationship suggests that the two measures provide different information and indicates that further exploration of the usage of sleep as a measure of training recovery within the integrated athlete monitoring cycle is merited.

Given the association between the two indices of sleep, the most obvious measure to compare to sleep duration is sleep quality. The relationship between sleep quality and longer wellness questionnaires has been considered in youths within education (Pilcher et al., 1997) and in adult marathon runners (Lastella et al., 2014). In these studies, using the POMS (McNair et al., 1971), sleep quality was correlated with fatigue (r = -0.28, p = 0.004 to r = -0.57, p < 0.001) and tension/anxiety (r = -0.21, p = 0.030 to r = -0.52, p < 0.01). Furthermore, Pilcher and colleagues (1997) identified correlations with depression/dejection (r = -0.52, p < 0.01) and confusion/bewilderment (r = -0.41, p < 0.05). However, despite this promise in longer wellness questionnaires, no study has yet considered the relationship between sleep quality and the short fatigue/wellness measures used within athlete monitoring processes.

Alongside the individual relationships sleep duration and sleep quality have with fatigue/wellness measures, it may also be useful to consider the interaction between the two sleep indices (termed ‘sleep index’ in this thesis) as a measure of the training recovery. To date, no study has considered the influence of a sleep index on fatigue/wellness measures, but it is reasonable to expect that nine hours of ‘good’ sleep

will provide greater recovery benefit than six hours of ‘good’ sleep, as it involves two further full cycles of sleep (Carskadon & Dement, 2011). Therefore, assessing these two measures in unison via this sleep index measure could hold a greater relationship with fatigue/wellness measures than sleep duration or sleep quality alone.

7.1.1 Aim

The aim of this study was to evaluate the use of different sleep indices (sleep duration, sleep quality and sleep index) as measures of training recovery within the integrated athlete monitoring cycle.

7.1.2 Objectives

- Evaluate the relationships sleep duration, sleep quality and sleep index (as training recovery measures) have with DWB and PRS (as fatigue/wellness measures)

7.2 Methods

7.2.1 Participants

Forty-eight youth athletes aged 16-18 years (age 17.3 ± 0.5 years, height 172.8 ± 18.3 cm, body mass 73.6 ± 12.8 kg) participated in this study. Participants were recruited from a local independent school in the UK, where they were members of the school's sport scholarship scheme. The sports; cricket (*n*=5), soccer (*n*=10), hockey (*n*=10), netball (*n*=10) and rugby union (*n*=13) were represented by athletes competing at club/school (*n*=29), professional academy (*n*=6), county/regional (*n*=10) and international (*n*=3) standard in their respective sports. Participants were recruited according to the procedures outlined in the general methods (section 3.3).

7.2.2 Design

This prospective cohort study used the same longitudinal, observational study design and dataset as study 3. A bespoke online wellness questionnaire, including DWB, PRS and details on the previous day's self-reported training load and sleep duration, was completed every weekday for a period of seven weeks. In total, 2727 observations were analysed for this study at a median response rate of 54/91 completions per person. Overall, 2181 training sessions, 292 matches and 991 rest days were included. All data were collected in terms 4 and 5 of the academic year, and data collection continued through the half-term breaks. The data collection period was thirteen weeks long, taking place between February and May 2016. As described in section 6.2.2, this dataset is considerably greater in duration, participant and observation numbers than two previous studies considering the relationships between measures of the athlete monitoring cycle (Buchheit et al., 2013; Thorpe et al., 2015)

7.2.3 Procedures

7.2.3.1 Data collection

Participants completed a bespoke daily wellness questionnaire, including DWB and PRS, seven days per week for a thirteen-week period. The wellness questionnaire was emailed to participants at 6am and completed online via Google Docs (Google Forms, Google, CA, USA). On training days, the questionnaire was completed before the first training session of the day. If necessary, verbal reminders were provided at 10.30am to remind athletes to complete the questionnaire by 11am. The wellness questionnaire also included details on the previous day's training load (evaluated via the s-RPE method) and self-reported sleep duration (in hours). Further details are provided in section 3.4.1 and Appendix 3A. To evaluate the relationships the different sleep indices held with fatigue/wellness measures, the sleep quality subscale was removed from DWB to create a four item $DWB_{no\text{-}sleep}$ scale scored out of 20. For this study, the TE and SWC for $DWB_{no\text{-}sleep}$ were calculated as 9.8%

and 6.4%. In study 1, the TE and SWC for PRS were established as 8.5% and 4.9% respectively.

7.2.3.2 Statistical analyses

Prior to analysis, the assumptions of residual normality, heteroskedasticity and linear relationship between dependent and independent variables were evaluated as outlined in section 3.5.1. Consequently, $DWB_{no\text{-}sleep}$, its individual subscales (fatigue, muscle soreness, stress and mood) and PRS scores were converted to scores out of 100. To evaluate the use of different sleep indices within the integrated athlete monitoring cycle, linear mixed models were used. The overall $DWB_{no\text{-}sleep}$ score, its individual subscales and PRS were used as the dependent variables. Sport (referring to the athlete's sport), week (referring to the week of the study), and day (referring to the day of the week) were added as fixed factors and provided estimated means for the fatigue/wellness scores for each factor. Training load was added as a time varying covariate, along with the dummy covariate exposure to match play (see section 6.2.3.2 for details). In separate models, sleep duration, sleep quality and sleep index (sleep duration multiplied by sleep quality) were added as time varying covariates. The effect of the covariates was calculated by assessing a 2 SD difference in the covariate (see section 3.5.1.4 for details). Sleep duration was analysed as a covariate again due to the removal of the sleep quality measure from DWB for this study's analysis, but the results of the fatigue, muscle soreness, stress, mood and PRS models were expected to be the same as study 3. Athlete*training load*sleep duration, sleep quality or sleep index (dependent on the model) was added as an unstructured random effect to allow for variation in the effect of the covariates on the dependent variables between individuals to be calculated. This random effect structure also accounted for the covariance between training load and sleep measures, given previous studies identifying a relationship between the two measures (Sargent et al., 2014; Thornton et al., 2017). In total, eighteen models were produced –

three for each scale/subscale (one for sleep duration, sleep quality and sleep index). Data were analysed using SAS University Edition (SAS Institute, Cary, NC).

Results were analysed for practical significance via MBI's using a pre-made Microsoft Excel spreadsheet (Hopkins, 2006a). Further details surrounding the MBI approach (section 3.5.2.4) and the ES used (section 3.5.2.2) are provided in the general methods. The individual responses to the covariates were evaluated using the random effect variance. The random effects were square rooted to provide the standard deviation, doubled to evaluate the effect for a 2 SD change (Hopkins, 2015a) and standardised by the observed standard deviation (Equation 3.7). Standardised random effects were compared against the same ES thresholds as the fixed effects but were not evaluated using the MBI method as their chi squared distribution does not allow for this type of analysis. The practically interpretable effect of a 2 SD change in the sleep indices on fatigue/wellness measures for a 'typical athlete' (i.e. one who's response falls within 1 SD of the mean response) was identified by adding and subtracting the standard deviation taken from the random effects to the mean coefficient of the covariate (see section 3.5.1.5.2). These values were then evaluated using the raw units to assess qualitatively how likely it was that a 'typical athlete' would experience a one unit change in the scale in response to a 2 SD change in the covariate. Normally distributed fixed effect ES are reported ES; ± 90% confidence intervals, chi square distributed random effects are reported ES; lower 90% confidence interval, upper 90% confidence interval.

7.3 Results

Across the thirteen week data collection period, the mean daily training load was 250 ± 317 AU and a 2 SD change was equivalent to 556 ± 208 AU. The mean sleep duration was 7.7 ± 1.5 hours, the mean sleep quality score was 4 ± 1 AU and the mean sleep

index was 29 ± 9 AU. A 2 SD change was equivalent to 2.6 ± 1.3 hours, 3 ± 1 AU and 14 ± 6 AU for sleep duration, sleep quality and sleep index respectively.

7.3.1 Relationships between sleep indices and fatigue/wellness measures

7.3.1.1 Statistical relationships

Figure 7.1 provides a graphical representation of the effect of self-reported sleep duration, sleep quality and sleep index on $DWB_{no\text{-}sleep}$, its individual subscales and PRS. All three sleep indices held substantial small positive relationships with $DWB_{no\text{-}sleep}$ (d = 0.31; ± 0.08 to d = 0.47; ± 0.08), fatigue (d = 0.42; ± 0.12 to d = 0.55; ± 0.11), and PRS (d = 0.25; ± 0.09 to d = 0.37; ± 0.08). Unlike sleep duration, sleep quality and sleep index also showed substantial small positive relationships with stress (d = 0.35; ± 0.07 and d = 0.29; ± 0.08 respectively) and mood (d = 0.41; ± 0.09 and d = 0.37; ± 0.10 respectively). No substantial relationships were observed between sleep indices and muscle soreness (d = 0.13; ± 0.08 to d = 0.18; ± 0.09).

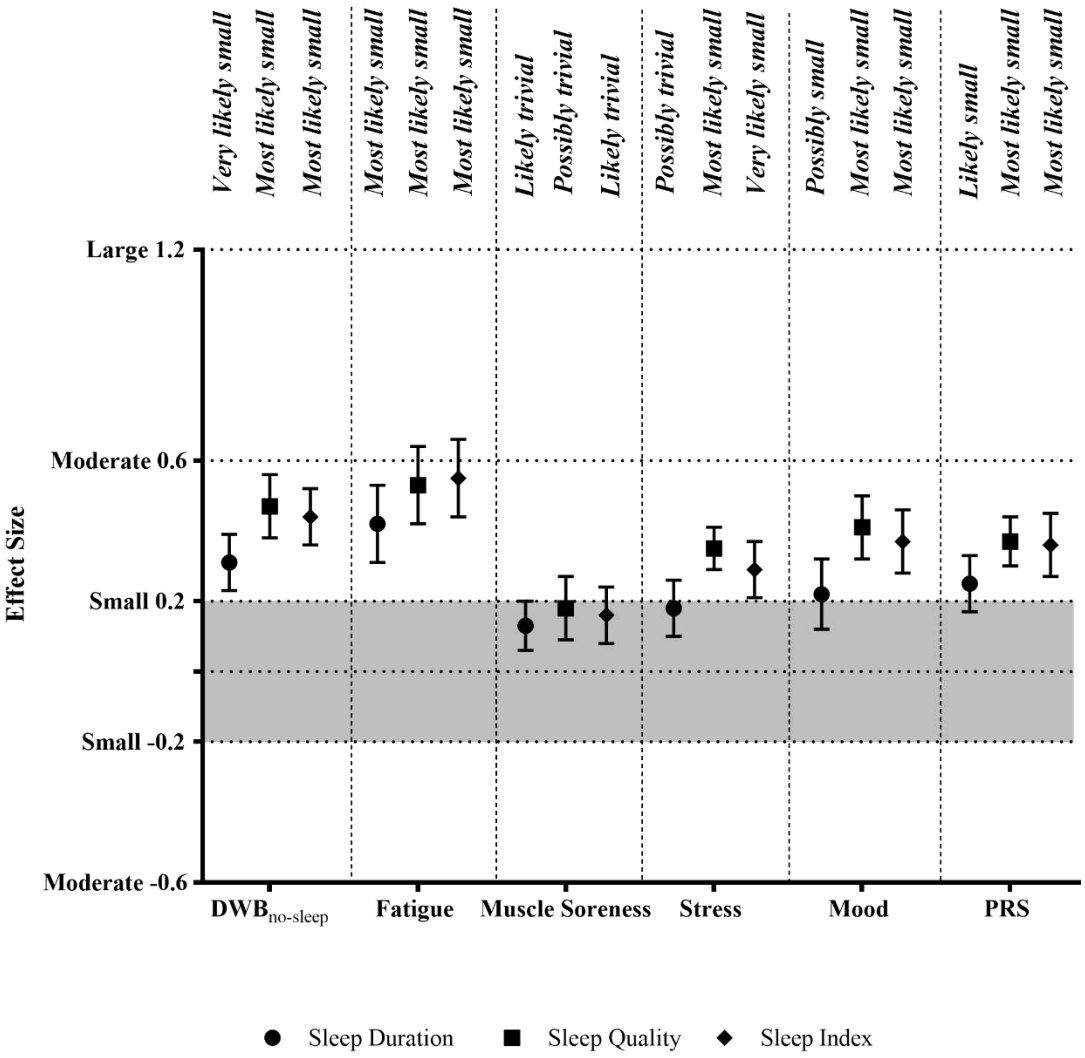


Figure 7.1: Visual representation of relationship between sleep indices and fatigue/wellness measures. The ES is shown for a 2 SD increase in the sleep measure. Data are presented ES ± 90% confidence intervals, shaded area represents SWC.

Table 7.1 outlines the individual responses to the relationship between the sleep indices and fatigue/wellness measures. With the exception of muscle soreness (trivial differences for sleep duration, small differences for sleep quality and muscle soreness) and PRS (trivial differences for sleep quality, small differences for sleep duration and sleep index), there were no meaningful differences in the individual responses to the relationships held between sleep indices and fatigue/wellness measures.

Table 7.1: Individual responses to the relationship between sleep indices and fatigue/wellness measures. ES are reported ES; lower 90% confidence interval, upper 90% confidence interval. Qualitative description is provided based on Cohen's *d* ES thresholds.

Scale	Sleep duration	Sleep quality	Sleep Index
$DWB_{no\text{-}sleep}$	0.24; 0.19, 0.34	0.24; 0.18, 0.34	0.22; 0.17, 0.32
	Small	Small	Small
Fatigue	0.38; 0.31, 0.51	0.34; 0.26, 0.47	0.37; 0.30, 0.50
	Small	Small	Small
Muscle Soreness	0.17; 0.12, 0.30	0.25; 0.19, 0.37	0.21; 0.16, 0.32
	Trivial	Small	Small
Stress	0.19; 0.14, 0.31	0.16; 0.12, 0.28	0.18; 0.13, 0.31
	Trivial	Trivial	Trivial
Mood	0.28; 0.22, 0.40	0.22; 0.16, 0.36	0.25; 0.19, 0.37
	Small	Small	Small
PRS	0.25; 0.19, 0.36	0.18; 0.12, 0.35	0.25; 0.18, 0.40
	Small	Trivial	Small

7.3.1.2 Practically interpretable relationships

Table 7.2 details the practically interpretable relationships between sleep indices and fatigue/wellness measures. None of the relationships resulted in a one unit change for a typical athlete, but the mean effect of sleep quality and sleep index on $DWB_{no\text{-}sleep}$ was greater than one unit.

Table 7.2: Practically interpretable relationships between sleep indices and fatigue/wellness measures. Values are presented in raw units as the mean response, with the range of responses within 1SD of the mean (i.e. for a 'typical athlete') in brackets.

Scale	Sleep duration	Sleep quality	Sleep Index
$DWB_{no\text{-}sleep}$	0.79 (0.48 to 1.10)	1.21 (0.91 to 1.52)	1.12 (0.84 to 1.40)
Fatigue	0.35 (0.19 to 0.52)	0.45 (0.31 to 0.59)	0.46 (0.30 to 0.61)
Muscle Soreness	0.11 (0.04 to 0.19)	0.16 (0.05 to 0.27)	0.15 (0.05 to 0.24)
Stress	0.17 (0.08 to 0.26)	0.32 (0.24 to 0.39)	0.27 (0.18 to 0.35)
Mood	0.16 (0.06 to 0.25)	0.28 (0.21 to 0.36)	0.26 (0.17 to 0.34)
PRS	0.53 (0.27 to 0.79)	0.78 (0.59 to 0.97)	0.75 (0.49 to 1.01)

7.3.2 Relationships between training load, match play exposure and fatigue/wellness measures

Table 7.3, Table 7.4 and Table 7.5 show the statistical and practically interpretable relationships training load and exposure to match play held within the sleep duration, sleep quality and sleep index models respectively. Most likely small relationships were observed between training load, muscle soreness (*d* = -0.43 to -0.44) and PRS (*d* = -0.37). Likely small relationships were observed between exposure to match play, muscle soreness (*d* = -0.26) and PRS (*d* = -0.25 to -0.26). The differences in relationships between models were negligible. In practice, only the relationship between training load and PRS with the additive effect of exposure to match play resulted in a one unit change for a typical athlete.

Table 7.3: Statistical and practically interpretable relationships between training load, match play exposure and fatigue/wellness measures within sleep duration model. ES are reported ES; ± 90% confidence intervals. Descriptor provides qualitative MBI and ES. Practically interpretable changes for training load (underneath training load) and training load plus additive exposure to match play (underneath match play exposure) are reported [mean raw change (range of values within 1 SD of mean raw change)].

	Training load		**Match play exposure**	
Scale	**ES**	**Descriptor**	**ES**	**Descriptor**
$DWB_{no\text{-}sleep}$	-0.19; ± 0.07	Possibly trivial	-0.12; ± 0.06	Likely trivial
	[-0.48 (-0.67 to -0.27)]		[-0.78 (-0.98 to -0.57)]	
Fatigue	-0.15; ± 0.08	Likely trivial	-0.07; ± 0.08	Most likely trivial
	[-0.13 (-0.22 to -0.05)]		[-0.19 (-0.28 to -0.10)]	
Muscle Soreness	-0.43; ± 0.09	Most likely small	-0.26; ± 0.09	Likely small
	[-0.38 (-0.50 to -0.27)]		[-0.62 (-0.74 to -0.50)]	
Stress	0.02; ± 0.07	Most likely trivial	0.01; ± 0.08	Most likely trivial
	[0.02 (-0.04 to 0.09)]		[0.03 (-0.03 to 0.09)]	
Mood	0.02; ± 0.06	Most likely trivial	-0.02; ± 0.10	Most likely trivial
	[0.00 (incomputable)]		[0.00 (incomputable)]	
PRS	-0.37; ± 0.08	Most likely small	-0.25; ± 0.08	Likely small
	[-0.79 (-1.03 to -0.55)]		[-1.31 (-1.55 to -1.07)]	

N.B: The linear mixed model was unable to compute the individual responses to the mood subscale due to a lack of variance within the measure (i.e. participants reported similar values most of the time). Consequently, the range of values within 1 SD of the mean raw change were incomputable.

Table 7.4: Statistical and practically interpretable relationships between training load, match play exposure and fatigue/wellness measures within sleep quality model. ES are reported ES; ± 90% confidence intervals. Descriptor provides qualitative MBI and ES. Practically interpretable changes for training load (underneath training load) and training load plus additive exposure to match play (underneath match play exposure) are reported [mean raw change (range of values within 1 SD of mean raw change)].

	Training load		**Match play exposure**	
Scale	**ES**	**Descriptor**	**ES**	**Descriptor**
$DWB_{no\text{-}sleep}$	-0.18; ± 0.07	Possibly trivial	-0.13; ± 0.07	Likely trivial
	[-0.48 (-0.68 to -0.28)]		[-0.83 (-1.03 to -0.63)]	
Fatigue	-0.16; ± 0.08	Likely trivial	-0.10; ± 0.08	Very likely trivial
	[-0.13 (-0.23 to -0.04)]		[-0.22 (-0.31 to -0.12)]	
Muscle Soreness	-0.44; ± 0.10	Most likely small	-0.26; ± 0.09	Likely small
	[-0.39 (-0.51 to -0.27)]		[-0.62 (-0.74 to -0.50)]	
Stress	0.02; ± 0.07	Most likely trivial	0.00; ± 0.08	Most likely trivial
	[0.02 (-0.06 to 0.10)]		[0.02 (-0.07 to 0.10)]	
Mood	0.00; ± 0.06	Most likely trivial	-0.02; ± 0.10	Most likely trivial
	[0.00 (incomputable)]		[-0.02 (incomputable)]	
PRS	-0.37; ± 0.09	Most likely small	-0.26; ± 0.08	Likely small
	[-0.78 (-1.03 to -0.53)]		[-1.33 (-1.58 to -1.07)]	

N.B: The linear mixed model was unable to compute the individual responses to the mood subscale due to a lack of variance within the measure (i.e. participants reported similar values most of the time). Consequently, the range of values within 1 SD of the mean raw change were incomputable.

Table 7.5: Statistical and practically interpretable relationships between training load, match play exposure and fatigue/wellness measures within sleep index model. ES are reported ES; ± 90% confidence intervals. Descriptor provides qualitative MBI and ES. Practically interpretable changes for training load (underneath training load) and training load plus additive exposure to match play (underneath match play exposure) are reported [mean raw change (range of values within 1 SD of mean raw change)].

	Training load		**Match play exposure**	
Scale	**ES**	**Descriptor**	**ES**	**Descriptor**
$DWB_{no\text{-}sleep}$	-0.19; ± 0.06	Possibly trivial	-0.12; ± 0.08	Likely trivial
	[-0.49 (-0.68 to -0.30)]		[-0.79 (-0.98 to -0.60)]	
Fatigue	-0.16; ± 0.08	Likely trivial	-0.08; ± 0.08	Very likely trivial
	[-0.13 (-0.22 to -0.05)]		[-0.20 (-0.29 to -0.12)]	
Muscle Soreness	-0.44; ± 0.10	Most likely small	-0.26; ± 0.09	Likely small
	[-0.39 (-0.51 to -0.27)]		[-0.62 (-0.74 to -0.50)]	
Stress	0.02; ± 0.07	Most likely trivial	0.01; ± 0.08	Most likely trivial
	[0.02 (-0.05 to 0.08)]		[0.03 (-0.04 to 0.09)]	
Mood	0.00; ± 0.06	Most likely trivial	-0.02; ± 0.10	Most likely trivial
	[0.00 (incomputable)]		[-0.01 (incomputable)]	
PRS	-0.37; ± 0.09	Most likely small	-0.25; ± 0.08	Likely small
	[-0.78 (-1.02 to -0.54)]		[-1.30 (-1.54 to -1.06)]	

N.B: The linear mixed model was unable to compute the individual responses to the mood subscale due to a lack of variance within the measure (i.e. participants reported similar values most of the time). Consequently, the range of values within 1 SD of the mean raw change were incomputable.

7.4 Discussion

The aim of this study was to evaluate the use of different sleep indices (sleep duration, sleep quality and sleep index) as measures of training recovery within the integrated athlete monitoring cycle. Statistically, the results indicate that sleep duration, sleep quality

and sleep index all held small relationships with $DWB_{no\text{-}sleep}$, fatigue and PRS. Sleep quality and sleep index also held small relationships with mood and stress. Amongst all associations, the influence of sleep quality and sleep index was greater than sleep duration (Figure 7.1). However, despite these statistical relationships, no sleep measure could guarantee a one unit change in the fatigue/wellness scales for a 'typical athlete'. In all models, a small relationship between training load, match play exposure and muscle soreness and PRS was present.

7.4.1 Sleep measures

7.4.1.1 Statistical relationships

The results of this study indicate that sleep duration, sleep quality and sleep index all have a small positive relationship with $DWB_{no\text{-}sleep}$ in youth athletes. The small influence of sleep duration on $DWB_{no\text{-}sleep}$ supports the results of study 3 showing a similar relationship between sleep duration and DWB (d = 0.45; ±0.09). However, upon removal of sleep quality from DWB, the relationship between sleep duration and $DWB_{no\text{-}sleep}$ was reduced. Although little correlation (r = -0.02 to 0.15) was reported between sleep duration and sleep quality in non-athletic youths in education (Pilcher et al., 1997), study 3 of this thesis identified a moderate relationship (d = 0.80; ±0.14) between self-reported sleep duration and the sleep quality subscale used in this study. It is therefore possible that this association between sleep duration and sleep quality, coupled with the relationship between sleep quality and other wellness subscales used in this study may have skewed the DWB overall score, resulting in inaccurately strong relationships being observed in studies 2 and 3. Regardless, the results from this study show that both the sleep quality and sleep index measures have stronger relationships with changes in $DWB_{no\text{-}sleep}$ than sleep duration. Furthermore, the relationship between sleep quality and $DWB_{no\text{-}sleep}$ supports the use of sleep quality as a measure of training recovery within the integrated athlete monitoring cycle rather than as part of a fatigue/wellness measure.

Sleep quality and sleep index also had a greater influence on PRS and the fatigue subscale than sleep duration, but all three sleep indices had the same small effect on both fatigue/wellness measures. The influence of sleep quality on fatigue is remarkably similar in size to the small correlation (r = -0.28, p = 0.004) observed in marathon participants prior to competitive performance (Lastella et al., 2014). Similarly, the relationship between sleep duration, PRS and fatigue is consistent with, but slightly smaller than, the moderate relationship (r = -0.36, p < 0.0001) identified by Oginska and Pokorski (2006). Given the focus on sleep quality within elite adult sport (Pitchford et al., 2017; Thornton et al., 2017), it would have been reasonable to expect a greater difference in the relationship between sleep duration and sleep quality. However, it is important to note that both of these studies took place in contact sports (Australian Rules Football and Rugby League respectively). In a recent meta-analysis, Irwin and colleagues (2016) identified sleep disturbances to be related to the inflammatory biomarkers C-reactive protein (ES = 0.12; 95% CI 0.05 – 0.19) and interleukin-6 (ES = 0.20; 95% CI 0.08 – 0.31). Consequently, it is possible that a greater difference in the relationships observed between fatigue/wellness measures and sleep duration/sleep quality would be present in collision sports, where the inflammatory response is induced, than in this study where only 13/48 participants came from collision sports.

Figure 7.1 depicts the small influence of sleep quality and sleep index on mood and stress, which was more certain than the small relationship observed between mood and sleep duration, and greater than the trivial relationship reported between stress and sleep duration. Sleep duration (r = -0.30, p < 0.0001) and sleep quality (r = -0.52, p < 0.01) have previously been related to changes in mood in longer questionnaires (Lastella et al., 2014; Oginska & Pokorski, 2006). The difference in the size of relationship between sleep indices and mood observed in this study is consistent with these findings and provides further evidence that sleep quality and sleep index are more appropriate measures of

training recovery within the integrated athlete monitoring cycle. Unlike mood, stress is normally considered along a stress-recovery continuum (Kellmann, 2010). Consequently, if recovery is reduced, an individual is likely to experience greater perceptions of stress. With this in mind it is logical that sleep quality, and by extension sleep index, have stronger relationships with stress than sleep duration. Sleep quality can have a highly individual meaning, but it may include number of sleep disturbances, sleep onset latency, sleep efficiency or total sleep duration dependent on the individual (Krystal & Edinger, 2008), each of which could reduce the restorative capacity of sleep by limiting rapid eye movement or non-rapid eye movement sleep durations (Vyazovskiy & Delogu, 2014). By accounting for each individual's perception of sleep quality rather than solely the amount of time they slept for, the perception of recovery experienced by an individual can be quantified more accurately. These results show that this greater accuracy in quantifying the training recovery experienced subsequently enhances the relationships observed with fatigue/wellness measures.

As with study 3, none of the sleep measures held a practically meaningful relationship with muscle soreness. Indeed, the spread between the three sleep indices' influence on muscle soreness (d = 0.05) was the smallest of all relationships measured in this study. This consistency in the lack of relationship between sleep and muscle soreness indicates that the previous explanation in study 3 may be correct (i.e. that a single night of sleep has limited restorative capacity due to the increasing soreness present in delayed onset muscle soreness up to 72 hours post-exercise). Future research may wish to evaluate the relationship between sleep (and training load) with muscle soreness using different statistical models, which can account for the known peaks and troughs of delayed onset muscle soreness.

7.4.1.2 Individual responses

Table 7.1 illustrates the individual responses for each of the sleep measures. Although there were some differences in the qualitative descriptors for the muscle soreness (trivial for sleep duration, small for sleep quality and sleep index) and PRS (trivial for sleep quality, small for sleep duration and sleep index) scales, the largest difference between sleep indices was equivalent to d = 0.08. Using ES thresholds consistent within this thesis, this figure would be considered trivial indicating that there were no practically meaningful differences in the individual responses to sleep duration, sleep quality or sleep index. This lack of practically meaningful difference in the individual responses to sleep indices is surprising given that objective measures of sleep duration, architecture and quality vary dramatically between individuals (Fullagar, Skorski et al., 2015). However, by using an individual's perception of sleep rather than the objective sleep measure, it is possible that these differences are accounted for in the subjective figures reported.

7.4.1.3 Practically interpretable relationships

Table 7.2 details the practically interpretable relationships between the sleep indices and fatigue/wellness measures. As with study 3, none of the relationships observed were guaranteed to induce a one unit change in any fatigue/wellness measure for a typical athlete, but the mean effect for sleep quality and sleep index on $DWB_{no\text{-}sleep}$ was greater than one unit. The mean effect of sleep duration on $DWB_{no\text{-}sleep}$ fell below one unit indicating that the removal of the sleep quality subscale had practical implications alongside the artificial inflation of the statistical relationship reported in section 7.4.1.1.

Both sleep quality and sleep index had similar effects on the fatigue/wellness measures. Such a finding is perhaps not surprising given sleep index includes the sleep quality scale within its calculation but suggests that either measure would be more appropriate for use within the integrated athlete monitoring cycle than sleep duration. Understanding which measure may be more useful in practice therefore requires the likelihood of a 2 SD

change occurring to be evaluated. For sleep quality, a 2 SD change was equivalent to 3 ± 1 units, whereas for sleep index it was 14 ± 6 AU. A change of 3 units in the sleep quality subscale represents a large proportion of the overall score suggesting it may be unlikely to happen in practice. On the other hand, a 14 unit change in sleep index could be considered more feasible as this is equivalent to a 3 hour reduction in sleep duration when 'very restful' sleep is reported or a reduction in sleep quality from 'very restful' to 'difficulty falling asleep' when an 8 hour sleep duration is reported. Based on this difference, and the incorporation of sleep duration and sleep quality measures into one score, the sleep index measure is recommended for use within the integrated athlete monitoring cycle. However, future studies may wish to consider larger sleep quality scales (e.g. 0-100 rather than 1-5), which may have more practically interpretable relationships with fatigue/wellness measures as this sleep characteristic holds considerable promise as a measure within the integrated athlete monitoring cycle.

7.4.2 Training load and exposure to match play

Table 7.3, Table 7.4 and Table 7.5 show the relationships training load and exposure to match play hold with the fatigue/wellness measures. These were included to ensure there were no major differences between the models rather than as an aim of the study. The results show there were negligible differences in the relationships assessed. Sections 6.4.1.1 and 6.4.2 discuss the statistical and practically interpretable relationships between training load, exposure to match play and fatigue/wellness measures.

7.4.3 Limitations

This study provides a considerable addition to the literature showing that sleep quality should be used as part of a training recovery metric rather than being embedded within fatigue/wellness measures in the integrated athlete monitoring cycle.It should be noted though that the results of this study are limited to this observation. Identifying a

relationship between training load, sleep index and fatigue/wellness measures is an important step in obtaining an understanding of the integrated athlete monitoring cycle. However, it is pivotal that the relationships between measures of the integrated athlete monitoring cycle are now considered together to evaluate their relationship with adverse outcome measures such as illness incidence. Identifying these relationships will allow for reference values to be obtained. Currently, it is suggested that anything above or below 1 SD outside of the athlete's mean response is considered a 'red flag' (McLean et al., 2010) by which action (e.g. reducing training load) should be considered but such a generalisation disregards how much of the change is expected. Now that an understanding of the practically interpretable changes has been provided, it is possible to plot a range of values each individual would be expected to provide given their training load, match exposure and sleep index. Such information could provide valuable information with regards to the 'red flags' that are highlighted. For example, if an athlete provides a score more than 1 SD below their mean the day after a match and poor night's sleep, it is reasonable to expect it is due to these factors and therefore not worthy of being a 'red flag'. Conversely, if this score is provided following a rest day and a good or average night's sleep, it could be considered a 'red flag'. Future studies should consider this intrinsic understanding of the integrated athlete monitoring cycle and how it can be used to provide a more intuitive 'red flag' system with regards to adverse outcome risk.

A further limitation of this study is the use of a 1-5 sleep quality subscale. Although it was logical to consider this measure within this thesis due to its inclusion within DWB, a 2 SD change of 3 ± 1 units was equivalent to over half of the scale's possible values, reducing its usefulness in practice. The measure still holds significant interest given its strong relationships with other fatigue/wellness measures but a new scale with a greater scoring system (e.g. 0-10 like RPE or 0-100) may provide more practically usable results.

Finally, it is important to note that the relationship between training load and sleep was not directly considered within this study. There is a growing body of research indicating training load can influence sleep duration or sleep quality, either via scheduling (Sargent et al., 2014) or its impact on biological measures (Irwin et al., 2016). The key aim of this thesis is to evaluate how training load and sleep can be used to identify illness risk so the relationship between training load and sleep was only accounted for within the random effects structure. However, practitioners should be aware that training load and sleep are directly related as this could influence the changes they make in response to 'red flag' situations.

7.5 Conclusions

In conclusion, the results of this study provide support for the use of the sleep quality subscale as a measure of training recovery rather than as a fatigue/wellness measure within the integrated athlete monitoring cycle. This support is provided by sleep quality and sleep index showing greater relationships with fatigue/wellness measures than sleep duration. Based on the difference in change required to elicit a change in fatigue/wellness measures and the incorporation of sleep duration and sleep quality into one measure, it is suggested that the sleep index, rather than the sleep quality subscale, is used. The use of this training recovery measure alongside measures of the training dose (training load and match play exposure) should now be incorporated into an integrated athlete monitoring cycle model to identify whether changes in fatigue/wellness measures ($DWB_{no\text{-}sleep}$ and PRS) are congruent with those expected. Furthermore, these expected and unexpected changes in $DWB_{no\text{-}sleep}$ and PRS should be considered with regards to their ability to predict adverse outcomes in youth athletes.

Chapter 8 STUDY 5

Understanding the link between objective and subjective fatigue/wellness measures and illness incidence in youth athletes

8.1 Prelude

The overarching aim of this thesis was to evaluate the true predictive ability of an integrated athlete monitoring cycle model with regards to illness incidence in youth athletes. To achieve this goal, study 1 identified the reliability of the fatigue/wellness and preparedness to play measures considered within this thesis. Subsequently, studies 2-4 identified the most appropriate combination of integrated athlete monitoring cycle measures to be used within youth athletes and the statistical and practically interpretable relationships held between these measures. The original aim of study 5 was to use these relationships to evaluate the ability of training load, match exposure, sleep duration, $DWB_{no\text{-}sleep}$ and PRS to predict self-reported illness (SRI) within youth athletes. This predictive ability would then have been compared against an objective measure of immune function, s-IgA, to evaluate the value of these subjective measures as predictors of SRI in youth athletes. Due to the success of the first four studies, the school, from which the participants were recruited, invested in a web-based application method (see section 3.4 and Appendix 3B for further details) between studies 4 and 5. Unfortunately, problems with this web-based application method resulted in the loss of all training load data rendering the original goals of study 5 unattainable. Consequently, the aims of this chapter were modified to best fit the original aim of the thesis with the data available, as described in the introduction below.

8.2 Introduction

Studies 1-4 of this thesis primarily concentrated on understanding the relationships between subjective, time and cost-efficient measures within the integrated athlete monitoring cycle (e.g. s-RPE training load, self-reported sleep duration and wellness questionnaires). These measures are more affordable than other options, such as GPS devices and s-IgA monitoring, and so could potentially be implemented into youth sport settings more easily. However, in order to truly understand the value of subjective

measures as predictors of SRI within youth athletes, it is important to compare them to an objective measure which has shown relationships with illness incidence.

S-IgA is an objective measure of immune function, which could be used as a fatigue/wellness measure within the integrated athlete monitoring cycle (Morgans et al., 2014; Putlur et al., 2004). Table 2.5 details the studies evaluating the relationship between s-IgA and illness risk. Despite studies stating that a three week transient drop in s-IgA concentration is related to increased illness incidence (Neville et al., 2008) and that s-IgA secretion rate was the only significant predictor of URTI incidence within a multiple linear regression analysis (Fahlman & Engels, 2005), the true predictive ability of s-IgA with regards to SRI incidence remains unknown. For example, Neville and colleagues (2008) could only predict 48% of illnesses using the percentage deviation from average healthy s-IgA concentration in elite adult yachtsmen, whereas Fahlman and Engels (2005) over predicted the number of illnesses by 12-42% in collegiate American Football players using the raw s-IgA secretion rate. Furthermore, both studies used data previously seen by the statistical models to obtain their estimates ensuring that the estimates did not provide a true understanding of the measures' predictive ability (Breiman, 2001b). Consequently, there is scope for future research considering the true predictive ability of s-IgA (concentration and secretion rate) with regards to illness in youth athletes using data previously unseen by the model.

Alongside understanding the true predictive ability of s-IgA (concentration and secretion rate) with regards to SRI incidence, it would be beneficial to confirm whether there is a difference in the relative importance of the two s-IgA measures dependent on the timing of the sample prior to illness onset. The evidence suggests that s-IgA concentration is a short-term risk factor (i.e. on a week to week basis) of illness risk (Cunniffe et al., 2011; Neville et al., 2008; Orysiak et al., 2017), whereas s-IgA secretion rate appears to be a better long-term risk factor (i.e. on approximately a monthly basis; Fahlman & Engels,

2005; Putlur et al., 2004). However, no study has considered the relative importance of both s-IgA measures as predictors of SRI at different timepoints in the four weeks prior to illness incidence to see if there is a crossover point where, for example, s-IgA secretion rate becomes more important than s-IgA concentration.

After evaluating the true predictive ability and relative importance of s-IgA measures with regards to SRI incidence in youth athletes, it would be valuable to consider its longitudinal changes over the duration of an academic year and compare these to the subjective fatigue/wellness measures previously considered within this thesis and SRI incidence. It has recently been established that both psychological (r = 0.39) and physical (r = -0.37) stressors can influence immune function (Edwards et al., 2018). Given that youth athletes are subjected to numerous psychological stressors (e.g. academic, maturational and social) alongside the physical demands of their sport (Mountjoy et al., 2008), there is scope for substantial changes in their immune function and/or subjective fatigue/wellness measures to occur over the course of an academic year. These changes could subsequently impact upon the athletes' illness risk above and beyond the training dose and recovery experienced. Despite this, no study has evaluated the longitudinal change in s-IgA or the subjective fatigue/wellness questionnaires used within the integrated athlete monitoring cycle in youth athletes, nor has a study evaluated whether these changes differ in response to qualitative factors relevant to youth athletes (e.g. academic examinations).

8.2.1 Aim

The two key aims of this study were to a) calculate the true predictive ability and relative importance of s-IgA measures with regards to illness incidence, and b) outline the longitudinal changes in objective and subjective fatigue/wellness measures over an academic year in youth athletes.

8.2.2 Objectives

- Evaluate the true predictive ability and relative importance of s-IgA concentration and secretion rate with regards to SRI in the four weeks prior to illness incidence in youth athletes
- Describe the longitudinal change in s-IgA concentration and secretion rate over the duration of an academic year in youth athletes
- Describe the longitudinal change in $DWB_{no\text{-}sleep}$, its individual subscales (fatigue, muscle soreness, stress and mood) and PRS over the duration of an academic year in youth athletes

8.3 Methods

8.3.1 Participants

Twenty-three youth athletes aged 16-18 years (age 16.7 ± 0.6 years, height 172.3 ± 6.7 cm, body mass 69.1 ± 11.1 kg) participated in this study. Participants were recruited from a local independent school in the UK, where they were members of the school's sport scholarship programme. The sports basketball (*n*=2), cricket (*n*=3), football (*n*=5), hockey (*n*=2), netball (*n*=5) and rugby union (*n*=6) were represented by athletes competing at club/school (*n*=10), professional academy (*n*=4), county/regional (*n*=6) and international (*n*=3) standard in their respective sports. Participants were recruited according to the procedures outlined in the general methods (section 3.3).

8.3.2 Design

For this prospective cohort study, a longitudinal, observational study design was used. Over 36 weeks, 14 saliva samples (for s-IgA analysis) were provided on a fortnightly basis unless external factors (e.g. school half-term breaks or away matches) dictated otherwise. In addition to this, a bespoke online wellness questionnaire including details on $DWB_{no\text{-}sleep}$, PRS and SRI symptoms was completed every day. In total, 211 saliva samples

were evaluated in this study, with a median of 9 collections (range 6-14) per participant. Additionally, 3,311 wellness questionnaire responses were obtained providing details surrounding $DWB_{no\text{-}sleep}$, PRS and 45 unique SRI episodes. Data were collected from terms 1-5 of the academic year, taking place between August 2016 and April 2017. Table 8.1 provides an overview of the timing of samples and other key events.

By obtaining 14 samples over 36 weeks, this study contains the second largest number of sampling time points of the four longitudinal s-IgA studies to date (Cunniffe et al., 2011; Fahlman & Engels, 2005; Neville et al., 2008; Orysiak et al., 2017). It has more sampling timepoints than Fahlman and Engels' (2005) 8 in 49 weeks, Cunniffe and colleagues' (2011) 11 in 43 weeks and Orysiak and colleagues' (2017) 8 in 21 weeks. For reference, Neville and colleagues' (2008) weekly collection over 50 weeks is the largest scale publication to date. Collecting samples on a fortnightly basis is also more frequent than all studies except Neville and colleagues (Neville et al., 2008). This frequency of sampling ensures it is possible to measure s-IgA concentration and secretion rate together on three occasions in the four weeks prior to SRI incidence (i.e. on the day, at 2 weeks and at 4 weeks). This has not been possible in other studies, whose sampling time points were too sparse (Cunniffe et al., 2011; Fahlman & Engels, 2005).

Table 8.1: Description of key events over the duration of the study.

Week	Month	Description
-1	August	Saliva sample collected for reliability purposes
0	September	Start of school term
1	September	Saliva sampling week 1
3	September	Saliva sampling week 2
5	October	Saliva sampling week 3
7	October	Half-term break (sampling delayed by one week)
8	November	Saliva sampling week 4
10	November	Saliva sampling week 5
12	November	Saliva sampling week 6
14	December	Saliva sampling week 7
15-17	December	Christmas break (sampling delayed by two weeks)
18	January	Saliva sampling week 8
19	January	Mock exam week
20	January	Saliva sampling week 9
22	February	Saliva sampling week 10
24	February	Half term break (sampling delayed by one week)
25	March	Saliva sampling week 11
27	March	Saliva sampling week 12
29	March	Away matches (sampling delayed by one week)
30	April	Saliva sampling week 13
30-31	April	Cup finals and coursework deadlines
31-32	April	Easter break (sampling delayed by one week)
33	April	Saliva sampling week 14
35	May	End of study and start of examinations/study leave

N.B.: August sample identified as week -1 as it was not used for the main analyses within the study. It was used with week 1 (the first sampling week) to obtain an understanding of the reliability of s-IgA measures (see below – section 8.3.3.1.2)

8.3.3 Procedures

8.3.3.1 S-IgA

8.3.3.1.1 Saliva sampling

Saliva samples were collected on the same weekday within a 30-minute period, between 10:15 and 10:45. Participants provided samples prior to their first exercise of the day and following a 2-hour period without eating or drinking. Upon arrival, 50 ml of water was provided for participants to rinse out their mouths. Saliva sampling (via the passive drool method) commenced 10 minutes later. Participants were instructed to sit upright with their head tilted downwards and provide an unstimulated saliva sample of approximately 1.5 ml into a 3.5ml cryogenic vial. The volume of the sample and the time taken to produce it were recorded prior to freezing at -80˚C for storage within 30 minutes of completion. All

standardisation and measurement methods mirrored those of previous studies (Fahlman & Engels, 2005; Neville et al., 2008).

8.3.3.1.2 Saliva analysis

Saliva samples were assessed in duplicate for s-IgA concentration by a service laboratory (ARU Biomarker Laboratory, Norwich, United Kingdom) using enzyme-linked immunosorbent assay (ELISA) in line with the manufacturer's protocols (Secretory IgA EIA Kit Research, Catalogue Number 1-1602-SAL, Salimetrics LLC, State College, PA). Prior to analysis, all reagents, microtitre plates and saliva samples were brought to room temperature and the saliva samples were centrifuged (1500g for 15 minutes at 4˚C) before the clear supernatant was extracted.

The saliva supernatant was diluted 1:2000 with the manufacturer's s-IgA diluent and mixed via inversion with goat anti-human s-IgA conjugated with horse radish peroxidase (1:120 dilution) in a test tube, prior to incubation at room temperature for 90 minutes. This solution was pipetted into microtitre plates coated in highly purified human s-IgA, covered and mixed on a plate rotator continuously at 400 rpm for 90 minutes at room temperature. The plates were washed six times using the manufacturer's wash buffer before tetramethylbenzidine was added. The plate was mixed on a plate rotator for 5 minutes at 500 rpm before the wells were covered and incubated in the dark for an additional 40 minutes at room temperature. Immediately following this incubation, the stop solution was added to each well and mixed on a plate rotator at 500 rpm for 3 minutes. The optical densities of each well were read at 450 nm within 10 minutes of exposure to the stop solution. Standards of known concentrations of IgA were included on the plate and the concentrations of the samples were calculated via interpolation of the results from the standards. The average coefficient of variation (CV) between duplicate samples was 3.30%. S-IgA results are expressed as a concentration (µg/mL) and secretion rate (concentration divided by time taken to provide sample in minutes; µg/min).

In order to ensure that SRI episodes were not systematically missed (e.g. through non-responding when ill if not at school), s-IgA samples were only included in analysis if a minimum number of daily wellness questionnaires were completed before the next sampling time point. The thresholds for inclusion were 7/14 for two weeks, 10/21 for three weeks and 14/28 for four weeks. To gain an understanding of the TE and SWC, a further saliva sample was obtained one week prior to the school year at a pre-season training camp (week -1) and compared to the week 1 sample. The TE and SWC were calculated for s-IgA concentration and secretion rate from the thirteen participants who did not suffer from illness at either time point. The TE was 31.1% for s-IgA concentration and 61.7% for s-IgA secretion rate; the SWC's were 9.5% and 20.7% respectively.

8.3.3.2 Online wellness questionnaire

Participants completed a bespoke daily wellness questionnaire, including $DWB_{no\text{-}sleep}$, PRS and details of SRI incidence, seven days per week for the duration of the study. The wellness questionnaire was emailed to participants at 6am and completed online via a web-based application (Sports Train, Nice, France). On training days, the questionnaire was completed before the first training session of the day. If necessary, verbal reminders were provided at 10.30am to remind athletes to complete the questionnaire by 11am. Further details are provided in section 3.4.1 and Appendix 3B.

8.3.3.2.1 Self-reported illness

As part of the questionnaire, participants provided daily SRI details. The question to report SRI was: *"Have you continuously experienced any of the following over the last 24 hours? Sore throat, runny nose, cough, scratchy throat, nasal congestion, headache, fever, hoarseness, sneezing and/or body aches and pains (not related to DOMS)?"* based on previously identified symptoms of URTI (Spence et al., 2007) and similar to other illness questions used within sport as part of wellness monitoring programmes (Thornton et al.,

2016). Participants also identified the number of days the symptoms were present. Illness episodes were only included in the analysis if the symptoms persisted continuously for 72 hours or longer and were not considered to be recurrent (i.e. those illnesses which began within seven days of the previous episode finishing; Neville et al., 2008). Those SRI episodes identified as occurring due to an allergy, established via discussion with the athlete in question, were also removed from analysis. As stated in section 2.7.1.2, the term 'SRI' was considered more appropriate than URTI for the illnesses experienced in this study because medical professionals were not consulted to confirm whether the participant was considered to be suffering from illness from a clinical perspective.

8.3.3.3 Statistical analyses

8.3.3.3.1 True predictive ability of s-IgA with regards to SRI

Two separate analyses were employed to reach the aims of this study. To identify the true predictive ability of s-IgA with regards to SRI at different time points in the four weeks prior to illness incidence using data previously unseen by the model, a machine learning approach was used as advocated within the literature review (section 2.9.3). For this analysis, three data sets were generated from the original data. SRI_{day} evaluated SRI incidence on the day of saliva sampling; SRI_{2wk} evaluated SRI incidence within the 2 weeks following sampling; and SRI_{4wk} evaluated SRI incidence within the 4 weeks following sampling. These timings were chosen to best replicate Neville and colleagues' (2008) study, which showed a three week transient decrease in s-IgA concentration prior to illness incidence, within the fortnightly sampling limitation of this study. Each dataset was divided into three stratified subsets for algorithm training (50%), validation (25%) and testing (25%), to provide a measure of out-of-sample predictive ability. The training dataset was z-score normalised and kernel smoothed bootstrapping (Silverman, 2018) was used to balance it, providing equal numbers of positive and negative SRI samples. Balancing the dataset ensured the bias from class imbalances was removed from the training process and the smoothing process forced more generalised class boundaries in

the data. These have the potential to improve the performance of a trained classifier when relatively small sample sizes are used (Silverman, 2018).

Based on previous research, three features were included in each dataset for s-IgA concentration and secretion rate: the average healthy measure, the percentage deviation from the average healthy measure, and the raw value of the measure (Fahlman & Engels, 2005; Neville et al., 2008). The average healthy measure was calculated by averaging all s-IgA concentration or secretion rate values over a minimum of four weeks before and two weeks after SRI incidence, matching as closely as possible to the three and one week periods previously used (Neville et al., 2008). To account for other potential confounding variables, the three classification features of sport group, sex and environment were also added to the model. All three classification features had previously shown relationships with illness incidence (He et al., 2014; Walsh, 2018). Due to the small sample size for each sport, the sport group variable clustered athletes into court based (basketball and netball), field based (football and hockey), contact (rugby) and summer (cricket) sports. Sex split the athletes based on their sex (female for netball and hockey, male for all other sports), and environment split the sports into indoor (basketball and netball) or outdoor (all others) sports. The outcome variable was a binary SRI or no SRI.

To establish the predictive ability and relative importance of s-IgA concentration and secretion rate with regards to SRI in youth athletes, the random forest machine learning algorithm was used. The random forest is an example of an ensemble classifier that aggregates the results of a number of classification trees, allowing it to provide a more accurate measure of the predictive ability of a set of features (Breiman, 2001a). The algorithm was chosen due to its high performance across a wide range of machine learning tasks and its ability to avoid overfitting to the training data (Breiman, 2001a). To provide a robust assessment of the predictive ability of the features in the models, 1000 trials were conducted. In each trial, new randomized, stratified samples were generated

for the training, testing and validation subsets and the random forest algorithm was run. The training and validation datasets were used for parameter selection and the predictive ability of the models was assessed using the testing dataset. The results are presented via box and whisker plots, which provide the median, interquartile range (IQR) and outlying results from the 1000 trials evaluated for each model.

The predictive ability of the models was evaluated using the area under the curve (AUC). The AUC is calculated based on the number of correct and incorrect predictions made by the model, providing a value between 0 and 1, where 0.5 indicates that the model has a 50% chance of predicting the right value. An AUC value greater than 0.75 was used as the threshold for a good predictive model (Fan et al., 2006). The relative feature importance was measured using the permutation method with mean decrease in accuracy reported as the metric for feature importance (Breiman, 2001a). The mean decrease in accuracy is measured in AU and a larger number is representative of a greater importance to the prediction of SRI. All analyses were completed using bespoke scripts in MATLAB version 9.4 (MathWorks, Natick, Massachusetts).

8.3.3.3.2 Longitudinal change in fatigue/wellness measures

To evaluate the longitudinal change in s-IgA, $DWB_{no\text{-}sleep}$, its individual subscales and PRS over the duration of an academic year, linear mixed models were used. Prior to analysis, the assumptions of residual normality, heteroskedasticity and linear relationship between dependent and independent variables were evaluated as outlined in section 3.5.1. Consequently, s-IgA measures were log transformed to ensure normality and non-uniformity of error. $DWB_{no\text{-}sleep}$, its individual subscales and PRS were converted to scores out of 100 as per studies 2-4. Within the linear mixed models, date was added as a fixed effect and participant was added as a random effect. Individual models were run for each s-IgA (concentration and secretion rate) and subjective fatigue/wellness ($DWB_{no\text{-}sleep}$, fatigue, muscle soreness, stress, mood and PRS) measure. The longitudinal trend in SRI

incidence was evaluated via the same linear mixed model (i.e. adding date as a fixed effect and participant as a random effect) with percentage of days ill as the dependent variable.

The back transformed least square means from the s-IgA and subjective fatigue/wellness measures are depicted in the results section. These provide the geometric mean for the s-IgA measures and the raw units for the subjective fatigue/wellness measures. The percentage of days with SRI symptoms are taken directly from the least square means. Results were analysed for practical significance via MBI's using a pre-made Microsoft Excel spreadsheet (Hopkins, 2006a). Further details surrounding the MBI approach (section 3.5.2.4) and the ES used (section 3.5.2.2) are provided in the general methods. ES are reported ES; ± 90% confidence intervals.

8.4 Results

The average healthy s-IgA concentration was 73.5 ± 42.9 $\mu g \cdot mL^{-1}$ and the average healthy s-IgA secretion rate was 63.5 ± 34.7 $\mu g \cdot mL^{-1}$. In total, 371 out of 3,311 completed questionnaires (11.2%) identified participants as suffering from SRI. When a drop below 70% of the individual's average healthy s-IgA concentration occurred, there was a 24% chance of SRI within two weeks and a 38% chance within four weeks. A drop below 40% of the individual's average healthy s-IgA concentration resulted in a 34% chance of SRI within two weeks and a 38% chance of SRI within four weeks. A drop below 70% of the average healthy value resulted in a 21% chance of SRI within two weeks and 34% chance of SRI within four weeks. Falling below 40% of the average healthy s-IgA secretion rate resulted in a 45% and 55% chance of SRI within two and four weeks respectively.

8.4.1 S-IgA predictive ability

Figure 8.1 depicts the AUC for SRI_{day}, SRI_{2wk} and SRI_{4wk}. It shows that the median AUC is not greater than the 0.75 practically meaningful threshold set in any of the models and that SRI_{2wk} had the lowest AUC of the three models.

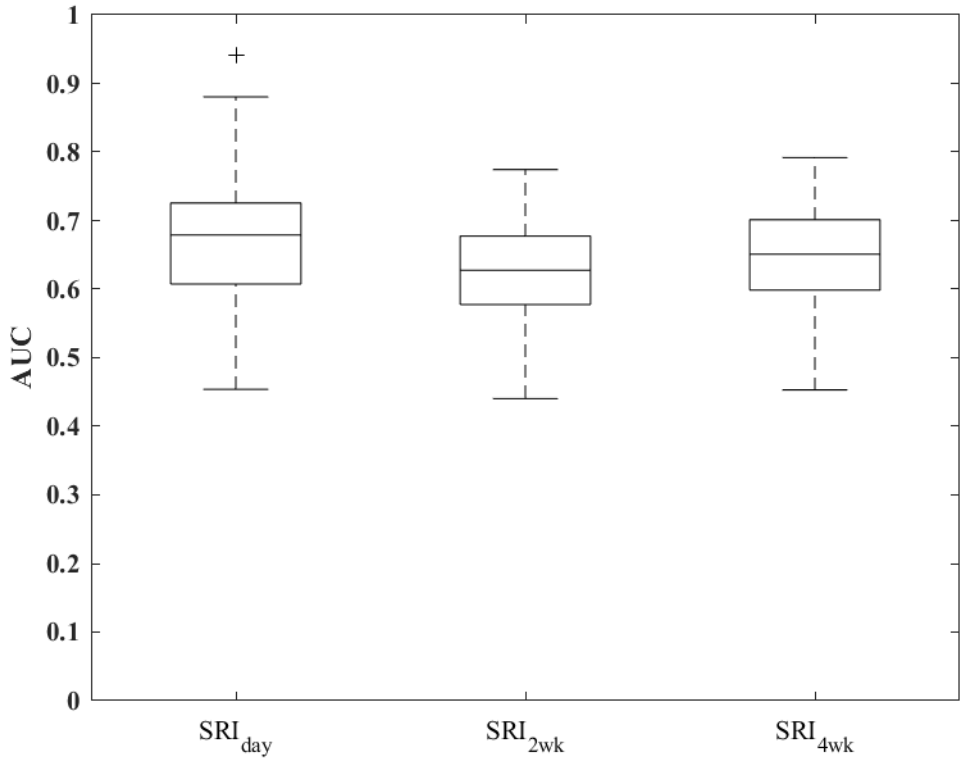


Figure 8.1: Box and whisker plot for the AUC of each s-IgA model. The box provides the median, lower and upper quartiles for the 1000 trials completed. The whisker extends to the minimum and maximum values, excluding outliers, which are denoted by crosses.

8.4.2 S-IgA relative importance

Figure 8.2, Figure 8.3 and Figure 8.4 show the relative importance of the features included within the SRI_{day}, SRI_{2wk} and SRI_{4wk} models. The positive values of the features across all three models indicate that all features improved the predictive ability of the model. However, from SRI_{day} to SRI_{4wk} there is a clear difference in the relative importance of two key variables: the percentage deviation from average healthy s-IgA concentration and the average healthy secretion rate. For the SRI_{day} model, the percentage deviation

from average healthy s-IgA concentration was the most important predictive feature (median relative importance 1.74, IQR 1.41-2.07), whereas for SRI_{4wk}, the average healthy secretion rate was most important (median relative importance 0.94, IQR 0.79-1.13). No feature was clearly more important than any other in SRI_{2wk}.

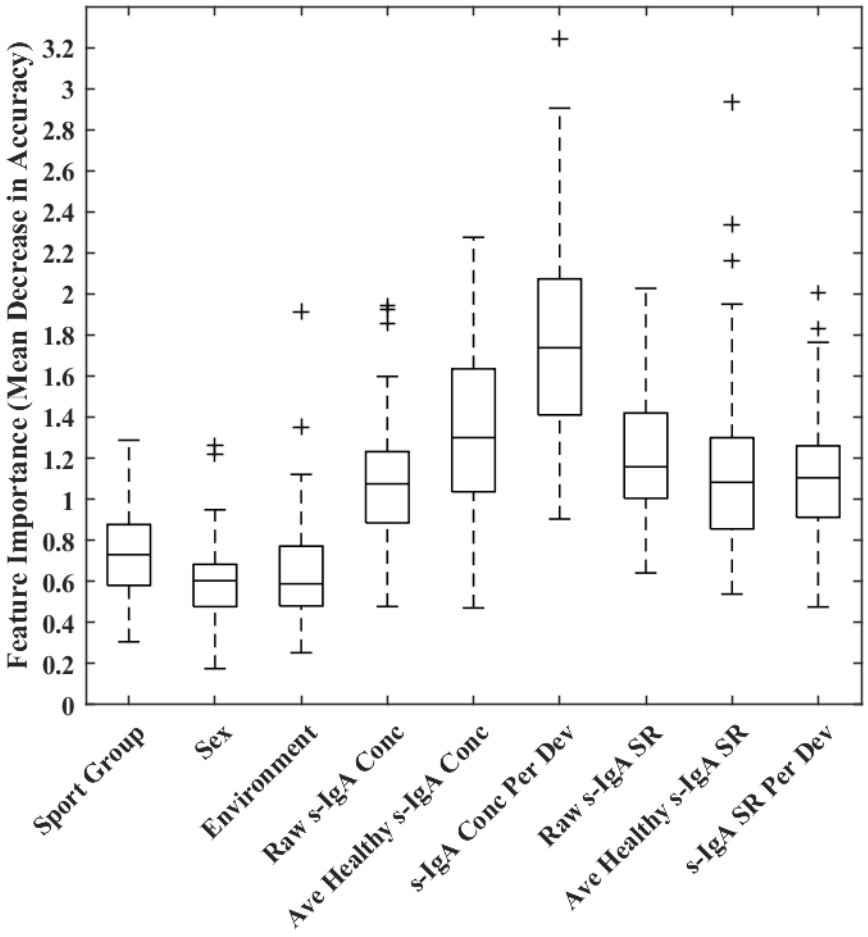


Figure 8.2: Box and whisker plot for the SRI_{day} model. The box provides the median, lower and upper quartiles for the 1000 trials completed. The whisker extends to the minimum and maximum values, excluding outliers, which are denoted by crosses. NB: Conc = concentration; SR = secretion rate; s-IgA Conc Per Dev = percentage deviation from average healthy s-IgA concentration; s-IgA SR Per Dev = percentage deviation from average healthy s-IgA secretion rate.

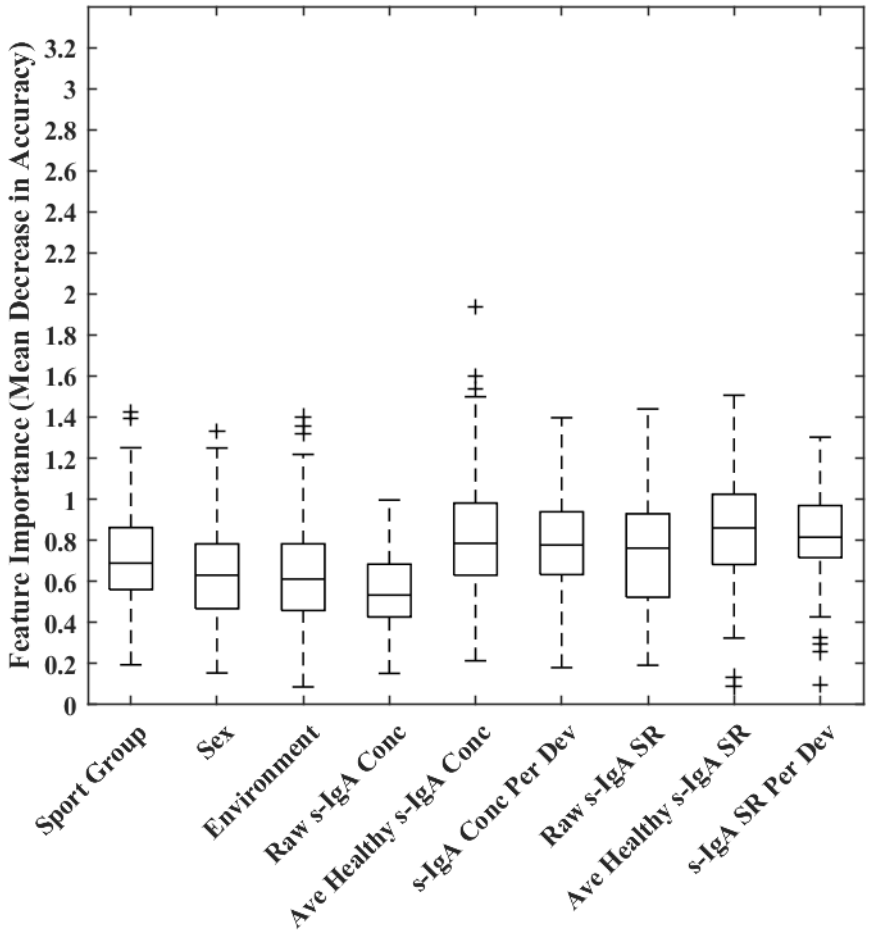


Figure 8.3: Box and whisker plot for the SRI_{2wk} model. The box provides the median, lower and upper quartiles for the 1000 trials completed. The whisker extends to the minimum and maximum values, excluding outliers, which are denoted by crosses. NB: Conc = concentration; SR = secretion rate; s-IgA Conc Per Dev = percentage deviation from average healthy s-IgA concentration; s-IgA SR Per Dev = percentage deviation from average healthy s-IgA secretion rate.

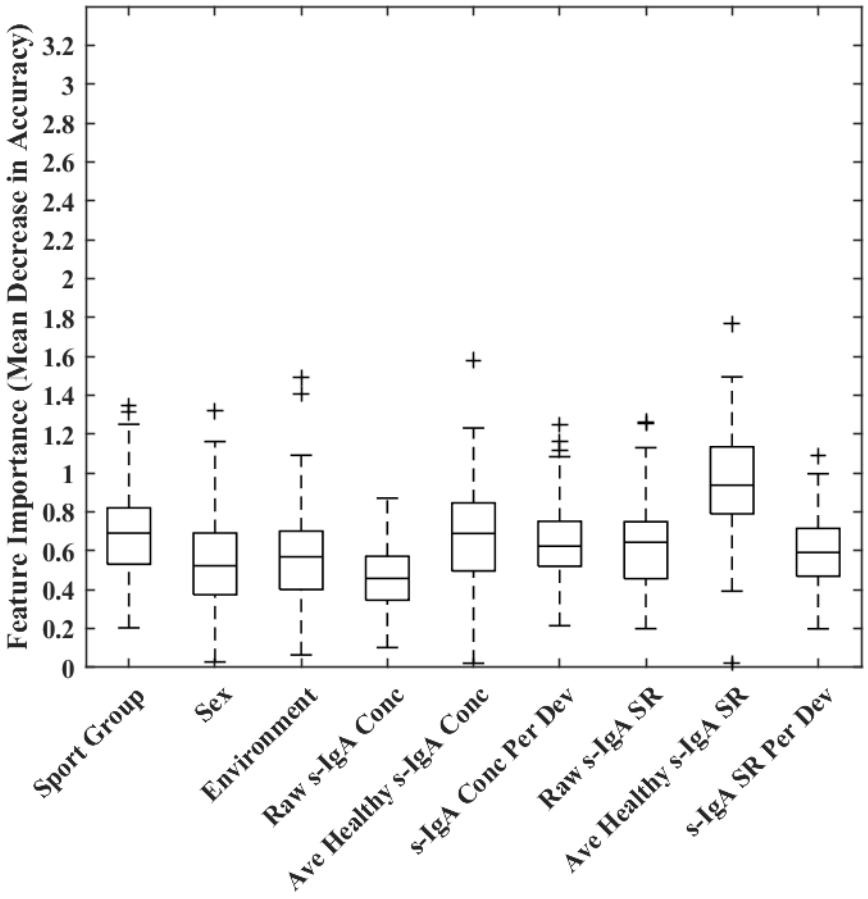


Figure 8.4: Box and whisker plot for the SRI_{4wk} model. The box provides the median, lower and upper quartiles for the 1000 trials completed. The whisker extends to the minimum and maximum values, excluding outliers, which are denoted by crosses. NB: Conc = concentration; SR = secretion rate; s-IgA Conc Per Dev = percentage deviation from average healthy s-IgA concentration; s-IgA SR Per Dev = percentage deviation from average healthy s-IgA secretion rate.

8.4.3 Longitudinal change in objective and subjective fatigue/wellness measures

Figure 8.5 and Figure 8.6 show the longitudinal change in the objective fatigue/wellness measures of s-IgA concentration and s-IgA secretion rate, and the subjective fatigue/wellness measures of $DWB_{no\text{-}sleep}$, its individual subscales and PRS over the duration of the academic year. Figure 8.7 depicts the percentage of days where SRI symptoms were present.

S-IgA concentration followed an inverted U trend, peaking at weeks 1 (74.4, 90% CI 60.6-91.5 µg·mL^{-1}) and 33 (79.1, 90% CI 63.5-98.5 µg·mL^{-1}), and troughing at week 14 (42.2, 90% CI 34.3-51.7 µg·mL^{-1}). This is equivalent to a very likely moderate difference between weeks 1 and 14 (*d* = -1.19; ±0.53) and between weeks 14 and 33 (*d* = 1.31; ±0.55). S-IgA secretion rate followed a two-step trend, whereby the values from weeks 1-14 (average s-IgA secretion rate 38.0 µg·mL^{-1}) were lower than weeks 18-33 (average s-IgA secretion rate 52.0 µg·mL^{-1}). This difference is shown within Figure 8.6 by the likely small difference between weeks 14 and 18 (*d* = 0.42; ±0.43).

Unlike s-IgA, the subjective fatigue/wellness measures did not follow a distinguishable trend for the duration of the study, but there were some similarities in their responses. From week 1 to 5 (term 1), $DWB_{no\text{-}sleep}$ (*d* = 0.51; ±0.37, likely small), fatigue (*d* = 0.53; ±0.44, likely small) and muscle soreness (*d* = 0.86; ±0.46, likely moderate) scores showed substantial increases. Substantial reductions in $DWB_{no\text{-}sleep}$ and fatigue were present between weeks 8-10 ($DWB_{no\text{-}sleep}$ *d* = -0.47; ±0.37, likely small, fatigue *d* = -0.47; ±0.44, likely small) and 18-20 ($DWB_{no\text{-}sleep}$ *d* = -0.36; ±0.35, likely small, fatigue *d* = -0.50; ±0.42, likely small). These reductions were followed by substantial rebounds from weeks 10-12 ($DWB_{no\text{-}sleep}$ *d* = 0.57; ±0.36, very likely small, fatigue *d* = 0.73; ±0.42, very likely small) and 20-22 ($DWB_{no\text{-}sleep}$ *d* = 0.42; ±0.35, likely small, fatigue *d* = 0.42; ±0.41, likely small). Muscle soreness followed this trend from weeks 18-22 (week 18-20 *d* = -0.39; ±0.45, likely small, week 20-22 *d* = 0.53; ±0.43, likely small), but not from weeks 8-12 (week 8-10 *d* = -0.04; ±0.47, unclear, week 10-12 *d* = 0.47; ±0.44, likely small). The fall in PRS from weeks 18-20 was not substantial (*d* = -0.34; ±0.39, possibly small), but the increase from weeks 20-22 was (*d* = 0.44; ±0.41, likely small). From weeks 25 to 30 (term 4), all subjective fatigue/wellness scores reduced. These differences were substantial for $DWB_{no\text{-}sleep}$ (*d* = -0.66; ±0.43, very likely small), muscle soreness (*d* = -0.68; ±0.54, likely small), stress (*d* = -0.58; ±0.45, likely small), mood (*d* = -0.53; ±0.57, likely small), and PRS (*d* = -0.59; ±0.49, likely small), but not for fatigue (*d* = 0.38; ±0.53, possibly small).

The majority of days with SRI symptoms present occurred prior to week 14 (weeks 1-14 average percentage of days ill = 16.1%, weeks 18-33 average percentage of days ill = 4.6%). Symptoms were generally present at the beginning of term 1 (week 1) and the end of term 2 (weeks 12 and 14), but a substantial increase in SRI symptoms was also present at week 20 (d = 0.43; ±0.55, likely small).

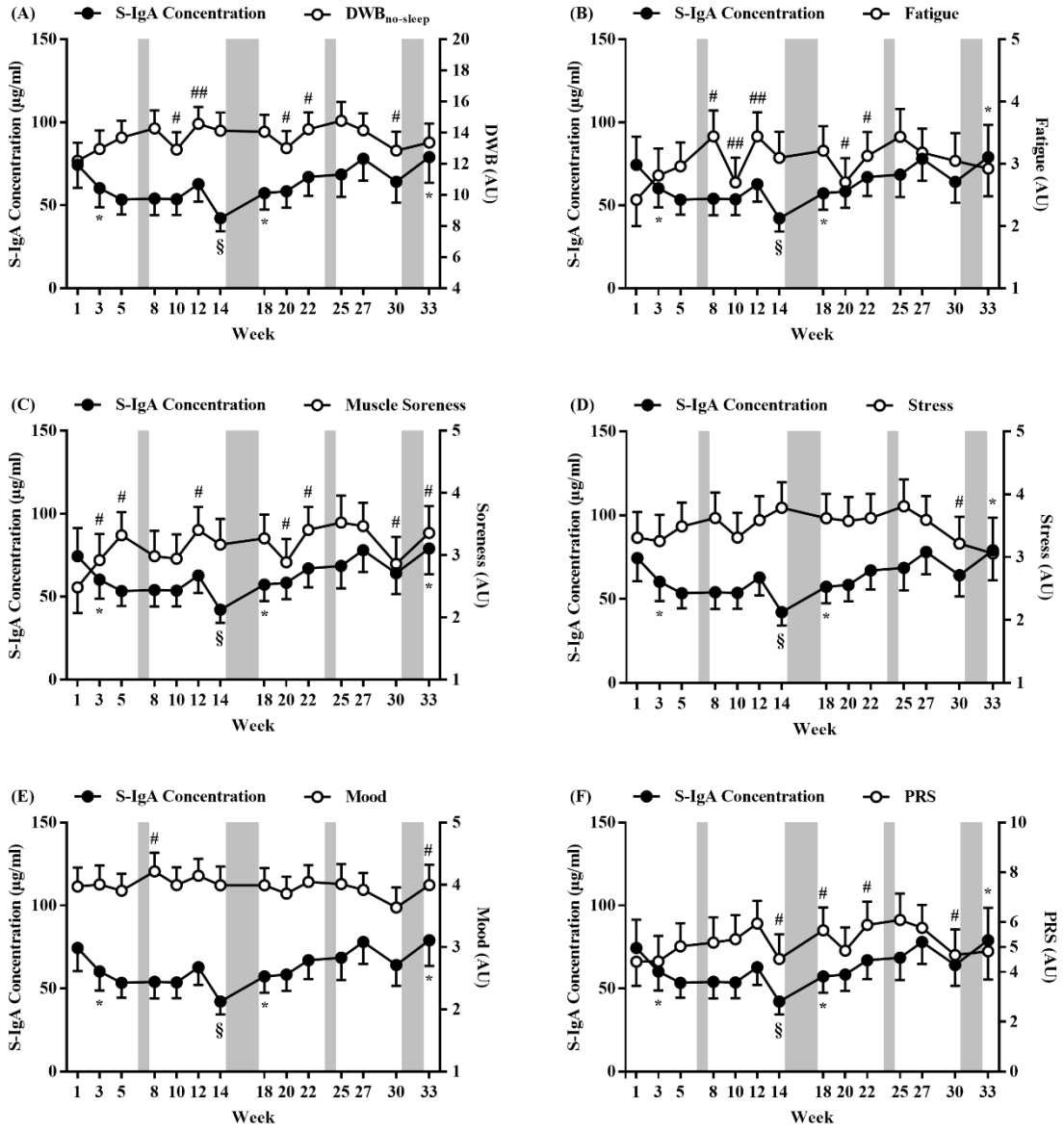


Figure 8.5: Visual representation of the longitudinal change in s-IgA concentration and $DWB_{no-sleep}$ (A), fatigue (B), muscle soreness (C), stress (D), mood (E) and PRS (F). Data are presented as back transformed least square means ± 90% confidence intervals. Shaded areas represent half-term breaks. Asterisks, hashtags and section signs denote likelihood that the change from the previous sampling timepoint is greater than the smallest worthwhile change: * likely; ** very likely small for s-IgA concentration; § likely moderate for s-IgA concentration; # likely, ## very likely small for subjective fatigue/wellness measures.

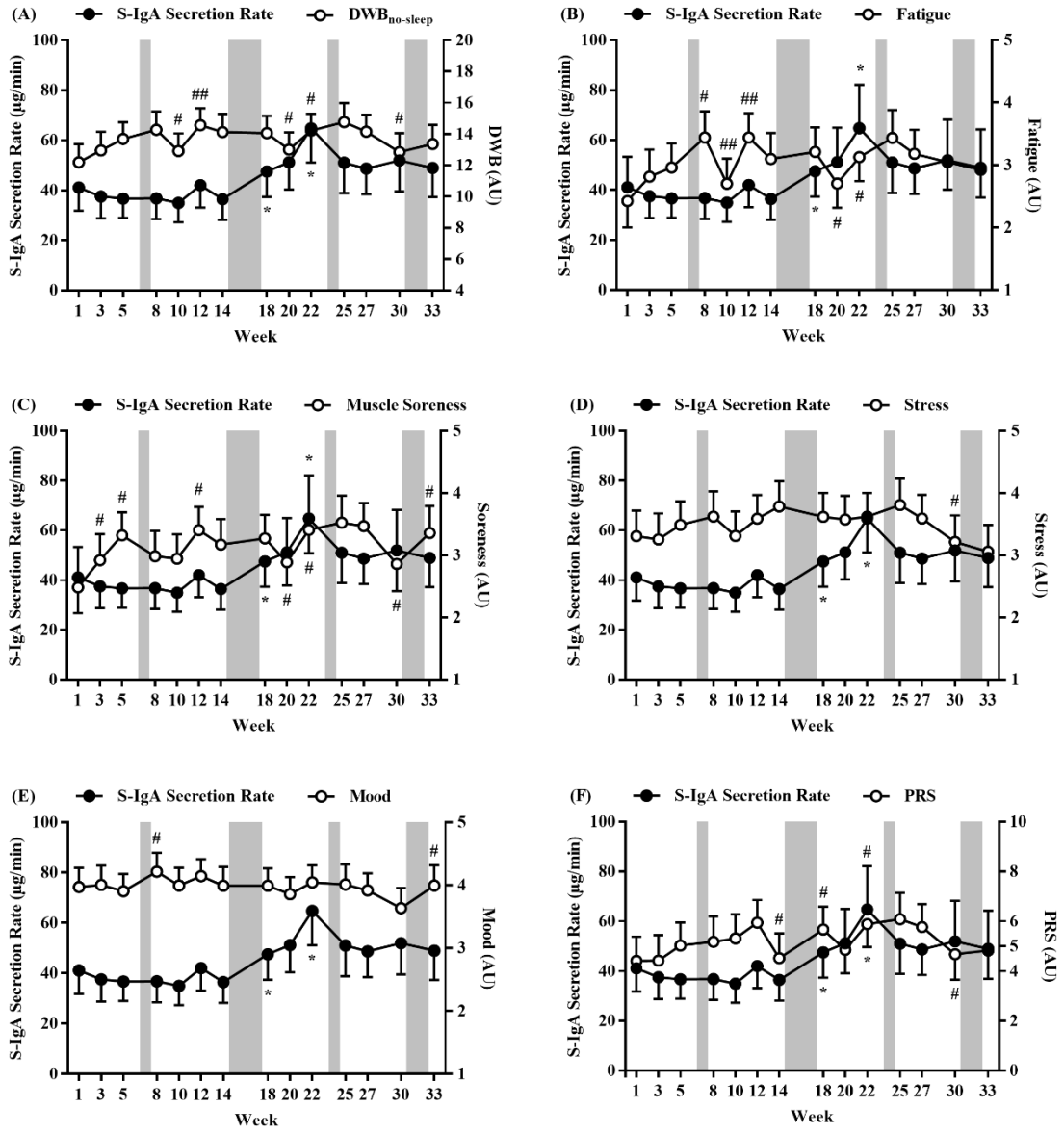


Figure 8.6: Visual representation of the longitudinal change in s-IgA secretion rate and $DWB_{no-sleep}$ (A), fatigue (B), muscle soreness (C), stress (D), mood (E) and PRS (F). Data are presented as back transformed least square means ± 90% confidence intervals. Shaded areas represent half-term breaks. Asterisks and hashtags denote likelihood that the change from the previous timepoint is greater than the smallest worthwhile change: * likely; ** very likely for s-IgA secretion rate; # likely, ## very likely for subjective fatigue/wellness measures.

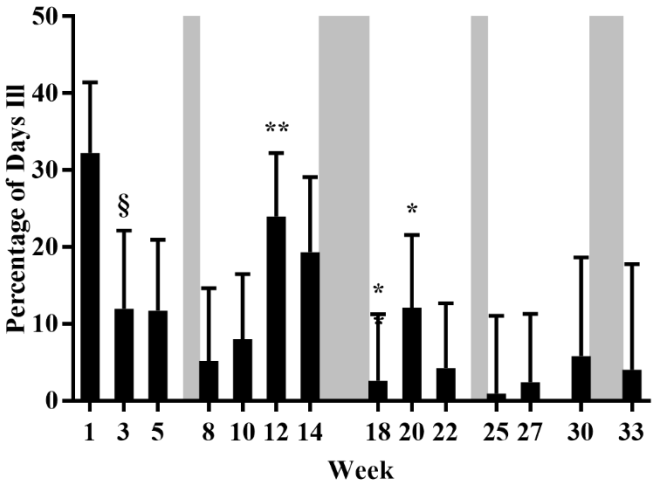


Figure 8.7: Visual representation of percentage of days with SRI symptoms present over the duration of the study. Percentages calculated between sampling collections (usually two weeks). Data are presented as least square means ± 90% confidence intervals. Shaded areas represent half-term breaks. Asterisks and section denote likelihood that the difference is greater than the smallest worthwhile change: * likely; ** very likely small; § likely moderate.

8.5 Discussion

This study had two key aims. The first was to calculate the true predictive ability and relative importance of s-IgA measures with regards to illness incidence in youth athletes. Using a prospective cohort study design, the results of this study showed that the AUC of all three models fell below the 0.75 AU threshold for a good predictor indicating that s-IgA measures cannot be used to accurately predict SRI at three individual time points within four weeks of SRI onset (i.e. SRI_{day}, SRI_{2wk} and SRI_{4wk}). Despite this lack of predictive ability, these findings demonstrate that the relative importance of the features within the predictive models differs depending on their timing prior to SRI onset. At SRI_{day}, the percentage deviation from the average healthy s-IgA concentration was the most important predictive feature of the model, whereas at SRI_{4wk} the average healthy s-IgA secretion rate was the most important. All features held similar importance in the SRI_{2wk} model.

The second aim of this study was to outline the longitudinal changes in objective and subjective fatigue/wellness measures over an academic year in youth athletes. The results show that over the duration of an academic year, s-IgA concentration followed an inverted-U trend, which peaked at weeks 1 and 33, but troughed at week 14. S-IgA secretion rate followed a two-step trend, where immune function was lower before week 14 than after. The subjective fatigue/wellness measures did not follow a similar trend but did show fluctuations throughout the year. As term 1 progressed, $DWB_{no\text{-}sleep}$, fatigue and muscle soreness all increased substantially. Similarly, as term 4 progressed, there was a substantial and progressive decline from weeks 25-30 in all fatigue/wellness measures except the fatigue subscale. Substantial short-term reductions, followed by immediate rebounds were identified between weeks 8-12 ($DWB_{no\text{-}sleep}$ and fatigue) and 18-22 ($DWB_{no\text{-}sleep}$, fatigue and muscle soreness).

8.5.1 S-IgA predictive ability

It is a notable observation that none of the models' AUCs were greater than the 0.75 threshold set for a good predictive model of SRI in youth athletes. These results indicate that while s-IgA measures can be used as a risk factor for illness, they cannot predict SRI incidence alone. No previous study has evaluated the difference between associative and predictive relationships within the illness literature. However, this finding mirrors recent conclusions within injury monitoring that statistical associations between independent and dependent variables are not always predictive (McCall et al., 2018). McCall and colleagues (2018) recently observed that despite the ACWR showing a significant and substantial relationship with non-contact soft tissue injury risk over two different time frames (Acute:chronic 1:4 RR 1.49; 95% CI 1.01-2.23, $P = 0.006$, likely harmful; Acute:chronic 1:3 RR 1.42; 95% CI 1.00-1.99, $P = 0.006$, likely harmful), neither time frame was able to predict future injury occurrence (Acute:chronic 1:4 AUC 0.58; 95% CI 0.52-0.64; Acute:chronic 1:3 AUC 0.56; 95% CI 0.50-0.62). Given the multi factorial risk

factors involved in illness incidence, including low energy availability, poor sleep, environmental conditions and stress/recovery balance (Drew et al., 2017; Walsh, 2018), it is perhaps not surprising that no predictive relationship was found.

Alongside the multifactorial risk factors associated with illness, the lack of predictive ability of immune measures with regards to SRI may also be related to their poor reliability. The results of this study indicated that the between day TE was 31.1% for s-IgA concentration and 61.7% for s-IgA secretion rate, but reliability values as high as 68% and 75% respectively have previously been observed (Dwyer et al., 2010). With a between day CV of 31.1%, a s-IgA concentration sample with a true value of 100 µg/ml could hold values from 68.9-131.1 µg/ml based on the test's error. This wide variation in the potential values of s-IgA concentration observed relative to its true value severely limits its predictive ability as the observed value could be much greater or smaller than the true value, resulting in numerous false positive or negative predictions of SRI.

It is interesting that the true predictive ability of s-IgA with regards to SRI was considered poor given the characteristics of the SRI question used within this study are remarkably similar to those of the URTI previously used by Neville and colleagues (2008). For example, in this study, 11.2% of days were classified as SRI, which is comparable with the 129/1424 weeks (9.1%) classified as URTI in their slightly longer 50-week study (Neville et al., 2008). Similarly, in this study, a drop below 40% of the average healthy s-IgA concentration resulted in SRI on 34-41% of occasions, and a drop of 70% below the healthy average resulted in SRI with 24-38% regularity. Neville and colleagues reported a 40% drop to result in a 48% chance of URTI incidence in the following three weeks, and a 70% drop to have a 28% chance of URTI (Neville et al., 2008). The similarity in these values suggests that despite s-IgA showing predictive associations with data seen by the model in question, these associations may not be representative in an unseen sample (as indicated by the results of this study). Consequently, it is recommended that all future

studies utilise a machine learning prediction-based approach with data previously unseen by the model when attempting to evaluate the true predictive ability of any measure.

8.5.2 S-IgA relative importance

The results of this study show there is a differentiation between the importance of s-IgA concentration and s-IgA secretion rate as predictors of SRI at different timepoints in the four weeks prior to SRI onset. It has previously been shown that the percentage deviation from the average healthy s-IgA concentration transiently drops in the three weeks prior to URTI incidence (Neville et al., 2008) and that s-IgA secretion rate has a greater association with URTI incidence than s-IgA concentration over periods of four weeks and greater (Fahlman & Engels, 2005). The predictive models within this study add further support to these differences by identifying the percentage deviation from the average healthy s-IgA concentration as the most important predictor for SRI_{day}, and the average healthy s-IgA secretion rate as the most important predictor for SRI_{4wk}. However, at SRI_{2wk} there appears to be a crossover in the importance of the two measures and there is no feature which is clearly more important than any other. It is possible that this can also be explained by the previously established three-week transient drop in s-IgA concentration prior to URTI incidence (Neville et al., 2008). In their study, Neville and colleagues (2008) only observed a significant difference in the percentage deviation from average healthy s-IgA concentration when URTI values were compared to four-weeks pre-incidence and measures of one and two weeks post-illness. It is therefore possible that although the percentage deviation from average healthy s-IgA concentration is important on the day of SRI, it may not fluctuate enough in the weeks leading up to illness to be useful in practice. Unfortunately, due to the fortnightly sampling employed in this study, we are unable to confirm the importance of the measure at one and three weeks prior to SRI onset. Future research may wish to consider these time periods alongside those used in this study to corroborate this hypothesis.

In addition to evaluating the predictive ability of s-IgA, some of the known risk factors for illness incidence (sport group, sex and environment) were added to the models to evaluate their relative importance over the four weeks prior to SRI onset. In this regard, the increasing importance of the sport group categorical feature relative to others from SRI_{day} to SRI_{4wk} is an interesting discovery. It is unsurprising that the sport of the athlete has relatively little importance as to whether they report SRI on the day of sampling, but the identification of sport group as a predictive risk factor above and beyond the previously identified risk factors of gender (He et al., 2014) and environment (Walsh, 2018) is novel. To date, research attempting to establish the relationship between s-IgA measures and illness incidence has taken place in basketball (Moreira et al., 2011), male and female soccer (Moreira et al., 2014; Putlur et al., 2004), rugby union (Cunniffe et al., 2011), American football (Fahlman & Engels, 2005), sailing (Neville et al., 2008) and ice hockey (Orysiak et al., 2017). By identifying sport group as an important feature within the prediction of SRI in the subsequent four weeks, above and beyond the influence of gender and environment, it can be inferred that more categorical risk factors (e.g. the sport evaluated) need to be considered alongside immune function in future models. For example, energy availability has previously been linked to URTI risk (Drew et al., 2017) and collisions have previously been linked to increased energy requirements in youth athletes (Costello et al., 2018), so it is possible that the collision-based sports of American football and rugby union have a much greater risk of SRI than other sports previously researched such as soccer or basketball. This difference in the risk of SRI could have a significant impact on the results shown as greater or larger deviations in s-IgA or any other predictive variable may be required to cause SRI onset. However, further research using larger cohorts is required to confirm that these differences are present.

8.5.3 Longitudinal change in objective and subjective fatigue/wellness measures

8.5.3.1 S-IgA concentration and secretion rate

With regards to the longitudinal change in s-IgA measures, s-IgA concentration and s-IgA secretion rate showed two distinctly different trends. S-IgA concentration followed an inverted-U trend, which troughed at week 14 (weeks 1-14 *d* = -1.19; ±0.53, very likely moderate decrease; weeks 14-33 *d* = 1.31; ±0.55, very likely moderate increase), whereas s-IgA secretion rate followed a two-step trend where immune function was lower from weeks 1-14 than it was for weeks 18-33 (weeks 14-18 *d* = 0.42; ±0.43, likely small). It is suggested that these changes are related to differences in the percentage of days where SRI was reported, but the results of the predictive model suggest if there is a relationship between the two, it is associative rather than predictive. This appears to be shown with s-IgA concentration where the only two substantial drops between consecutive weeks occurred from weeks 1-3 (*d* = -0.44; ±0.53, likely small decrease), which coincided with the largest percentage of days reported ill at any one sample (32.2% between weeks 1 and 3), and weeks 12-14 (*d* = -0.83; ±0.49, likely moderate decrease), which occurred in between the two samples with the greatest combined SRI incidence (24.0% from week 12-14, 19.3% from week 14-18). These results are congruent with multiple studies showing that s-IgA concentration is significantly lower (by 15-28%, *p* = 0.002 to *p* = 0.008) during periods of illness (Cunniffe et al., 2011; Neville et al., 2008; Orysiak et al., 2017).

The changes in s-IgA secretion rate shown in this study are also congruent with regards to previous associative literature as s-IgA secretion rate remained depressed even when SRI incidence was reduced from weeks 3-10. Fahlman and Engels (2005) previously reported that s-IgA secretion rate over-estimated URTI incidence in collegiate American Football players by 12-42%. With this depressed period of s-IgA secretion rate despite SRI incidence remaining relatively low, it is conceivable that by conducting a similar analysis,

s-IgA secretion rate would have over-estimated illness incidence in weeks 3-10. However, by remaining low during the periods of high SRI incidence and increasing in the periods with low SRI incidence, including with a likely small increase at week 22 (*d* = 0.38; ±0.40, likely small increase), two weeks prior to the lowest two samples of SRI incidence, the importance of s-IgA secretion rate as a long-term risk factor for SRI is promoted by this study.

8.5.3.2 Subjective fatigue/wellness measures

This is the first study to evaluate the longitudinal changes in subjective fatigue/wellness questionnaires used within athlete monitoring processes over an academic year in youth athletes. Unlike s-IgA concentration and secretion rate, the subjective fatigue/wellness measures did not follow a specific trend for the duration of the academic year. Instead, there were four instances (terms 1 and 4, weeks 8-12 and weeks 18-22) where substantial changes in multiple scales were present. All four of these changes can be explained qualitatively based on known stressors (e.g. start of school term, academic deadlines or occurring just before a large number of SRI episodes were present), suggesting that $DWB_{no\text{-}sleep}$, its individual subscales and PRS may be more responsive to short-term changes in the training or life-based stress and recovery that youth athletes are subjected to over the duration of an academic year than s-IgA measures. However, the changes observed did not always follow a consistent or expected pattern.

Over the duration of term 1, there was a substantial increase in $DWB_{no\text{-}sleep}$, fatigue and muscle soreness scores (*d* = 0.51; ±0.37, likely small to *d* = 0.86; ±0.46, likely moderate). This increase in fatigue/wellness measures over the duration of the term was unexpected but is likely due to contextual factors surrounding the start of the academic year. In term 1, returning athletes came back to the school after a 10-week summer break to a training load they were accustomed to but had likely not experienced over the 10-week summer break. Conversely, new athletes to the school were joining the scholarship scheme for the

first time and would have required time to adapt to the higher training load imposed upon them. Consequently, both groups of athletes would have experienced a spike in training load, which likely contributed to increased perceptions of fatigue and DOMS (Bompa & Haff, 2009; Bourdon et al., 2017). Furthermore, it is likely both groups of athletes would have needed to adapt to the earlier wake up time required to arrive at school in time for the 8.30am start. Previous studies have shown that, within adolescents, this is usually achieved by waking up earlier without going to sleep earlier, resulting in reduced sleep durations (Carskadon et al., 2004; Carskadon et al., 1998). Studies 2-4 highlighted the impact that reduced sleep duration can have on the fatigue/wellness measures used within this thesis, so it is unsurprising that adding this potential for reduced recovery to the increased training dose resulted in negative fatigue/wellness measure responses until the athletes became accustomed to the demands of the scholarship scheme at the end of term 1 (week 5).

In term 4, all fatigue/wellness measures except the fatigue subscale substantially decreased (d = -0.53; ±0.57, likely small to d = -0.68; ±0.54, likely small). Unlike in term 1 (weeks 1-5), participants were accustomed to the training dose imposed upon them by term 4 (weeks 25-30), so it is reasonable to suggest that the cup finals and coursework deadlines that took place in weeks 30-31 may have influenced the observed reduction in fatigue/wellness measures. This suggestion is strengthened by previous research, which showed a strong positive correlation between number of homework hours completed and subjective stress (r = 0.71, p < 0.001) and mood (r = 0.55, p < 0.001) in Australian high school students (Kouzma & Kennedy, 2002). Given that this prolonged period of academic stress is the only time when meaningful reductions in stress and mood were observed alongside other fatigue/wellness measures, it seems likely that it was a factor in the changes. No other study has evaluated whether the short fatigue/wellness measures used within the integrated athlete monitoring cycle are related to elements such as academic

stress, so it would be exciting from an athlete monitoring perspective if a future study could confirm this hypothesis.

In addition to the term-long changes in fatigue/wellness measures observed in terms 1 and 4, there were two occasions where multiple fatigue/wellness measures substantially dropped but immediately rebounded to their original level potentially indicating exposure to an acute stressor. These short-term reductions occurred between weeks 8 and 10 ($DWB_{no\text{-}sleep}$ and fatigue), and between weeks 18 and 20 ($DWB_{no\text{-}sleep}$, fatigue and muscle soreness) before rebounding by weeks 12 and 22 respectively. The second of these acute reductions, at week 20, could potentially be explained by the academic stress caused by the mock exam period in week 19 and subsequent increase in SRI prevalence in week 20. However, there is no obvious contextual reason for the sharp decline in fatigue (and, by extension, $DWB_{no\text{-}sleep}$) at week 10. Interestingly, this happens one sample and two weeks prior to the two time points with the highest combined SRI incidence. It is known that a virus can lie dormant in the human body for as many as three weeks prior to the onset of illness incidence (Schwellnus et al., 2016) so it is possible that this unexpected change in fatigue is related to SRI incidence in this cohort. This theory is supported by the substantial reduction in fatigue which occurs at week 20 and coincides with an increase in SRI prevalence. Furthermore, it is supported by the subjective fatigue/wellness changes which occurred in term 4, where the fatigue subscale was the only measure not to substantially reduce over the duration of the term, which also coincided with no substantial changes in SRI incidence. It is beyond the scope of this study to state with clarity whether the two measures are related, but it seems plausible that changes in the fatigue subscale could be related to SRI in either an associative or predictive manner, making this an interesting avenue for future research.

8.5.4 Limitations

Although the results of this study provide substantial additions to the literature, not least by providing an understanding of the true predictive ability of s-IgA with regards to illness incidence and by outlining the longitudinal change in objective and subjective fatigue/wellness measures, it is important that the limitations of the study are discussed. The most prominent of these is the study design. Despite collecting samples more regularly than any previous study of this length in youth athletes (Fahlman & Engels, 2005; Orysiak et al., 2017), this study still only collected three s-IgA samples in a four week period prior to SRI. It is therefore possible that a sample which could have predicted SRI was lost in the twenty-five days where sampling was not possible. However, although they are becoming more commonly used in sporting situations (Coad et al., 2015), s-IgA tests still have a large inherent error, as evidenced by the large TE's observed in this study, which may limit their usefulness when collected on a more frequent basis. An exception to this may be within extremely intensive schedules, where large fluctuations in immune function can occur in short periods of time (Morgans et al., 2014). Similarly, although this is the first study to consider longitudinal changes in the short fatigue/wellness measures used within the integrated athlete monitoring cycle, it could be argued that only analysing the measure once every two weeks limits its interpretability. However, only analysing subjective fatigue/wellness measures provided at the same time as the saliva samples was a deliberate decision to allow comparison between the objective and subjective measures and provides evidence that subjective fatigue/wellness questionnaires may be more responsive to contextual factors than the objective s-IgA measures. Future research should now attempt to conduct studies with more regular sampling (e.g. every week) to confirm these differences in response to contextual factors.

Although due to factors outside of the author's control (section 8.1), it should be noted that some of the findings within this study are limited, or subject to caveats, because data

related to the training dose and training recovery experienced by the participants was not available. For example, it was suggested that the substantial reduction in the fatigue and $DWB_{no\text{-}sleep}$ scales at week 10 was related to the increased future prevalence of SRI but it could also have been related to unmeasured changes in the training dose or recovery experienced by participants. Similarly, by only considering contextual factors qualitatively, the changes cannot be attributed to a specific cause. To this end, although it is suggested that academic stress is related to reductions in fatigue/wellness measures twice, it is unclear whether this is due to the requirements of completing the academic work itself, the stress induced by expectations of performance in academic examinations and coursework, a reduction in sleep duration or quality experienced by the athletes at this time or any other specific cause under the umbrella of academic stress. That said, the aim of this part of the study was to longitudinally evaluate the changes in objective and subjective fatigue/wellness measures and the results successfully achieve this goal. Future research may now wish to break down these qualitative factors further to confirm specific causes.

Finally, as with the rest of this thesis, it is important to consider the statistical *vs* practically interpretable relationship debate. All longitudinal relationships reported in this study are statistical by nature (i.e. based on Cohen's *d* effect sizes). Understanding how likely these changes are to occur is important as it provides more generalisable information, but how these changes may manifest themselves in practice should also be evaluated. To this end, it should be noted that on the majority of occasions the four $DWB_{no\text{-}sleep}$ subscales failed to elicit a one unit change even when the MBI's suggested the changes were practically important. Similarly, only the difference in s-IgA concentration between weeks 12 and 14 was greater in percentage terms than the TE of the measure. Consequently, the usefulness of the changes identified in this study could be questioned in practice.

8.6 Conclusions

In conclusion the results of this study identify the true predictive ability and relative importance of s-IgA concentration and secretion rate with regards to SRI incidence. They also outline the longitudinal change in objective (s-IgA) and subjective fatigue/wellness ($DWB_{no\text{-}sleep}$, its individual subscales and PRS) measures used within the integrated athlete monitoring cycle. The results show that s-IgA measures cannot be used to accurately predict SRI onset at three time points in the four weeks prior to onset. However, the findings do show that there is a differentiation in the roles of s-IgA concentration and secretion rate in the four weeks prior to SRI incidence. The percentage deviation from the average healthy s-IgA concentration was identified as the most important predictor in SRI_{day}, indicating it may be a useful short-term risk factor for SRI incidence. However, the strength of this conclusion is limited by its unclear importance relative to other variables at SRI_{2wk}. The average healthy s-IgA secretion rate was identified as the most important feature at SRI_{4wk}, indicating that the athlete's healthy s-IgA secretion rate could be taken as a useful long-term risk factor for illness. These results are congruent with the previous associative relationship research (Fahlman & Engels, 2005; Neville et al., 2008).

Longitudinally, the results show that s-IgA concentration (inverted-U) and secretion rate (two-step) follow distinct trends over the duration of the academic year and that these appear to be associated with the percentage of days where SRI symptoms were present at any given time point. The subjective fatigue/wellness measures did not show a specific trend over the year but appeared were more responsive to key qualitatively described events including the start of the school year and periods of high academic stress (either through mock exams or coursework deadlines) than s-IgA concentration or secretion rate. Given this responsiveness to these qualitative events, future research should attempt to consider the predictive ability of subjective fatigue/wellness measures with regards to SRI

incidence. In particular, the fatigue subscale of $DWB_{no\text{-}sleep}$ deserves further consideration as this showed substantial reductions close to SRI incidence on two occasions and was the only measure not to show a substantial reduction over the duration of term 4 when SRI incidence remained unchanged.

Chapter 9 Summary Discussion

9.1 Introduction

The overarching aim of this thesis was to evaluate the true predictive ability of an integrated athlete monitoring cycle model with regards to illness incidence in youth athletes. In order to achieve this aim, the results of the thesis could be split into three parts. The first (study 1) identified the reliability and usefulness of the training response measures (i.e. DWB and PRS (fatigue/wellness); CMJ (preparedness to play)). The second (studies 2, 3 and 4) evaluated the relationships present between the measures of the integrated athlete monitoring cycle (i.e. training load and match exposure (training dose); sleep duration, sleep quality and sleep index (training recovery); DWB, $DWB_{no\text{-}sleep}$ and PRS (fatigue/wellness); and CMJ (preparedness to play)). Finally, the third (study 5) aimed to evaluate the true predictive ability of an integrated athlete monitoring cycle model with regards to illness incidence by accounting for the relationships found in studies 2-4 (i.e. those between the training dose, training recovery and training response measures). Unfortunately, due to the web-based application issues outlined in section 8.1, it was not possible to complete this final part. However, the evaluation of the predictive ability of s-IgA with regards to illness incidence and longitudinal analysis of objective (s-IgA) and subjective ($DWB_{no\text{-}sleep}$ and PRS) fatigue/wellness measures suggest there is scope for further consideration the integrated athlete monitoring cycle model in future research. Despite being unable to evaluate the true predictive ability of an integrated athlete monitoring cycle model, the results of this thesis have three important, and novel, implications.

The first of these, that a measure of training recovery should be included within the athlete monitoring cycle, is applicable to all sports cohorts. It is surprising given the known importance of recovery to athletic performance models (Banister, 1991; Bompa & Haff, 2009) and the recent increase in sleep based literature (Fullagar, Skorski et al., 2015; Halson, 2014; Taylor et al., 2016) that the inclusion of a training recovery measure has not

yet been considered as part of the athlete monitoring cycle. The results of this study now provide support for its inclusion within the integrated athlete monitoring cycle and its use in this manner is worthy of further attention in all sports cohorts.

Secondly, the results show that despite statistically significant results being shown on multiple occasions, they rarely resulted in practically interpretable changes occurring. Thorpe and colleagues (2015) previously hinted at this anomaly by identifying a 400 m difference in high speed running required for a one unit change in their fatigue scale. However, it has been widely under reported within the literature. Whether the lack of responsiveness to training load is meaningful in practice is not yet known as it has not been considered with regards to athletic performance, development or adverse outcome incidence yet. Study 5 originally aimed to understand how these relationships interacted to predict illness and the integrated athlete monitoring cycle model proposed is highlighted as a future direction for research in section 9.9.

Finally, the results of study 5 highlight key periods of increased susceptibility to illness in school sport scholarship athletes. These centre around the start of term and periods of increased academic stress, which is congruent with previous research (Mann et al., 2016). Given the previously mentioned impact of illness for as many as four days following removal of clinical symptoms (section 2.3.2), practitioners may wish to consider the training dose imposed upon their athletes at this time.

The following sections will discuss the results of this thesis as they pertain to the integrated athlete monitoring cycle and the potential ability of an integrated athlete monitoring cycle model to predict illness incidence in youth athletes. The challenges of collecting longitudinal data for athlete monitoring purposes within a school sport scholarship environment and the practical applications of the results will be evaluated in

further detail. The limitations of the studies completed and directions for future research will also be considered.

9.2 Reliability and usefulness of training response measures

The first study of this thesis identified the reliability (measured via the TE) and usefulness (measured via the TE:SWC ratio) of the three training response measures initially considered within this thesis – DWB and PRS (fatigue/wellness) and CMJ (preparedness to play). The results showed that DWB had a TE of 11.7% and an SWC of 6.2%, PRS had a TE of 8.5% and an SWC of 4.9%, and CMJ had a TE of 2.8% and an SWC of 3.9%. Study 4, which removed the sleep quality subscale from DWB to create $DWB_{no\text{-}sleep}$, measured its TE and SWC as 9.8% and 6.4% respectively. Based on previously used thresholds (<5% TE for a reliable measure (Cormack et al., 2008; Roe, Darrall-Jones, Till, Phibbs et al., 2016) and TE:SWC ratio < 1 for good usefulness (Hopkins, 2000)), none of the subjective fatigue measures were classified as reliable or useful, but the preparedness to play measure of CMJ was classified as both reliable and useful. These results could be interpreted as indicating that none of DWB, $DWB_{no\text{-}sleep}$ or PRS were appropriate for further consideration in this cohort. However, this conclusion was contested by our assertion that the reliability and usefulness may prove acceptable when the relationship these fatigue/wellness measures have with adverse outcomes (e.g. illness) is known. For example, although the TE of PRS is 8.5%, the smallest reduction in PRS required to predict illness incidence is not yet known. When discovered, if this value was greater than 8.5%, the PRS would become both reliable and useful with regards to the prediction of illness even though statistically the results from study 1 suggest otherwise.

This understanding of the SWC is particularly important in the case of the PRS, where a one unit change is equivalent to 10% (i.e. greater than the 8.5% TE). Conversely, in DWB a one unit change was equivalent to 4% (against a TE of 11.7%), and in $DWB_{no\text{-}sleep}$ a one

unit change was equivalent to 5% (against a TE of 9.8%). As this thesis progressed, it became clear that PRS held stronger relationships than DWB and $DWB_{no\text{-}sleep}$ with the training dose and recovery experienced by participants. Whether these differences are a consequence of the scaling of the questionnaires as suggested in studies 3 and 4 or differences within the framing of the questionnaires, it is clear that the PRS appeared more reliable when evaluating a one unit raw change against the TE than DWB and $DWB_{no\text{-}sleep}$.

Unfortunately, it was not possible to evaluate the differences between the elements of the two questionnaires, but it was hoped that the statistical properties obtained from study 1 could be implemented into the analysis conducted in study 5 to provide an understanding of an illness prediction SWC before the issues with the web-based application occurred. This model will now be considered as a possible future direction for research (section 9.9) and should be considered within the published literature following this thesis as researchers' understanding of athlete monitoring and the integrated athlete monitoring cycle continues to evolve.

9.3 Understanding the relationships between measures of the athlete monitoring cycle

Having established the reliability of the training response measures considered within this thesis (DWB, $DWB_{no\text{-}sleep}$, PRS and CMJ), it was important to understand the relationships present between the different measures of the integrated athlete monitoring cycle so they could be used within an integrated athlete monitoring cycle model. Figure 9.1 depicts the integrated athlete monitoring cycle considered in this thesis. In this thesis, no measure of external training load was used but s-RPE was included as a measure of internal training load. The decision to omit external training loads and use s-RPE as a measure of internal training load was based on the requirements of practitioners within school sport

scholarship environments (i.e. that the measures used are time and monetary cost-efficient and easy to use (Bergeron et al., 2015; Murray, 2017)). Self-reported sleep duration, self-reported sleep quality and, subsequently, sleep index were considered as measures of training recovery. Subjective fatigue/wellness questionnaires (DWB, $DWB_{no\text{-}sleep}$, their individual subscales and PRS) were evaluated as fatigue/wellness measures and CMJ was considered as a preparedness to play measure.

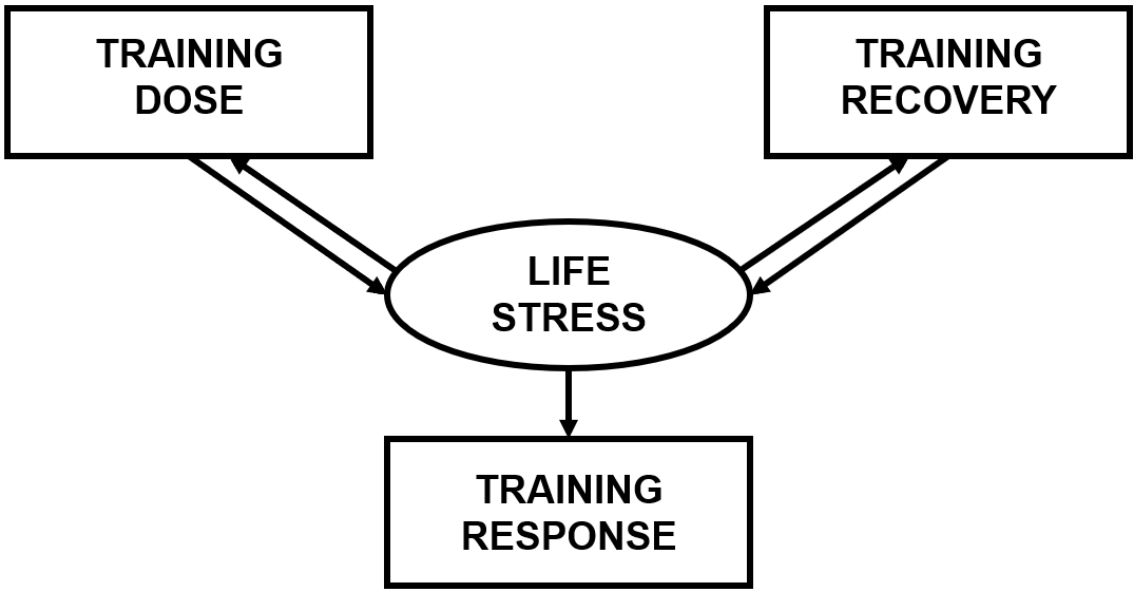


Figure 9.1: Integrated athlete monitoring cycle previously shown in Figure 1.2.

The key aim of this part of the thesis was to identify the relationships that training response measures held with the training dose and recovery experienced by the athlete. By accounting for these relationships, the response to training could provide an understanding as to when adverse outcomes may occur. For example, it is well established that delayed onset muscle soreness could be present for up to 72 hours following a hard training session (Cheung et al., 2003). However, if this soreness is present following an easy training session it could be indicative of a maladaptive training response and could therefore be a warning sign of future adverse outcome incidence. No study has yet considered the prediction of adverse outcomes in this integrated manner

and so it was important that the relationships held between measures of the training dose, recovery and response were evaluated before the prediction of illness was considered. Studies 2, 3 and 4 considered three fatigue/wellness measures (DWB, $DWB_{no\text{-}sleep}$ and PRS) and one preparedness to play measure (CMJ). Their relationships with the training dose and recovery experienced are discussed below and compared to the current literature.

9.3.1 Training dose

Throughout this thesis, s-RPE was used to measure the training dose imposed upon the athlete. This is the same as three previous studies considering the athlete monitoring cycle in elite adult Australian Rules football players (Buchheit et al., 2013; Gallo et al., 2017; Montgomery & Hopkins, 2013), but differs from the high speed running distance (Thorpe et al., 2015) and PlayerLoad (Rowell et al., 2017) measures previously considered in elite adult soccer players. In studies 3 and 4, building upon the work by Montgomery and Hopkins (2013), a dummy covariate was added to the model to account for the additional impact of match related stress on subjective fatigue/wellness measures. These were the first two studies to consider this concept in youth sport.

9.3.1.1 Subjective fatigue/wellness measures

9.3.1.1.1 Statistical relationships

Table 9.1 provides an overview of the relationships between the training dose and subjective fatigue/wellness measures observed in this thesis. Only the muscle soreness DWB subscale in studies 3 and 4, and the PRS in studies 2, 3 and 4 showed substantial relationships with the training dose imposed upon the athlete.

In study 2, a *likely* trivial relationship between training load and DWB was reported. This relationship was less than the clear and small relationships observed by Buchheit and

colleagues (2013) in their high training volume pre-season period, but agreed with the lack of relationship observed by Gallo and colleagues (2017) whose training volume was similar to that used within this study (neither study provided exact ES's). The results of studies 3 and 4 showed that the trivial relationship observed between training load and DWB and $DWB_{no\text{-}sleep}$ portrayed a masking effect whereby the muscle soreness subscale was related to training load and exposure to match play, but the fatigue, sleep quality, stress and mood subscales were not. These findings were congruent with a recent systematic review, which suggested that researchers should be aware of masking effects when adding multiple scales together to provide an overall score (Saw et al., 2016).

The results of the DWB and $DWB_{no\text{-}sleep}$ analyses with training load and match play exposure indicate that the training dose may not be as important to changes in youth athletes' wellness as it is for elite adult professional athletes. For example, Buchheit and colleagues (2013) observed clear and small relationships between s-RPE measured training load and all of the wellness subscales utilised within this study in their pre-season training period in elite adult Australian Rules football players (exact ES not reported). Similarly, Thorpe and colleagues (2015) observed relationships as strong as the large relationship between high speed running distance and their fatigue scale in elite adult soccer players (r = -0.51; ±0.11, p < 0.001). It is possible that this difference is due to the unique social, academic and maturational demands placed upon youth athletes (Mountjoy et al., 2008) which, aligned with the reduced physical demands of youth sport relative to adult sport (Read, Weaving et al., 2017; Roberts et al., 2008), may result in other factors affecting their wellness to a greater extent than the training dose. Similarly, it is possible that the extreme circumstances present in both Buchheit and colleagues' (2013) and Thorpe and colleagues' (2015) studies (10,000 AU training weeks and 400 m high speed running distance changes required for a one unit change in the fatigue subscale respectively) do not occur in youth athletes because their training schedules can involve multiple clubs and competitions taking place at the same time resulting in limited

opportunities for training load to fluctuate between days (Lloyd et al., 2015; Phibbs et al., 2018). Regardless, the results of this thesis show that the training response as measured by DWB, $DWB_{no\text{-}sleep}$ and its individual subscales differs for youth athletes relative to the published literature surrounding adult athletes, except for the muscle soreness subscale which shows negative relationships with increased training load in both populations.

Table 9.1: Overview of statistical relationships observed between training dose and subjective fatigue/wellness measures within this thesis.

	Study 2	**Study 3**		**Study 4**	
Scale	**Training Load**	**Training Load**	**Match Play Exposure**	**Training Load**	**Match Play Exposure**
DWB	-0.05; ±0.06 *LT*	-0.15; ±0.07 *LT*	-0.10; ±0.07 *VLT*		
$DWB_{no\text{-}sleep}$				-0.19; ±0.06 *PT*	-0.12; ±0.08 *LT*
Fatigue		-0.15; ±0.08 *LT*	-0.07; ±0.08 *MLT*	-0.16; ±0.08 *LT*	-0.08; ±0.08 *VLT*
Muscle Soreness		-0.43; ±0.10 *MLS*	-0.26; ±0.09 *LS*	-0.44; ±0.10 *MLS*	-0.26; ±0.09 *LS*
Stress		0.02; ±0.07 *MLT*	0.01; ±0.08 *MLT*	0.02; ±0.07 *MLT*	0.01; ±0.08 *MLT*
Mood		0.02; ±0.07 *MLT*	-0.02; ±0.10 *MLT*	0.00; ±0.06 *MLT*	-0.02; ±0.10 *MLT*
Sleep Quality		0.06; ±0.09 *VLT*	0.04; ±0.10 *VLT*		
PRS	-0.23; ±0.05 *MLS*	-0.37; ±0.09 *MLS*	-0.25; ±0.08 *LS*	-0.37; ±0.09 *MLS*	-0.25; ±0.08 *LS*

N.B: Italics represent likelihood of *r* or ES occuring relative to SWC: *P* possibly; *L* likely; *VL* very likely; *ML* most likely; *T* trivial; *S* small

The results of study 2 are reported as correlation coefficients: *r*; ±90% confidence intervals. The results of study 3 and 4 are reported as Cohen's *d* ES: *d*; ±90% confidence intervals for a 2SD increase in training load, and the dummy covariate of match play exposure. Study 4 results are taken from the sleep index model.

Unlike DWB, $DWB_{no\text{-}sleep}$ and its individual subscales, PRS showed substantial relationships with the training dose across studies 2-4, from the most likely small correlation observed in study 2 (r = -0.23; ±0.05) to the most likely small relationship with training load (d = -0.37; ± 0.09) and likely small relationship with match play exposure (d = -0.25; ± 0.08) in study 4. It is possible that this is a function of the scientific rigour with which the scales were conceptualised. The PRS was developed in a laboratory setting and validated against the performance observed in a standardised high-intensity intermittent sprint protocol (Laurent et al., 2011), but had not yet been considered within a field-based setting. This contrasts with DWB, which was devised based on previous recommendations for prevention of the overtraining syndrome in athletes (Hooper & Mackinnon, 1995; McLean et al., 2010). This concern was briefly considered in section 2.7.2.1.1 as a rationale for evaluating the PRS as a fatigue/wellness measure within this thesis. The results of studies 2-4 justify the inclusion of the PRS within the athlete monitoring cycle with regards to the relationships it holds with the training dose and recovery (section 9.3.2.1.1).

A further possibility with regards to the discrepancy in findings between DWB measures and PRS is that the scaling itself is a factor. The PRS is essentially an inverse category-ratio 10 RPE scale, beginning at 0 (very poorly recovered/extremely tired) and ending at 10 (very well recovered/highly energetic). It could therefore be considered unsurprising that it has a stronger relationship with training load than the 1-5 individual wellness subscales also considered in this thesis. However, it is unclear from the analyses conducted within this thesis whether this is due to the scaling itself (e.g. category-ratio 0-10 *vs* linear 1-5) or differences within the participants' interpretation of the scales' meaning (see section 9.3.2.3 below). Developing similar category-ratio 0-10 scales for each of the individual DWB subscales and evaluating these scales' relationships with an athlete's training load and exposure to match play could help confirm this hypothesis in the future.

9.3.1.1.2 Practically interpretable relationships

Although the muscle soreness subscale and PRS both showed statistical relationships with the training load and additional stresses associated with match play, only the relationship between PRS and training load with match exposure resulted in a clear one unit change for a typical athlete and was therefore the only relationship deemed practically interpretable. Indeed, despite the masking effect with other subscales within $DWB_{no\text{-}sleep}$, it was the overall score which held the greatest practically interpretable relationship with training load and match play (0.79 ± 0.19 units), not the muscle soreness subscale. These results are congruent with the large changes in the training dose required to provide a one unit change in previous studies (Buchheit et al., 2013; Thorpe et al., 2015). This lack of responsiveness to the training dose may be perceived as a limitation of the questionnaires. However, it is only by considering the integrated relationships within the athlete monitoring cycle and how these can be used to predict adverse outcome incidence that this perceived limitation can be confirmed.

9.3.1.2 Preparedness to play measures

9.3.1.2.1 Statistical relationships

The results of study 2 provided evidence of a possibly trivial relationship between CMJ and s-RPE training load in youth athletes (r = -0.09; ±0.06). Although the uncertainty within the confidence intervals suggested there was a chance the relationship could have been small, the preparedness to play measure also showed no meaningful relationship with sleep duration (see section 9.3.2.2.1) and so was not considered beyond study 2. The lack of meaningful relationship between CMJ and training load is congruent with Malone and colleagues' (2015) observations in youth soccer players, but contradicts those of Rowell and colleagues (2017) in elite adult soccer players. In contrast to our initial hypothesis that the difference between these observations was due to the statistical

analysis employed, it seems more likely that the difference could be a function of the differing demands between adult and youth sports (Chandler et al., 2014; Cormack et al., 2014; Read, Weaving et al., 2017; Roberts et al., 2008). The reduced physical demands of youth sport relative to adult sport may result in reduced neuromuscular fatigue and, subsequently, a reduced need for a neuromuscular preparedness to play measure as part of the integrated athlete monitoring cycle in this cohort.

9.3.2 Training recovery

The inclusion of a training recovery measure within the integrated athlete monitoring cycle is a novel element within this thesis. In studies 2-4, sleep was considered as a measure of training recovery due to difficulties conceptualising a single measure of life stress (Gunnar & Quevedo, 2007; Neil et al., 2011) and the inability of youths to accurately calculate portion sizes for food diaries (Kolodziejczyk et al., 2012). Table 9.2 provides an overview of the relationships between the training recovery and subjective fatigue/wellness measures observed in this thesis. In studies 2 and 3, the training recovery was measured by self-reported sleep duration before the concept was explored further by evaluating the use of the sleep quality DWB subscale and a sleep index measure in study 4. Unlike with the training dose, all DWB measures and subscales, except muscle soreness, showed substantial relationships with at least one measure of the training recovery considered in this thesis.

Table 9.2: Overview of statistical relationships observed between training recovery and subjective fatigue/wellness measures within this thesis.

	Study 2	**Study 3**		**Study 4**	
Scale	**Sleep Duration**	**Sleep Duration**	**Sleep Duration**	**Sleep Quality**	**Sleep Index**
DWB	0.28; ±0.05 *MLS*	0.45; ±0.09 *MLS*			
$DWB_{no\text{-}sleep}$			0.31; ±0.08 *VLS*	0.47; ±0.09 *MLS*	0.44; ±0.08 *MLS*
Fatigue		0.42; ±0.11 *MLS*	0.42; ±0.11 *MLS*	0.53; ±0.11 *MLS*	0.55; ±0.11 *MLS*
Muscle Soreness		0.13; ±0.07 *LT*	0.13; ±0.07 *LT*	0.18; ±0.09 *PT*	0.16; ±0.08 *LT*
Stress		0.18; ±0.08 *PT*	0.18; ±0.08 *PT*	0.35; ±0.06 *MLS*	0.29; ±0.08 *VLS*
Mood		0.22; ±0.10 *PS*	0.22; ±0.10 *PS*	0.41; ±0.09 *MLS*	0.37; ±0.09 *MLS*
Sleep Quality		0.80; ±0.14 *VLM*			
PRS	0.12; ±0.06 *PS*	0.25; ±0.09 *LS*	0.25; ±0.09 *LS*	0.37; ±0.07 *MLS*	0.36; ±0.09 *MLS*

N.B: Italics represent likelihood of *r* or ES occuring relative to SWC: *P* possibly; *L* likely; *VL* very likely; *ML* most likely; *T* trivial; *S* small; *M* moderate. The results of study 2 are reported as correlation coefficients: *r*; ±90% confidence intervals. The results of study 3 and 4 are reported as Cohen's *d* ES: *d*; ±90% confidence intervals for a 2SD increase in the sleep measure.

9.3.2.1 Fatigue/wellness measures

9.3.2.1.1 Statistical relationships

The results of this thesis provide a progressively increasing understanding of the relationship between perceptions of sleep and subjective fatigue/wellness measures. In study 2, although a small correlation between sleep duration and DWB was observed (r = 0.28; ±0.05, most likely small), z-score grouping analysis indicated that this was primarily a result of it being responsive to low sleep durations (d = -0.33; ±0.11, likely small low *vs* moderate, d = 0.15; ±0.23, possibly trivial high vs moderate) rather than showing a linear relationship with both high and low sleep durations. Similarly, study 2 suggested that PRS was not related to sleep duration (r = 0.12; ±0.06, possibly small). However, the results of studies 3 and 4 showed all of the fatigue/wellness measures, except muscle soreness, were related to the training recovery experienced. The results of study 2 were therefore attributed to the homogenous dataset collected over four weekdays (709/825 observations fell within 1 z-score of the athlete's mean and were therefore placed within the moderate group). Given this data collection frequency is similar to previous studies considering wellness questionnaires in applied sport environments (Gallo et al., 2017; McLean et al., 2010; Montgomery & Hopkins, 2013), it is important that researchers are conscious that by collecting data for a limited number of days per week it is possible for their results to be skewed, as occurred in study 2 of this thesis.

Studies 3 and 4 showed that sleep quality and sleep index held larger relationships with the subjective fatigue/wellness measures considered in this thesis than sleep duration. This finding was unsurprising given Pilcher and colleagues' (1997) observations in university students. For example, Pilcher and colleagues (1997) found sleep quality to have a much greater impact on the students fatigue than sleep duration (r = -0.57, p < 0.001 *vs* r = -0.23, p > 0.05) so it is understandable that this relationship would be maintained within this thesis, despite a different fatigue scale being used. In the same study, sleep quality was also significantly related to tension/anxiety (r = -0.52, p < 0.01),

depression/dejection (r = -0.52, p < 0.01) and confusion/bewilderment (r = -0.41, p < 0.05) providing a prior understanding of the range of fatigue/wellness measures it can influence. The increased strength of these relationships was particularly important for the stress (possibly trivial to very/most likely small) and mood (possibly small to most likely small) subscales whose relationships with training recovery became statistically substantial when sleep quality and sleep index were evaluated.

Despite the wide range of fatigue/wellness measures that sleep quality, and, by extension, sleep index could influence, muscle soreness was not related to any of the training recovery measures considered in this population (strongest relationship with sleep quality d = 0.18; ±0.09, possibly trivial). Such an observation was surprising given muscle soreness showed substantial relationships with both training load and match play exposure in studies 3 and 4. Recent studies have extolled the virtues of sleep and recovery with regards to athletic and neuromuscular performance (Fullagar et al., 2015; Mah et al., 2011) so it would be reasonable to assume that sleep could help muscle soreness in a similar manner. That it did not is likely due to the time course of delayed onset muscle soreness, which can increase for up to 72 hours post-training (Cheung et al., 2003). In this context, the restorative capacity of one night's sleep is limited when compared against the three days of soreness progression which could occur.

9.3.2.1.2 Practically interpretable relationships

Although the statistical relationships between the training recovery and fatigue/wellness measures were stronger than those held with the training dose, the practically interpretable relationships were not. Indeed, only the mean change in $DWB_{no\text{-}sleep}$ was greater than one unit (1.12 ± 0.28 units) in response to a 2 SD increase in sleep index. The mean change was less than half a unit for all $DWB_{no\text{-}sleep}$ subscales and only high PRS responders (i.e. those greater than 1 SD above the mean response) would be expected to change by one unit in response to the same 2 SD increase in sleep index.

Unlike the training dose, where the change in training load required to elicit a one unit change has previously been evaluated (Thorpe et al., 2015), there is no literature to compare these results to. However, the results provide valuable information as to the expected changes in fatigue/wellness scales, which will be considered in the future directions (section 9.9).

9.3.2.2 Preparedness to play measures

9.3.2.2.1 Statistical relationships

In study 2, alongside its possibly trivial relationship with training load (see section 9.3.1.2.1), CMJ showed a very likely trivial relationship with sleep duration (r = 0.01; ±0.06). Although these results contradict recent literature indicating that both increased and reduced sleep durations can have an impact on athletic performance (Mah et al., 2011; 2019), they are logical when considered together. In this regard, there was limited reduction in neuromuscular function due to the training loads considered in study 2 (251 ± 301 AU) so it could be argued that there was limited opportunity for the training recovery experienced by the athlete to improve neuromuscular function as it wasn't reduced beforehand. This theory provides further support for the conclusion that a preparedness to play measure was not required within the integrated athlete monitoring cycle in this youth athlete cohort.

9.3.2.3 Conclusions

In conclusion, studies 2, 3 and 4 together completed the second part of the thesis by evaluating the relationships between measures of the athlete monitoring cycle. The results showed that the training dose was related to the muscle soreness and PRS scales, whereas the training recovery was related to the $DWB_{no\text{-}sleep}$, fatigue, stress, mood and PRS scales, but not muscle soreness. However, despite these statistical relationships, the practically interpretable changes in response to the training dose and recovery experienced by the athlete were limited. The CMJ held no statistical relationships with the

training dose or recovery experienced by the athlete and so was not considered beyond study 2.

The relationships present in this thesis support the use of the integrated athlete monitoring cycle. In particular, the importance of training recovery relative to training dose measures to changes in fatigue/wellness measures questions the current applied sport science literature whereby sleep quality is evaluated within fatigue/wellness measures as part of the training response (Buchheit et al., 2013; McLean et al., 2010; Thorpe et al., 2015). It is understandable that researchers have progressed down this route given multiple studies have shown that increased training load is related to reduced sleep quality (Leduc et al., 2019; Pitchford et al., 2017). However, in this thesis, more advanced statistical methods were employed, which accounted for the relationship between training load and sleep within the random effects covariance structure. This covariance structed allowed us to obtain an accurate understanding of the relationships between sleep indices and fatigue/wellness measures, while accounting for the relationship between training load and sleep. Consequently, it can now be stated with confidence that sleep indices are related to the fatigue/wellness response and should therefore be considered as a measure of training recovery rather than within the training response.

Despite statistical support for the integrated athlete monitoring cycle, the small number of practically interpretable changes in fatigue/wellness measures following 2 SD changes in training load or sleep index continued a concerning trend when added to the poor reliability of the fatigue/wellness measures shown in study 1. However, without understanding how these changes relate to future adverse outcome incidence, it is not possible to establish how significant this lack of responsiveness to the training dose and recovery experienced is.

9.4 The use of an integrated athlete monitoring cycle model to predict illness in youth athletes

The final part of the thesis aimed to establish how the statistical properties of fatigue/wellness questionnaires identified in study 1 and the relationships between measures of the integrated athlete monitoring cycle evaluated in studies 2, 3 and 4 could be used to predict illness incidence in youth athletes. The aim was to use an integrated athlete monitoring cycle model where the expected fatigue/wellness response of an athlete based on the training dose and recovery experienced was compared to their actual response to establish whether this could be predictive of SRI incidence. The predictive ability of this model would then have been compared to the objective immune function measure of s-IgA to establish which method was a better predictor. Unfortunately, this was not possible for the reasons outlined in section 8.1 and the model will now be outlined in the future directions (section 9.9).

In place of the original aim, the predictive ability of s-IgA measures with regards to SRI was evaluated and an understanding of the longitudinal changes in objective (s-IgA) and subjective fatigue/wellness measures ($DWB_{no\text{-}sleep}$, its individual subscales and PRS) was obtained. The results of these studies together suggest that future studies may find an integrated athlete monitoring cycle model to be predictive of illness.

9.4.1 S-IgA predictive ability

The results of study 5 indicated that s-IgA concentration and secretion rate were unable to predict SRI in youth athletes when samples were obtained on a fortnightly basis. Three separate predictive models fell below the 0.75 AUC threshold set for a good predictor: SRI_{day}, which predicted illness on the day of sampling (median AUC 0.68, LQ 0.61, UQ 0.73); SRI_{2wk}, which predicted illness at any point within the next two weeks (median AUC 0.63, LQ 0.58, UQ 0.68); and SRI_{4wk}, which predicted illness at any point within the next

four weeks (median AUC 0.65, LQ 0.60, UQ 0.70). This poor predictive ability is likely due to the poor reliability of the s-IgA measures (TE's of 31.1% for s-IgA concentration and 61.7% for s-IgA secretion rate were reported in section 8.3.3.1.2) and/or the 'snapshot' study design, where only one sample was obtained over a fourteen day period. Such a study design was necessary given the time and cost of s-IgA collection and analysis but increases the number of missed opportunities to collect the predictive sample (if such a sample exists). For example, in SRI_{2wk}, there were a maximum of thirteen days where samples were not collected in the fortnightly sampling period before illness onset. In SRI_{4wk}, the maximum number of samples not collected was twenty seven. These potential missed opportunities should be built into the decisions made by researchers as to which measure of the training response to consider in their athlete monitoring processes.

Despite showing limited predictive ability, study 5 showed that the most important short-term predictive feature was the percentage deviation from the average healthy s-IgA concentration and the most important long-term predictive feature was the average healthy s-IgA secretion rate. Study 5 was the first study to consider both measures of s-IgA in the same analysis and provides evidence that the importance of s-IgA measure changes as the time prior to illness increases. This difference was hypothesized based on the available literature, whereby Neville and colleagues (2008) showed a three week transient decrease in s-IgA concentration prior to illness incidence in elite adult yachtsmen and Fahlman and Engels (2005) showed s-IgA secretion rate to be the only significant variable within their multiple linear regression model in collegiate American Football players. That the prediction-based models obtain similar conclusions to the correlation-based models adds confidence to the findings, but it is still unclear where the crossover point in the importance of the two measures occurs (study 5 suggests approximately two weeks pre-SRI incidence).

9.4.2 Longitudinal change in s-IgA and subjective fatigue/wellness measures

Alongside the issues with sampling frequency, a potential cause of the poor predictive ability of s-IgA is a lack of responsiveness to the stress and recovery experienced by youth athletes over the duration of the academic year. Unfortunately, it was not possible to evaluate this quantitatively as training dose and recovery data were unavailable (see section 8.1). However, by assuming that these two factors remained constant throughout the year, the response of s-IgA and $DWB_{no\text{-}sleep}$, its individual subscales and PRS to qualitative descriptors of key events could be considered. When considered in this manner, the results indicate that subjective fatigue/wellness measures are much more responsive to qualitative events than s-IgA (an objective fatigue/wellness measure) and may therefore prove to be better predictors of SRI in future studies.

9.4.2.1 S-IgA measures

Over the duration of the academic year, both s-IgA concentration (inverted-U) and secretion rate (two-step) showed specific annual trends, which did not fluctuate in response to qualitative factors. The peaks of s-IgA concentration's inverted-U shape were similar in magnitude and occurred at both the start and end of the study (weeks 1 and 33), whereas the trough occurred at week 14 (just before Christmas). It was also between weeks 14 and 18 where the substantial increase in s-IgA secretion occurred for its two-step trend. In both cases, this appears to be related to SRI incidence, which was most prominent prior to week 14 but it seems likely this is a reactive rather than predictive relationship. Aside from the AUC values for the predictive models stated above, this is perhaps best indicated by s-IgA concentration reaching its trough in the middle of, rather than before, the four week period with the highest percentage of days affected by SRI (week 14).

There is limited research observing the longitudinal change in s-IgA measures within sport (Cunniffe et al., 2011) as the majority of longitudinal studies have focussed on its relationship with illness (Fahlman & Engels, 2005; Neville et al., 2008; Orysiak et al., 2017). These results partially agree with those of Cunniffe and colleagues (2011), who also found a significant reduction in s-IgA concentration in December in elite adult rugby union players ($p < 0.05$). Indeed, this reduction in s-IgA concentration also occurred in the middle of the four weeks with highest illness incidence, adding strength to the suggestion that the relationship between s-IgA concentration and illness may be reactive rather than predictive. No study has previously evaluated the longitudinal changes in s-IgA secretion rate. The results therefore provide a novel insight into its two-step change over the course of the academic year. Furthermore, its greater stability (with only two substantial week-to-week changes compared to s-IgA concentration's four) confirms Brandtzaeg's (2003; 2013) assertions that it is the most stable s-IgA measure and helps to explain its importance as a long-term predictor of SRI.

9.4.2.2 Subjective fatigue/wellness measures

Unlike s-IgA, the subjective fatigue/wellness measures of $DWB_{no\text{-}sleep}$, its individual subscales and PRS did not follow specific trends over the duration of the academic year. They did show substantial differences across four timepoints though, which could potentially be explained by qualitative descriptors. Furthermore, on three of these occasions, there was a substantial change in the percentage of days affected by SRI relative to the previous or following time point.

At the start of the academic year, $DWB_{no\text{-}sleep}$ ($d = 0.51$; ±0.37, likely small), fatigue ($d = 0.53$; ±0.44, likely small) and muscle soreness ($d = 0.86$; ±0.46, likely moderate) scores progressively increased from weeks 1-5. The percentage of days affected by SRI was highest over this period, with the highest single time point of SRI incidence occurring in week 1 before reducing at week 3 and again at week 5. It is likely that these scores were

artificially poor at the beginning of term as participants encountered likely higher training loads and reduced sleep durations than they had become habituated to over the summer, resulting in increased feelings of fatigue and soreness (Bourdon et al., 2017; Carskadon et al., 1998; Taylor et al., 2016). However, as the athletes adapted to the training dose and recovery over the subsequent four weeks, the fatigue/wellness scores progressively improved to reflect this. This progressive improvement was also shown by SRI incidence (the adverse outcome to the training process considered within this thesis), which continuously reduced over the first three sampling time points, but not by s-IgA.

Similar differences between the objective and subjective fatigue/wellness measures occurred at week 10, where substantial reductions in $DWB_{no\text{-}sleep}$ (*d* = -0.47; ±0.37, likely small) and fatigue (fatigue *d* = -0.47; ±0.44, likely small) were present but no meaningful difference in s-IgA was reported, and at week 20, where substantial reductions in $DWB_{no\text{-}sleep}$ (*d* = -0.36; ±0.35, likely small), fatigue (*d* = -0.50; ±0.42, likely small) and muscle soreness (*d* = -0.39; ±0.45, likely small) and a non-substantial reduction in PRS (*d* = -0.34; ±0.40, possibly small) were present without any changes in s-IgA measures. In both of these situations, a spike in SRI incidence was located close to these sharp reductions (in weeks 12-14 the two highest combined percentage of days affected by SRI occurred, and in week 20 there was a substantial increase in SRI relative to week 18 (*d* = 0.43; ±0.55, likely small)) hinting again at a potential relationship between subjective fatigue/wellness measures and SRI incidence, but not between s-IgA and SRI incidence. In week 20, the reduction in subjective fatigue/wellness measures and increase in SRI incidence could be related to the mock examination period that took place in week 19. However, no such qualitative event took place around week 10, except the substantial increase in SRI incidence at week 12. Consequently, it is possible that the reductions in $DWB_{no\text{-}sleep}$ and fatigue were early warning signs for this increase in SRI incidence.

In particular, the fatigue subscale is worthy of further consideration given it is the only scale not to have shown substantial reductions between weeks 25 and 30 as final coursework deadlines and cup finals approached (*d* = 0.38; ±0.53, possibly small). Unlike fatigue, substantial reductions were present in all other subjective fatigue/wellness measures over this period ($DWB_{no\text{-}sleep}$ (*d* = -0.66; ±0.43, very likely small), muscle soreness (*d* = -0.68; ±0.54, likely small), stress (*d* = -0.58; ±0.45, likely small), mood (*d* = -0.53; ±0.57, likely small) and PRS (*d* = -0.59; ±0.49, likely small)) This was the only time that these reductions were not accompanied by a substantial change in SRI incidence (*d* = 0.22; ±0.72, unclear). This lack of substantial change in both fatigue and SRI incidence, despite substantial reductions in all other subjective fatigue/wellness measures, aligned with the three previous occasions where greater fatigue was experienced prior to, or at the same time as, SRI incidence suggests that there may be a relationship between the two measures. It is impossible to state from the results of this study whether this relationship is reactive (i.e. fatigue increases when an athlete is already suffering from SRI) or predictive (i.e. fatigue increases prior to an athlete suffering from SRI), but future studies should be able to provide further information in this regard.

9.5 Practical applications

The results of this thesis have important implications for athlete monitoring practices at schools, clubs and universities around the world. Traditionally, these practices have involved measuring the training dose and the training response to identify whether any modifications need to be made for specific individuals. However, it has recently been argued that match exposure has a greater impact on the muscle soreness response than a typical training session (Montgomery & Hopkins, 2013). Furthermore, the basis of the current athlete monitoring cycle (Gabbett et al., 2017) is weakened by it not including a measure of the training recovery. Such an omission may result in sessions being cancelled inappropriately because a ‘maladaptive response’ to training is identified

following a night of poor sleep which wasn't recorded in the monitoring process (see section 2.4.1). By cancelling these sessions, opportunities to maximise athletic performance and development may have been unnecessarily lost and peak performance may not have been achieved.

The results of this thesis improve athlete monitoring processes in several ways. Firstly, they identify the additive effect of match exposure on the fatigue/wellness response in youth athletes. Secondly, they identify the importance of using sleep as a measure of training recovery rather than as part of fatigue/wellness measures. Thirdly, they provide an understanding of the practically interpretable changes that can be expected based on the training dose and recovery experienced so practitioners have a greater ability to modify their athletes' training doses more accurately. Finally, the longitudinal study 5 highlights key periods of increased susceptibility to illness incidence, which practitioners may wish to consider when periodizing their training plans. All four of these improvements have significant application to current practices or provide future directions for research in all levels of sport whether the goal is peak sporting performance, optimising athletic development or attempting to minimise adverse outcome incidence.

9.5.1 The integrated athlete monitoring cycle

9.5.1.1 The training dose

Increasing practitioners' and researchers' understanding of the training dose, the results of this thesis identify match exposure as a cause of additive fatigue/wellness fluctuations above and beyond any increases in s-RPE load, which may be present. For example, if two athletes complete a 60 minute session at an RPE of 7 (s-RPE of 420 AU) but only one of them participates in a match (the other in a team training session), the athlete who completed the match would be expected to experience greater fatigue and subsequently provide lower fatigue/wellness scores relative to their normal, potentially indicating they

have a greater need for their training to be modified. Such a finding is particularly important within youth sport where athletes can be expected to compete in multiple competitions simultaneously (Lloyd et al., 2015; Phibbs et al., 2018) and so may compete in multiple matches on different days. The ability to differentiate between the impact of typical training session and match play exposure on a youth athlete's fatigue/wellness via this dummy covariate allows for enhanced decision making with regards to the training undertaken by the athlete.

9.5.1.2 The training recovery

A further important finding from this thesis is sustained support for the inclusion of a training recovery measure within the integrated athlete monitoring cycle. Sleep duration, sleep quality and sleep index all showed substantial relationships with fatigue/wellness measures through studies 2, 3 and 4 before sleep index was identified as the most usable measure in practice. The relationships sleep index held with $DWB_{no\text{-}sleep}$, fatigue, stress, mood and PRS were wider ranging than the relationships training load held with muscle soreness and PRS (see Table 9.1 and Table 9.2) indicating that the training recovery is more important than the training dose, with regards to an athlete's fatigue/wellness, in this cohort.

9.5.1.3 The integrated athlete monitoring cycle: A practical example

Figure 9.2 depicts an athlete monitoring form based on the integrated athlete monitoring cycle. It was developed and implemented after all data collection and analysis for this thesis had been completed. The form utilises the same questions as this thesis, but to simplify the process the responses are transformed into individualised z-scores and compared to each other before providing a comment and an action. The use of z-scores is important as it compares the current score to the average previous scores, allowing practitioners to evaluate how it relates to the athletes habitual training dose, recovery or response. Furthermore, simplifying the score in this manner is necessary to obtain buy in

from coaches in the face of an incomplete research process with regards to the ability of the integrated athlete monitoring cycle model to predict SRI in youth athletes. The form is programmed into Google Drive and automatically updates upon any individual athlete's response.

Today's Date	12/10/18	Wellness data					Today's wellness advice		Self-reported Symptoms				
Player Name	Latest	zWellness	zPRS	zSleepIndex	zDailyLoad	Match	Comment	Action	Illness	Impact	Injury	Injury Description	Impact
	04/12/2018	-2.15	-1.29	-0.34	-0.23	Yes	Poor wellness - Explained	Speak to athlete, structured recovery needed soon	Yes	No impact	No		No impact
	25/05/2019	-1.25	-0.88	-1.44	0.42	No	Wellness OK	Continue training as normal	No	No impact	No	0	No impact
	13/01/2019												
	21/01/2019												
	21/10/2018												
	03/12/2018	-0.04	-1.28	1.82	-0.20	No	Wellness OK	Continue training as normal	No	No impact	No		No impact
	14/12/2018	-0.08	-0.14	-0.42	1.99	Yes	Wellness OK	Continue training as normal	No	No impact	No		No impact
	17/12/2018	-0.90	-0.99	-0.95	2.50	Yes	Wellness OK	Continue training as normal	No	No impact	No		No impact
	11/02/2019	-2.25	-1.35	1.04	0.36	No	Poor wellness - Unexplained	Speak to athlete, potentially at risk of adverse outcome	No	No impact	No		No impact
	17/01/2019	-0.80	-1.13	0.85	0.52	No	Wellness OK	Continue training as normal	No	No impact	No		No impact

Figure 9.2: Athlete monitoring form based on the integrated athlete monitoring cycle, developed following the results of this thesis.

The athlete monitoring form compiles the athlete's data and provides three separate sections for the coach to view: wellness data; today's wellness advice; and self-reported symptoms. Each section is colour coded to help coaches visualise the results. Green cells are good (e.g. last night's sleep index z-score greater than 1, yesterday's training load z-score less than -1 or wellness/PRS z-scores greater than 1). Amber cells require further investigation, but the outcome of this investigation could be either positive or negative (e.g. if the athlete had a match, it may or may not be necessary for them to experience a period of recovery dependent on their response to it). Red cells also require further investigation, but the results are expected to be negative (e.g. if last night's sleep index z-score is less than -1, it is expected that the wellness/PRS z-scores will be less than -1, which could be indicative of the athlete needing additional recovery).

The ‘wellness data’ section provides details of the overall $DWB_{no\text{-}sleep}$ score, the PRS, the previous night’s sleep index, the previous day’s training load and whether the athlete participated in a match on the previous day. The overall $DWB_{no\text{-}sleep}$ score is still used at the school for simplification purposes despite concerns surrounding a masking effect in its relationship with the training dose (see study 3, section 6.4.1.1). This data is then analysed to provide a comment on the current wellness status and an action for coaches to consider in the ‘today’s wellness advice’ section. The comments and actions are automatically generated from outlying results (i.e. those above and below 1 z-score from the mean) via an if-then decision tree method, which is programmed into Google Drive and depicted in Figure 9.3. Finally, the ‘self-reported symptoms’ section provides details on the athlete’s perceptions of any injury or illness that they believe they are suffering from and the impact they perceive this to have on their performance.

The model used in practice can be criticised as it assumes a simplified version of the relationships between the training dose and training recovery and therefore does not account for the differing relationships we have shown sleep index and training load/match exposure to hold with $DWB_{no\text{-}sleep}$ and PRS (see studies 3 and 4 or section 9.3). Similarly, an athlete is only suggested to be at risk of adverse outcome incidence when both $DWB_{no\text{-}sleep}$ and PRS z-scores fall below -1, which may be too conservative a threshold. However, given the relationship between the athlete monitoring cycle and illness incidence has not yet been elucidated within the athlete monitoring cycle, it provides a simple set of guidelines which can be followed by sports coaches to try and minimise the risk of illness without stopping athletes from training too frequently when there is little reason to modify their training dose.

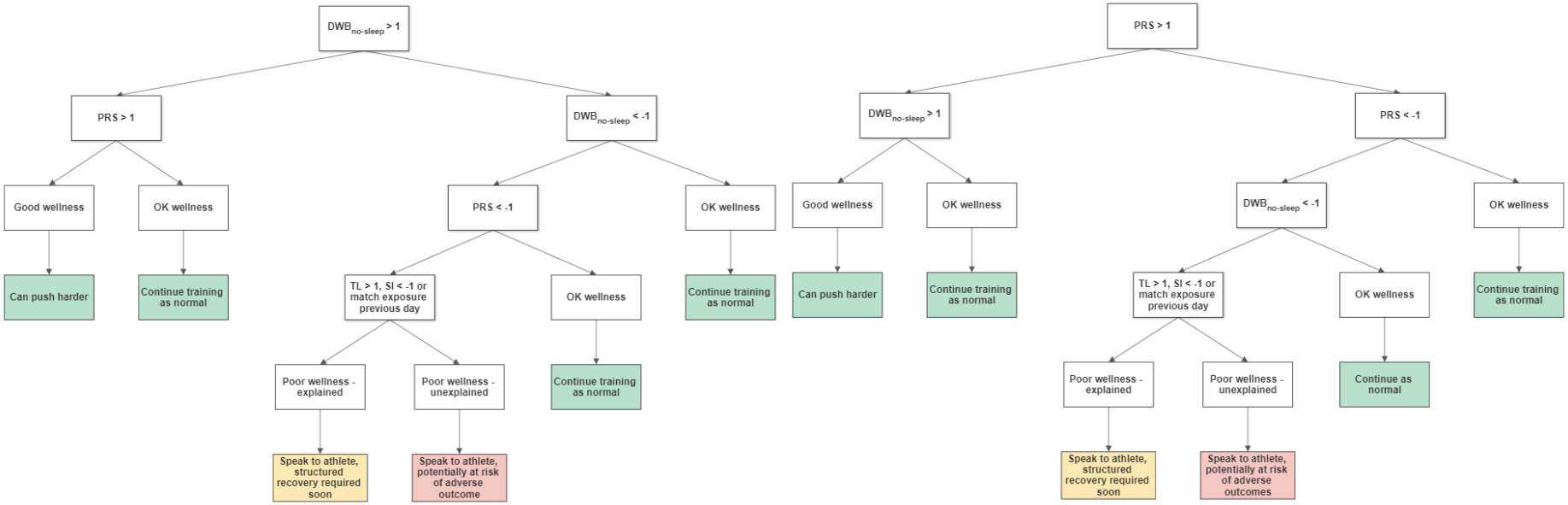


Figure 9.3: Decision tree depicting formulas of athlete monitoring form currently in use. At each split, the left option portrays the “yes” response, the right option denotes the “no” response. **N.B.:** TL = training load; SI = sleep index.

The use of this model as a set of guidelines, rather than a directive, is shown most prominently by the final actions of “speak to athlete - structured recovery needed soon” and “speak to athlete – potentially at risk of adverse outcome”. The first of these (“speak to athlete - structured recovery needed soon”) is used to denote that the athlete’s fatigue/wellness is low but this reduction can be explained by the training process and so the athlete will need recovery soon, but it does not necessarily need to be immediate if this is a planned heavy training phase. The second (“speak to athlete - potentially at risk of adverse outcome”) indicates that the athlete’s fatigue/wellness is low but it cannot be explained by the training process so it is important to discuss potential reasons why it may have occurred with the athlete so the training dose can be modified appropriately. For example, fatigue/wellness measures may be low due to academic stress, which would require training dose modification to minimise adverse outcome risk, or because the athlete had just broken up with his/her partner, which may not. Within this framework, it is possible for practitioners to make independent decisions based on the literature available and the data generated from these decisions can be analysed in the future to further improve decision making ability as the scientific literature progresses.

9.5.2 Periods of increased susceptibility to illness

Alongside supporting the use of the integrated athlete monitoring cycle in practice, the results of this thesis provide important contextual information with regards to periods of increased susceptibility to illness in youth athletes across the academic year. The results of study 5 indicate that practitioners should be most aware of illness risk at the start of the academic year, in the final weeks before the Christmas break and during periods of heightened academic stress. The results of this thesis are such that it is not possible to elucidate the causal effects, but previous research provides some understanding of the factors researchers should be aware of. For example, the risk of illness early in the academic year is likely a consequence of spikes in training load and reductions in sleep

duration relative to the summer period (Anderson et al., 2003; Carskadon et al., 1998; Walsh, 2018), whereas the academic stress periods of increased illness risk may be due to the influence of this life stress on immune function via the HPA axis alongside the physical stress of training load (Gunnar & Quevedo, 2007). Practitioners may therefore wish to pay careful attention to the training dose, recovery and response measures exhibited by their athletes in these time periods (either via the monitoring model suggested in the previous section or simply through conversations with their athletes) in an attempt to minimise the risk of illness caused by the training process at these times.

Interestingly, the results of study 5 also showed that s-IgA monitoring has little practical usage within this population. Despite being expensive (by youth sport standards) to implement, neither s-IgA concentration nor s-IgA secretion rate (or any combination of the two measures) were able predict illness incidence within the next four weeks when collected on a fortnightly basis. Furthermore, when considered at the same time points, subjective fatigue/wellness measures (in particular the fatigue subscale) showed potential relationships with substantial increases in SRI. Given there is no guarantee that the predictive ability of s-IgA would improve if collected on a more frequent basis, but the cost would become more expensive, it is not possible to recommend its usage in practice based on the findings of this thesis.

9.6 Challenges associated with the collection of longitudinal data in youth athletes

In section 9.5.1.3, it was suggested that practitioners may be able to understand the risk of their athletes suffering from illness using either an athlete monitoring model or via conversation with the athlete in question. Although implementing an athlete monitoring model allows for a more systematic (and perhaps more accurate) approach to data analysis to be considered, it is fraught with difficulties as the failure to complete the initial

overarching aim of this thesis shows. Recently, Saw and colleagues (2015) identified two key areas through which implementation of the athlete monitoring cycle using subjective measures can be affected in elite adult athletes: factors related to the measure, and factors related to the social environment. These factors provide an ideal framework from which this section can reflect on the challenges experienced within the collection of longitudinal data in youth athletes.

9.6.1 Factors related to the measure

In order of importance in elite adult athletes, factors related to the measure include: data output and analysis; mode; question design factors; time burden and accessibility (Saw et al., 2015). Throughout any longitudinal data collection period, the data output and analysis factor provides possibly the biggest challenge. In this applied environment, it is possible to provide feedback as it is directly related to the sports performance that the scholarship aims to achieve. However, it can be extremely time demanding for staff. During the 13-week data collection period for studies 2-4, countless hours were spent manually evaluating athletes' scores every day to provide feedback and reminders if they had not completed the questionnaire. The introduction of the web-based application for study 5 massively beneficial in this regard as immediate feedback was provided, but this was never fully tailored to the requirements of the school due to budget constraints and the time lag for any changes requested was extremely high.

The mode and accessibility issues were never an issue within this environment because the model would not have worked if data were manually input by the staff. With approximately 100 youth athletes on the scholarship programme it was pivotal that an online system was used, and the athletes were able to use the school WiFi system to provide their details. Question design factors and time burden were considerable challenges to the implementation of the questionnaire though. Although all athletes were

familiarised to the questionnaire with a dummy run, which took one hour per sport and answered any questions the athletes had, some participants complained that they did not understand the questions half way through the year or admitted that they filled the data in incorrectly “just to get it done”. These participants were removed from all statistical analyses within this thesis, but it is important to be aware of these issues in an applied environment.

Just below the four factors described above, compatibility and interface were considered lesser issues within elite adult athletes (Saw et al., 2015). Reflecting on the work in this thesis, it would be suggested that these were particularly important issues in youth athletes. In particular, it is important that the technology implemented is bug free and is able to provide a complete subjective fatigue/wellness questionnaire on one page or with seamless transitions between pages. The Google Form used for studies 2-4 and subsequently within practice now provides these characteristics, whereas the web-based application used for study 5 did not. This aligned to the poor response time given by the developer resulted in the loss of data and athlete buy in through no fault of the researchers. Although these issues may not be present in elite adult athletes where more money can be invested in athlete monitoring systems, the issues faced within this thesis suggest it may be more appropriate for researchers to consider free technology (e.g. Google Forms or Microsoft Forms) rather than cheaper web-based applications which may not provide the support or functionality necessary for the questionnaires to be implemented successfully.

9.6.2 Factors related to the social environment

In terms of the social environment, athlete buy in, reinforcement, staff buy in and reminders (in that order) were identified as key factors in elite adult athletes (Saw et al., 2015). When collecting longitudinal data within the school sport environment, it is

suggested that the order would be slightly different as, anecdotally, staff buy in was easily the most important factor. It was noticeable that when the head coach bought into the process, the athletes completed the questionnaire with much greater compliance rates than those sports whose coaches were either ambivalent towards or did not buy into the monitoring process. When completing longitudinal research in youth athletes, it is therefore imperative that researchers are able to build good relationships with the coaches of the sport in order to obtain their buy in to the project and help promote its success.

Although staff buy in was important on a team basis, the athletes who bought into the process would still complete the questionnaire if other members of the team were not doing so. This observation is congruent with Saw and colleagues' (2015) finding that peer influence was not a majorly important factor within the process. However, the quote for peer influence in Saw and colleagues' (2015) review stated that "people stop... and then everyone stops doing it and it stops completely", which does mirror some compliance issues observed outside of the study periods from this thesis. Consistency in the implementation process is therefore pivotal as athletes are more likely to renege on longitudinal data collection periods if they feel they feel their peers are not asked to do the same as them, having previously been asked to do so. Interestingly, this does not appear to be an issue in youth sport when the same expectations were not previously set between peers (i.e. if only one of the two peers has been expected to complete the questionnaire at any point, that athlete did not then decide to renege on completing th questionnaire).

9.7 The researcher/practitioner

One of the key benefits of this thesis is that its fully applied nature, possible due to the researcher/practitioner role held by the author (see section 1.1.3). Such a role allows truly applied research with enormous ecological validity to be conducted, but this comes at a

cost of absolute scientific validity. The role of a researcher/practitioner, as identified by authors such as Jones and colleagues (2019), is to bridge the gap between laboratory-based studies with pure scientific validity and field-based studies with pure ecological validity. To this end, the skillsets required are very similar, but the method by which they are applied is different. Researchers apply all elements of critical thinking with regards to the literature towards scientific validity (and question, which is the most scientifically accurate way of conducting a study), whereas practitioners apply all elements of their critical thinking towards ecological validity (and question, which is the best way of conducting this study in the field). Indeed, there is a common perception that if practitioners work solely based on the evidence available, they will constantly be less informed than their more ambitious opponents. The researcher/practitioner attempts to bridge this gap by providing the maximum possible amount of scientific validity, whilst also considering the extent to which these processes will work in practice.

There are a number of methods used within this thesis, which highlight this balancing act. The first of these is the use of short subjective wellness questionnaires, such as DWB (McLean et al., 2010) and PRS (Laurent et al., 2011), despite longer questionnaires such as the REST-Q (Kellmann & Kallus, 2001) and POMS (McNair et al., 1971) currently receiving more support within the literature. In practice, it is not possible to spend 10-15 minutes per day asking an athlete to fill out a REST-Q or POMS questionnaire, but the use of short subjective wellness questionnaires, which take 1-2 minutes to complete is more viable. Unfortunately, the scientific usefulness of these questionnaires is yet to be fully validated and it is the role of the researcher/practitioner to try and study these questionnaires used in practice to evaluate whether they have any scientific validity, as has been attempted within this thesis.

A further consideration for researcher/practitioners is the cost of equipment required for ‘gold standard’ techniques. Within this thesis, polysomnography or actigraphy may both

have been more accurate methods of evaluating sleep objectively, but the cost of equipment and burden to participants made both impractical within this setting. Finally, the pressures of the applied environment were borne out in the statistical method chosen. Traditionally, NHST and ES have been used for statistical inference, but neither of these methods allows the results to be compared quantitatively against a reference change, nor do they provide probabilistic statements with regards to the likelihood of an event occurring. Consequently, MBI's were used within this thesis, but it is important to note that although seen as progressive at the time this thesis was written, this method has subsequently been heavily criticised (Sainani, 2018; Welsh & Knight, 2015), once again highlighting the difficulties between ecological and scientific validity that a researcher/practitioner must circumnavigate.

9.8 Limitations of this thesis

Although the results of this thesis provide significant contributions to the literature by improving researchers' understanding of athlete monitoring processes both practically and statistically, introducing novel statistical methodologies and identifying periods of increased susceptibility to illness in youth athletes, they are not without their limitations. Individual limitations for each study are provided in sections 4.4.3, 5.4.4, 6.4.3, 7.4.3 and 8.5.4. This section will focus on the overall limitations of the thesis.

One of the key limitations surrounding this thesis is its inability to conclusively validate the use of $DWB_{no\text{-}sleep}$ and PRS within the integrated athlete monitoring cycle. Validity occurs in many forms including: face validity, construct validity, ecological validity and predictive validity. Given the research surrounding fatigue/wellness questionnaires within sport (Laurent et al., 2011; McLean et al., 2010; Thorpe et al., 2015), face validity was assumed in this cohort. Likewise, construct validity was assumed, but the results of this thesis would indicate that there are differences in the construct validity of fatigue/wellness

questionnaires in youth athletes relative to adult athletes given their different responses to the training dose (Montgomery & Hopkins, 2013; Thorpe et al., 2015). Alongside this construct validity, it would be prudent to consider the internal consistency of DWB, $DWB_{no\text{-}sleep}$ and PRS to confirm the subscales provide consistent information (e.g. if the stress subscale highlighted extremely high levels of stress, this is not indicative of positive mood and so the mood subscale should also show this). Typically, this is evaluated using Cronbach's alpha, but a more appropriate measure for these questionnaires may be McDonald's Omega (Peters, 2014).

Throughout this thesis, attempts have been made to maximise ecological validity by evaluating the relationships between measures of the athlete monitoring cycle across all athletes over all sports involved in each study. This has enabled larger sample sizes to be considered than previous research but could potentially have resulted in a masking effect whereby, for example, the sport of rugby may be expected to have a greater response to training load than netball. To a certain extent, this is accounted for within the random effects of the model, as the individual trends are likely to be similar in similar sports and the mean effect for sport was included as a fixed effect. However, the analysis conducted has not considered how the relationship between measures of the athlete monitoring cycle may differ based on the sport considered. Such an analysis was not possible within this thesis due to the relatively low sample size numbers that would have been encountered when split across multiple sports. Future studies may therefore wish to consider comparing the responses between sports, which could be achieved with larger sample sizes or across multiple years of data.

Similar to the issue with a masking effect between sports, the use of only one school sport scholarship scheme limits the generalisability of the results within the literature. It is commonplace within the athlete monitoring cycle literature for only one team to be considered as, typically, this is the only data researchers have access to (Buchheit et al., 2013; Rowell et al., 2017; Thorpe et al., 2015). However, every team will have its own

unique set of cultures, values and issues which influence the results so it is uncertain whether the relationships will hold. Consequently, a collaborative approach could provide further insights. At a school sports scholarship level, this would benefit all parties and the development of these partnerships to provide generalisable and insightful data should be considered in the future.

The final two limitations of this thesis refer to the practical importance of SRI and the subjective fatigue/wellness measures used within this thesis. With regards to SRI, a strong case was made for its importance to youths in terms of athletic development in sections 2.3.2 and 2.3.4. The author stands by the argument that attempting to reduce illness incidence is important in youth athletes. However, there is no direct literature confirming that illness has a detrimental effect on athletic development in youths and, given the multifactorial nature of both illness and athletic development, it seems unlikely that a study will show this relationship in the near future. Researchers should be aware of this limitation when implementing the findings of this study.

Finally, the practically interpretable relationships evaluated within this thesis should be considered. Although numerous statistical relationships were observed between the different measures of the athlete monitoring cycle, when these were considered in raw unit terms, only the relationship between a 2 SD increase in training load (with match exposure) and PRS could be expected to result in a one unit change for a typical athlete. This trend continued in study 5 where the majority of substantial changes in subjective fatigue/wellness measures were less than one unit in magnitude. It will not be possible to elucidate whether this is an important limitation of the questionnaires until the ability of the athlete monitoring cycle to predict illness (i.e. the predictive validity) is confirmed but the finding is congruent with previous research (Thorpe et al., 2015). One method by which more practically interpretable changes may be found is by re-evaluating the scoring systems used within fatigue/wellness measures in the athlete monitoring cycle.

Throughout this thesis, 1-5 scored individual subscales were used along with a category ratio-10 (0-10) PRS scale. The granular nature of responses from these questionnaires may have been a factor in their ability to provide substantial small statistical changes which did not equate to raw unit changes when considered from a practically interpretable perspective. Considering this issue, future studies may find it beneficial to consider larger fatigue/wellness scales (e.g. 0-10 category-ratio 10 for all measures, or even 0-100 continuous scales) which may provide more practically interpretable differences in response to the training dose and recovery experienced by the athlete.

9.9 Future directions

The results of this thesis provide several directions for future research. Some of these were highlighted above as they integrated with the limitations of the study, others have a greater focus on developing the athlete monitoring cycle model further. In the author's opinion, the most interesting development direction is through further consideration of the integrated athlete monitoring cycle model proposed in this thesis.

The author's vision of how this integrated model may work within practice to predict illness is depicted in Figure 9.4. In this model, the training dose and recovery reported by the athlete is used to plot an expected response, which is expanded to provide a range of values the athlete could be expected to report based on the typical error of the questionnaire. All those values within or above the expected response are considered acceptable, but those below the lower bound could be considered unexpected and may therefore be early warning signs for future illness risk.

In Figure 9.4, the dark lines represent the upper and lower bounds of expected responses, the green dots represent those responses that fall within the expected responses and the red dots represent those responses which are not expected and may therefore be early

warning signs for future illness. The shaded are represents a period of SRI. In this example, the SRI episode is preceded by two red dots in the seven days prior to its occurrence. It is suggested that these could be considered warning signs for SRI incidence that practitioners could use to modify their athlete's training schedules as they deem appropriate prior to SRI onset.

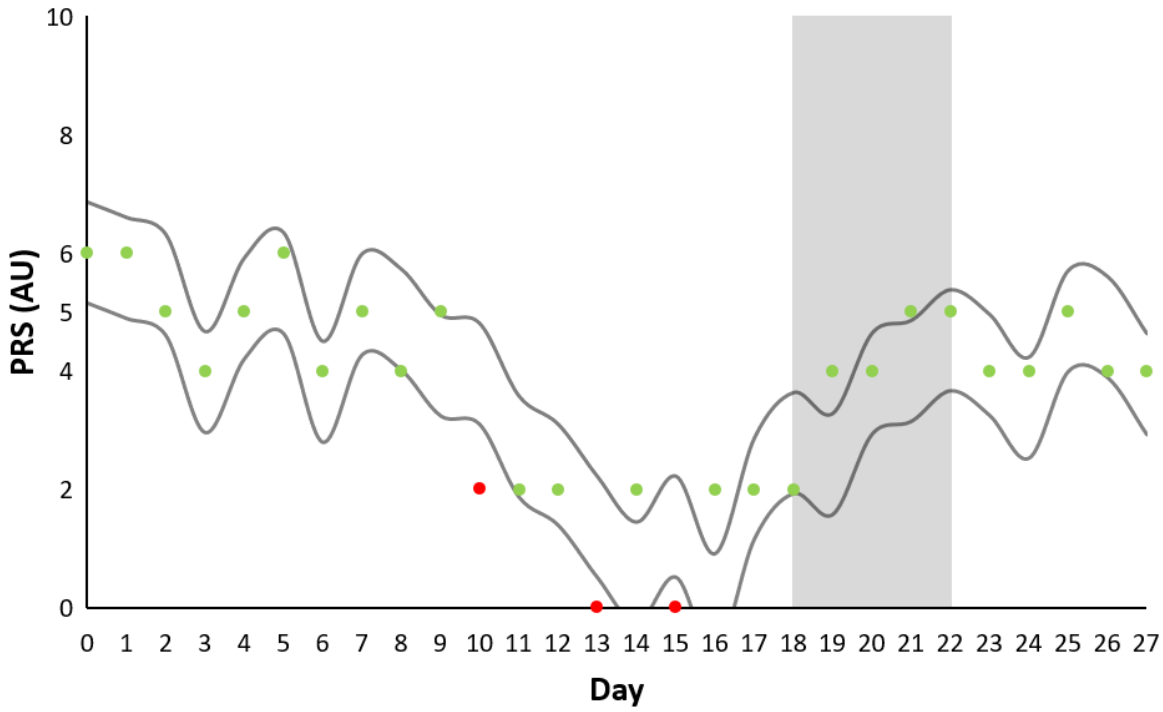


Figure 9.4: Visual representation of how an integrated athlete monitoring cycle model could be used to predict illness incidence in youth athletes.

To provide further understanding with regards to the model, the equations involved are considered below. The data are based on the mean practically interpretable relationships presented in study 4 but could easily be converted to an individual's practically interpretable relationships by manipulating the random effects in the linear mixed models from which they were produced. At a mean level, a 2 SD change in training load was equivalent to 556 AU and would be expected to reduce the PRS score by 0.78 units. Match exposure would be expected to reduce the score by a further 0.52 units. Conversely, a 2 SD change in sleep index was equivalent to 14 AU and would be

expected to increase the PRS score by 0.75 units. The typical error of PRS was identified as 8.5% in study 1 so a 0.85 unit bound either side of the mean response was used.

At day 0, the participant reported a PRS score of 6 following a day with 0 AU training load and a sleep index of 32 AU. On day 1, they reported a 300 AU training load and a sleep index score of 35 AU. They did not participate in match play. To obtain the expected PRS response, the training load and sleep index differences must be found using Equation 9.1.

Equation 9.1: Calculation of difference in training load and sleep index between two days for expected fatigue/wellness response.

$$Difference\ in\ measure\ = Today's\ score - Yesterday's\ score$$

Where the measure refers to training load or sleep index. The differences for this example were therefore 300-0 = 300 AU for training load and 35-32 = 3 AU for sleep index.

The score obtained from Equation 9.1 must then be divided by a 2 SD difference in the measure to find the fraction of change required (Equation 9.2).

Equation 9.2: Calculation of fraction of change required for expected fatigue/wellness response

$$Fraction\ of\ change\ required = \frac{Difference\ in\ measure}{2\ SD\ change\ in\ measure}$$

Where measure refers to training load or sleep index. The fraction of changes required for this example were therefore 300/556 = 0.54 for training load and 3/14 = 0.21 for sleep index.

The fraction of changes required are then multiplied by their respective 2 SD practically interpretable changes and added together to provide the expected change in fatigue/wellness measures.

Equation 9.3: Calculation of expected change due to a measure for expected fatigue/wellness response.

$$Expected\ change\ due\ to\ measure = Fraction\ of\ change\ required \times 2\ SD\ practically\ interpretable\ change$$

Where measure refers to training load or sleep index. The expected change due to training load is therefore 0.54*-0.78 = -0.42 units and the expected change due to sleep index is 0.21*0.75 = 0.16 units. Adding the two values together (-0.42 + 0.16) gives an overall expected change of -0.26 units or when the 0.85 unit TE is added and subtracted gives an overall expected range of -1.11 to +0.59 units.

9.10 Conclusions

The overarching aim of this thesis was to evaluate the predictive ability of an integrated athlete monitoring cycle model with regards to illness incidence in youth athletes. To achieve this aim, the thesis was split into three sections: study 1 identified the reliability and usefulness of the fatigue/wellness measures to be considered; studies 2-4 considered the relationships between measures of the athlete monitoring cycle; and study 5 evaluated the predictive ability of s-IgA and the longitudinal changes in objective (s-IgA) and subjective fatigue/wellness measures ($DWB_{no\text{-}sleep}$, its individual subscales and PRS), and SRI over an academic year in youth athletes.

In study 1, the results showed that when compared to statistical thresholds, the fatigue/wellness questionnaires used within this thesis have poor reliability and marginal usefulness. However, as it was not possible to establish the relationship these

questionnaires have with the outcome measure of SRI, it is not yet possible to state that their reliability and usefulness are poor in practice.

In studies 2-4, the relationships between measures of the athlete monitoring cycle in youth athletes were evaluated. The training dose, measured via s-RPE training load, was related to the muscle soreness subscale (*d* = -0.44; ±0.10, most likely small) and PRS (*d* = -0.37; ±0.09, most likely small). The additive impact of match exposure on subjective fatigue/wellness measures was also considered for the first time and showed substantial small relationships with muscle soreness (*d* = -0.26; ±0.09, likely small) and PRS (*d* = -0.25; ±0.08, likely small). Taken together, these results show that the training dose has a smaller relationship with youth athletes than it does with elite adult athletes (Buchheit et al., 2013; Thorpe et al., 2015). Despite identifying relationships between the training dose and subjective fatigue/wellness measures, studies 2-4 showed that the training recovery was related to more of these measures in youth athletes. A sleep index measure (self-reported sleep duration multiplied by self-reported sleep quality) was related to the $DWB_{no\text{-}sleep}$ overall score (*d* = 0.44; ±0.08, most likely small), fatigue (*d* = 0.55; ±0.11, most likely small), stress (*d* = 0.29; ±0.08, very likely small), mood (*d* = 0.37; ±0.09, most likely small) and PRS (*d* = 0.36; ±0.09, most likely small). These studies were the first to consider the training recovery alongside the training dose within an athlete monitoring cycle and provide strong evidence for its inclusion to be maintained in the future. However, despite a number of substantial relationships being reported, only the relationship between training load (with match exposure) and PRS was able to elicit a one unit change in the subjective fatigue/wellness measure for a typical athlete so the results should be treated with caution at this point. Unfortunately, CMJ was not related to the training dose or training recovery experienced by youth athletes and so cannot be recommended for use within the athlete monitoring cycle in this cohort.

In study 5, it was not possible to integrate these relationships between measures of the athlete monitoring cycle into a predictive study due to issues with a web-based application as was originally aimed. This model is now depicted as a future direction in section 9.9. However, the results of study 5 provide optimism that the model may be useful in the future. Study 5 showed that s-IgA could not accurately predict SRI incidence on the day of sampling (median AUC 0.68, LQ 0.61, UQ 0.73), at any point within two weeks of sampling (median AUC 0.63, LQ 0.58, UQ 0.68) or at any point within four weeks of sampling (median AUC 0.65, LQ 0.60, UQ 0.70). Alone, these results do not provide optimism, however when the longitudinal changes in subjective fatigue/wellness measures were considered alongside s-IgA concentration and secretion rate, it became clear that they were much more responsive to qualitative descriptors (e.g. start of the academic year, mock exams and final coursework deadlines/cup finals) and future SRI incidence. It was not possible to consider the predictive ability of these subjective fatigue/wellness measures with regards to illness incidence in this thesis, but it seems likely that the fatigue measure may be the most important measure in any predictive model, alongside muscle soreness and PRS.

Chapter 10 References

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Chapter 11 Appendices

11.1 Appendix 1 - Ethical Approval

Ethical approval for this thesis was provided in three parts. Application numbers are provided below, followed by the application forms. All applications were copied into the online system where computer signatures were accepted so no signatures are provided within the forms in the section.

Application Ref: 24829

Applicant Name: Thomas Sawczuk

Project Title: Between and within day reliability of a range of athletic performance measures

Application Ref: 24828

Applicant Name: Thomas Sawczuk

Project Title: Sensitivity of daily wellbeing measures to changes in training load

Application Ref: 26978

Applicant Name: Thomas Sawczuk

Project Title: The influence of training load and wellbeing on injury, illness and athletic development

11.2 Appendix 2 – Participant Information and Consent Forms

Participant Information Sheet and Consent Form

Title of Research Study
Between and within day reliability of a range of athletic performance measures

Background
It is common practice within adolescent sport to undertake fitness testing protocols to measure athletic performance and development. Whilst these tests of physical attributes such as strength, power, speed, change of direction ability and aerobic fitness have been shown to differentiate between different standards of players and the playing time they receive, their reliability within adolescent athletes has received less attention. Reliability is used to assess whether the test will give the same result if completed on two separate occasions. From this we can decide whether the change in performance over a period of time occurs because you have adapted to the training you are given or whether it is down to chance. The aim of this study is to confirm the reliability of five commonly used physical tests - one each for strength, power, speed, change of direction speed and aerobic fitness.

Why have you been invited to take part in this study?
You have been selected as you are aged 16-18 and regularly participate in competitive sport alongside your school studies.

Do I have to take part?
No. Prior to providing consent, you will be given this information sheet to keep for your reference and asked to sign the consent form. Should you provide your consent, you will be free to withdraw at any time up to the onset of data analysis without giving a reason. You will be able to ask questions at any time before, during or after the study.

What will happen if I take part?
The study will take place on consecutive weeks. You will be taken through a short warm up including leg swings, squats, lunges and a progressive increase in heart rate, achieved by five 20 yard sprints at 50%(x2), 75%(x2) and 100% of your maximal sprint speed. Following this, on day 1 you will be asked to complete 3 maximal isometric mid-thigh pulls and 3 countermovement jumps. On day 2, you will complete 3 40m sprints, 3 5-0-5 Agility Tests. One week after you complete the first set of tests, you will complete them again, on the same day, at the same time. The difference between the scores from trial to trial and between weeks will allow us to calculate the reliability of the tests. On day 1, we will also take your height and weight as descriptive participant characteristics.

What are the benefits of taking part?
The results will allow you to see your current physical condition. For those of you who cannot attend regional/national fitness camps, you could then provide these results to show your physical development since the last set of tests. Furthermore, understanding the results can allow the strength and conditioning coaches at the school to modify your training programmes to best suit your needs.

What are the risks of taking part?
As part of a physical testing protocol, there are inherent risks with maximal exercise. These include the risk of soft tissue injuries during the sprinting tests. It is also possible that those with asthma or other underlying issues could be at risk during the aerobic fitness test. In order to minimise the risk of both of these problems, we will take you through a comprehensive warm up and will be asking you to fill out a health questionnaire prior to participation in the study.

What happens if something goes wrong?
Although there are no risks to this study above and beyond your normal training for your school or club team and the investigators have significant experience running these field based tests, the maximal nature of the testing means that there is a risk of injury/illness occurring. To counter this, a member of staff with first aid training will be present or in close contact at all times during testing. This individual will be able to provide first aid support should it be required.

If you experience any physical complaints or issues during the testing protocols, it is imperative that you inform Tom Sawczuk of these as soon as possible so you can be provided with the appropriate care. Should you be harmed in any way whilst participating in this study, the University maintains Clinical Indemnity insurance, which will respond in the event that the University is deemed to be legally liable for incidents that occur, as a direct result of the study.

Will taking part in the study be kept confidential?
All information collected will be kept strictly confidential, other than to those of us who are directly involved with the study and your coaches, should you consent to it. This includes sensitive data, such as your height and weight, which will be stored on a password protected computer. Your names will be coded on a separate spreadsheet to the data spreadsheet. Any information that leaves Leeds Beckett University will have names and addresses removed so that you cannot be recognised from it.

What will happen to the results of the study?
The results will be analysed and written up as part of PhD theses', for publication in academic journals, and conference abstracts and presentations. The study findings will be made available to interested participants at request. At no time will any personal data be used.

Contacts for further information
Should you have any further questions, please do not hesitate to contact me via email (t.sawczuk@leedsbeckett.ac.uk) or in person.

Alternatively, please contact any of the following for any further information:

Dr Ben Jones (Supervisor) - b.jones@leedsbeckett.ac.uk
Dr Kevin Till (Director of Studies) - k.till@leedsbeckett.ac.uk
Dr Kevin Deighton (Local Research Ethics Co-ordinator) - k.deighton@leedsbeckett.ac.uk

Thank you for your participation,
Tom Sawczuk

Participant Consent Form

Title of Research Study: Between and within day reliability of a range of athletic performance measures		**Circle as appropriate**
1	I confirm that I have read and understand the participant information sheet; for the above programme and have had the opportunity to ask questions.	Yes No
2	I understand that all data collected throughout the study will be kept safely and securely, and that, for research purposes, it will remain anonymous.	Yes No
3	I understand that my participation in this research study is voluntary and that I am free to withdraw at any time up to the onset of statistical analysis, without giving any reason and without affecting my future care.	Yes No
4	I understand that upon my request any personal data will be removed from the study database should I wish to withdraw participation.	Yes No
5	I consent that my personal data can be retained in a database by the study investigators for the purposes of research and statistical analysis. These data may be made available with my anonymity protected to research students for the purposes of fulfilling their postgraduate research projects.	Yes No
6	I understand that the data collected from my participation in this programme can be published in academic/ professional journals, and can also be presented at conferences. My anonymity will be protected at all times and no individual names will be ascribed to any publication.	Yes No
7	I agree to participate and understand all responsibilities and requirements that are necessary for the study, as detailed in the participant information sheet.	Yes No
8	I consent to the sharing of my data between my coaches and understand any training or match-related decisions made as a consequence of this are made in the interests of my wellbeing	Yes No
Name of Participant (Print Name): Signature: Date:		

Participant Information Sheet and Consent Form

Title of Research Study
Sensitivity of Daily Wellbeing Measures to Changes in Training Load

Background
Research suggests that psychological wellbeing (i.e. how stressed, moody or fatigued you are) could affect how often an athlete gets injured or ill. In order to fully understand this impact however, we must first evaluate the most appropriate method of calculating wellbeing from the questionnaires available and understand how this changes in relation to a normal weekly variation in training loads and neuromuscular fatigue. This study will therefore assess changes in daily wellbeing via a daily wellbeing questionnaire and perceived recovery scale, monthly wellbeing using the RESTQ-Sport Questionnaire, neuromuscular performance via countermovement jump performance and training loads using sessional-RPE. The data analysis will attempt to understand the relationships between these variables so that we can optimise our monitoring strategies going forwards. A secondary aim is to validate the use of 24 hour training load recall.

Why have you been invited to take part in this study?
You have been selected as you are aged 16-18 and regularly participate in competitive sport alongside your school studies.

Do I have to take part?
No, although you provide some of the data as part of your enrolment on the Sport Elite Pathway programme, the decision to allow us to use this data for research purposes is completely up to you. Furthermore, you are not obliged to provide the extra information required for this study. Should you wish to know more about this study, you will be provided with this participant information sheet. You will be able to ask questions at any time before, during or after the study. In order to participate you will be asked to complete the consent form at the end of this sheet. Your choice to or not to participate in this study will not affect your training or match participation at the school in any way.

What will happen if I take part?
The study will take place over thirteen weeks. At the beginning of the study we will take some descriptive characteristics of height and weight. You will be asked to complete a short daily wellbeing questionnaire online every day. The questionnaire will include a five point question on sleep quality, mood, stress, fatigue and muscle soreness, as well as details on sleep length and the perceived recovery scale. At the beginning of your first SEP session of the day from Monday-Thursday, you will be asked to perform 3 countermovement jumps following a short warm up. These will be measured on a force plate and will provide an understanding of neuromuscular fatigue. You will also be asked to complete the RESTQ-Sport Questionnaire in the first, sixth and thirteenth weeks of the study. On one week to validate the 24 hour training load recall, you will be asked to provide your school session times and RPE's after the session. We will then log these and compare them to the values you provide the following day in your daily wellbeing questionnaire.

What are the benefits of taking part?
The information provided will help us to optimise our understanding of training load and wellbeing monitoring for you. You will receive regular updates on your wellbeing, training load and countermovement jump as requested. Furthermore, following the completion of the study we can retrospectively look at the data and attempt to understand whether any of the variables (e.g. sleep or stress) are more prominent in their impact on

neuromuscular fatigue and attempt to provide interventions to reduce the impact they have on you.

What are the risks of taking part?
There are no risks to this study outside of those normally associated with participating in competitive sport (e.g. soft tissue injuries when jumping or landing). There is a small intellectual risk of you being identified due to the online nature of the questionnaire, however we will provide you with a numerical code as soon as possible to protect your identity.

What happens if something goes wrong?
As with all jumping and landing exercises, there is a very small risk of injury when completing the physical testing required in this study. To counter this, a member of staff with first aid training will be present or in close contact at all times during testing. This individual will be able to provide first aid support should it be required.

If you experience any physical complaints or issues during the testing protocols, it is imperative that you inform Tom Sawczuk of these as soon as possible so you can be provided with the appropriate care. Should you be harmed in any way whilst participating in this study, the University maintains Clinical Indemnity insurance, which will respond in the event that the University is deemed to be legally liable for incidents that occur, as a direct result of the study.

Will my data from this study be kept anonymous?
All information collected will be kept strictly confidential, other than to those of us who are directly involved with the study and your coaches, should you consent to it. This includes sensitive data, such as your height and weight, which will be stored on a password protected computer. Your names will be coded on a separate spreadsheet to the data spreadsheet. Any information that leaves Leeds Beckett University will have names and addresses removed so that you cannot be recognised from it.

What will happen to the results of the study?
The results will be analysed and written up as part of PhD theses', for publication in academic journals, and conference abstracts and presentations. The study findings will be made available to interested participants at request. At no time will any personal data be used.

Contacts for further information
Should you have any further questions, please do not hesitate to contact me via email (t.sawczuk@leedsbeckett.ac.uk) or in person.

Alternatively please contact any of the following for any further information:

Dr Ben Jones (Supervisor) - b.jones@leedsbeckett.ac.uk
Dr Kevin Till (Director of Studies) - k.till@leedsbeckett.ac.uk
Dr Kevin Deighton (Local Research Ethics Co-ordinator) - k.deighton@leedsbeckett.ac.uk

Thank you for your participation,
Tom Sawczuk

Participant Consent Form

Title of Research Study: Training Loads and Psychological Wellbeing in Youth Sport: Implications for Injury and Illness		
		Circle as appropriate
1	I confirm that I have read and understand the participant information sheet; for the above programme and have had the opportunity to ask questions.	Yes No
2	I understand that all data collected throughout the study will be kept safely and securely, and that, for research purposes, it will remain anonymous.	Yes No
3	I understand that my participation in this research study is voluntary and that I am free to withdraw at any time, without giving any reason and without affecting my future care.	Yes No
4	I understand that upon my request any personal data will be removed from the study database should I wish to withdraw participation.	Yes No
5	I consent that my personal data can be retained in a database by the study investigators for the purposes of research and statistical analysis. These data may be made available with my anonymity protected to research students for the purposes of fulfilling their undergraduate/postgraduate research projects.	Yes No
6	I understand that the data collected from my participation in this programme can be published in academic/ professional journals, and can also be presented at conferences. My anonymity will be protected at all times and no individual names will be ascribed to any publication.	Yes No
7	I agree to participate and understand all responsibilities and requirements that are necessary for the study, as detailed in the participant information sheet.	Yes No
8	I confirm that I am not suffering from any injury which may be made worse by performing a countermovement jump. Should I sustain an injury which would be made worse by performing a countermovement jump I will inform an investigator and not perform the jumps.	Yes No
9	I consent to the sharing of my data between my coaches and understand any training or match-related decisions made are not the responsibility of the researcher.	Yes No
Name of Participant (Print Name): Signature: Date:		

Participant Information Sheet and Consent Form

Title of Research Study
The influence of training loads and wellbeing on injury, illness and athletic development

Background
Research suggests that player wellbeing (i.e. how stressed, moody or fatigued you are) could affect how often an athlete gets injured or ill. Furthermore, it is possible that these changes are necessary to allow you to develop as an athlete. As a consequence, daily wellbeing questionnaires have been used to monitor changes in wellbeing and use this to modify training loads. However, there is little research confirming that the responses to these questionnaires are actually related to the risk of injury and illness, or athletic development. This study will therefore assess the use of daily wellbeing questionnaires and the RESTQ-Sport questionnaire as a method of understanding athletic development and risk of injury and illness. It will also consider changes in immune function and how these are related to the wellbeing responses. An understanding of all these factors will provide significant scope to ensure that our training strategies are optimised to provide the best possible training stimulus, without increasing the amount of time spent injured/ill.

Why have you been invited to take part in this study?
You have been selected as you are aged 16-18 years and regularly participate in competitive sport alongside your school studies.

Do I have to take part?
No, although you provide some of the data as part of your enrolment on the Sport Elite Pathway programme, the decision to allow us to use this data for research purposes is completely up to you. Furthermore, you are not obliged to provide the extra information required for this study. Should you wish to know more about this study, you will be provided with this participant information sheet. You will be able to ask questions at any time before, during or after the study. In order to participate you will be asked to complete the consent form at the end of this sheet. Your choice to participate or not in this study will not affect your training or match participation at the school in any way.

What will happen if I take part?
The study will initially take place over one academic year, although this could be extended to two. At the beginning of the study we will take some descriptive characteristics of height and weight, you will also be asked to complete the State Trait Inventory for Cognitive and Somatic Anxiety questionnaire to see whether your personality affects your responses to the questionnaire. You will be asked to complete a short daily wellbeing questionnaire online every day. The questionnaire will include a five point question on sleep quality, mood, stress, fatigue and muscle soreness, as well as details on sleep length, the perceived recovery scale and self-reported injury and illness. You will also be asked to complete the RESTQ-Sport on a monthly basis.

If you are chosen, you will also be asked to provide a salivary sample every fortnight. This will involve you coming to the half time room before your match every other Wednesday and allowing your saliva to drip through a tube into a container. This will take no more than 5-10 minutes. It will allow us to measure your immune function in response to the training and academic stressors you are subjected to.

In addition to this, you will complete your fitness testing weeks with strength (mid-thigh pull), power (countermovement jump), speed (40m sprint), change of direction (5-0-5 test) and fitness (30:15) measures as normal. Should you consent, we will compare this to your training loads and wellbeing to assess their impact on your athletic development. We

would also ask for a 4 day food diary from you during every fitness testing week. Full details on how to complete this will be provided.

What are the benefits of taking part?
The information provided will help us to optimise our understanding of training load and wellbeing monitoring for you. You will receive regular updates on your wellbeing and training load as requested. Unfortunately, as we will be assessing all samples at the end of the study, we will not be able to provide any up to date measures of immune function. However, at the end of the study when assessing all of these factors we will be able to provide individualised interventions based on the most important factors affecting injury and illness risk, and athletic development.

What are the risks of taking part?
There are no risks to this study outside of those normally associated with participating in competitive sport (e.g. soft tissue injuries when jumping or landing). There is a small intellectual risk of you being identified due to the online nature of the questionnaire, however we will provide you with a numerical code as soon as possible to protect your identity.

What happens if something goes wrong?
As with all maximal testing protocols, there is a small risk of injury when completing the physical testing required in this study. To counter this, a member of staff with first aid training will be present or in close contact at all times during testing. This individual will be able to provide first aid support should it be required.

If you experience any physical complaints or issues during the testing protocols, it is imperative that you inform Tom Sawczuk of these as soon as possible so you can be provided with the appropriate care. Should you be harmed in any way whilst participating in this study, the University maintains Clinical Indemnity insurance, which will respond in the event that the University is deemed to be legally liable for incidents that occur, as a direct result of the study.

Will my data from this study be kept anonymous and confidential?
Yes, all information collected will be kept strictly anonymous and confidential, other than to those of us who are directly involved with the study and your coaches, should you consent to it. This includes sensitive data, such as your height and weight, which will be stored on a password protected computer. Your names will be coded on a separate spreadsheet to the data spreadsheet. Any information that leaves Leeds Beckett University will have names and addresses removed so that you cannot be recognised from it.

What will happen to the results of the study?
The results will be analysed and written up as part of PhD, MSc and BSc (Hons) theses, for publication in academic journals, and conference abstracts and presentations. The study findings will be made available to interested participants at request. At no time will any personal data be used.

Contacts for further information
Should you have any further questions, please do not hesitate to contact me via email (t.sawczuk@leedsbeckett.ac.uk) or in person.

Alternatively please contact any of the following for any further information:

Dr Ben Jones (Supervisor) - b.jones@leedsbeckett.ac.uk
Dr Kevin Till (Director of Studies) - k.till@leedsbeckett.ac.uk

Independent Contact
Dr Kevin Deighton (Local Research Ethics Co-ordinator) - k.deighton@leedsbeckett.ac.uk

Thank you for your participation,
Tom Sawczuk

Participant Consent Form

Title of Research Study: The influence of training loads and wellbeing on injury, illness and athletic development			
		Circle as appropriate	
1	I confirm that I have read and understand the participant information sheet; for the above programme and have had the opportunity to ask questions.	Yes	No
2	I understand that all data collected throughout the study will be kept safely and securely, and that, for research purposes, it will remain anonymous.	Yes	No
3	I understand that my participation in this research study is voluntary and that I am free to withdraw at any time, without giving any reason and without affecting my future care.	Yes	No
4	I understand that upon my request any personal data will be removed from the study database should I wish to withdraw participation.	Yes	No
5	I consent that my personal data can be retained in a database by the study investigators for the purposes of research and statistical analysis. These data may be made available with my anonymity protected to research students for the purposes of fulfilling their undergraduate/postgraduate research projects.	Yes	No
6	I understand that the data collected from my participation in this programme can be published in academic/ professional journals, and can also be presented at conferences. My anonymity will be protected at all times and no individual names will be ascribed to any publication.	Yes	No
7	I agree to participate and understand all responsibilities and requirements that are necessary for the study, as detailed in the participant information sheet.	Yes	No
8	I understand that in the event of any adverse findings, I will be provided with an outline of the findings and advised to seek medical advice from a GP	Yes	No
9	I consent to the sharing of my data between my coaches and understand any training or match-related decisions made are not the responsibility of the researcher.	Yes	No
10	I confirm that at the onset of data collection I am not injured. Should I sustain an injury which would be made worse by participation in fitness training as part of this study, I will inform an investigator and not participate in the testing.	Yes	No
Name of Participant (Print Name): Signature: Date:			

11.3 Appendix 3 – Integrated athlete monitoring cycle questionnaires

11.3.1 Appendix 3A: Google Sheets questionnaire used for studies 1-4

Daily Wellbeing Questionnaire

To be filled in every day prior to your first training session of the day.

* Required

Name *

Please type your full name (first name and surname)

Sport *

Fatigue Levels *

Which of the following best describes your current fatigue levels?

- ○ Very fresh
- ○ Fresh
- ○ Normal
- ○ More tired than normal
- ○ Always tired

Sleep Quality *

Which of the following best describes your sleep quality last night?

- ○ Very restful
- ○ Good
- ○ Difficulty falling asleep
- ○ Restless sleep
- ○ Insomnia

Sleep Length *

How much sleep (in hours) did you get last night based on the time you last turned all lights off and started trying to sleep, and the time you got out of bed this morning.

Muscle Soreness *

Which of the following best describes your current muscle soreness?

- ○ Feeling great
- ○ Feeling good
- ○ Normal
- ○ Increase in soreness/tightness
- ○ Very sore

Stress Levels *

Which of the following best describes your current stress levels?

- ◯ Very relaxed
- ◯ Relaxed
- ◯ Normal
- ◯ Feeling stressed
- ◯ Highly stressed

Mood *

Which of the following best describes your current mood?

- ◯ Very positive mood
- ◯ Generally good mood
- ◯ Less interested in others and activities than usual
- ◯ Snappy with team mates, family and fellow students
- ◯ Highly irritable, annoyed or down

Symptoms *

Have you continuously experienced any of the following over the last 24 hours? Sore throat, runny nose, cough, scratchy throat, nasal congestion, headache, fever, hoarseness, sneezing and/or body aches & pains (not related to DOMS)

- ◯ Yes
- ◯ No

Symptoms Length *

For how many continuous days have you experienced the above symptoms? (If longer than 10 days, please select "10" until you stop feeling the symptoms)

Injury *

Did you suffer from an injury that caused you do modify your training in any way yesterday (e.g. missed session, only doing upper body in the gym, dropping out early etc)

- ◯ Yes
- ◯ No

Injury Description *

Please give a description if you answered yes to the injury question (e.g. tight hamstring, bruised knee, broken foot etc)

Session 1 Type *

Please provide details on your training sessions from yesterday

- ○ School - Technical Training
- ○ School - Strength and Conditioning
- ○ School - Match
- ○ PE Lesson
- ○ Recovery Session
- ○ Club - Technical Training
- ○ Club - Strength and Conditioning
- ○ Club - Match
- ○ Nothing
- ○ Other:

Session 1 Duration *

Please type the duration of this session in minutes. If you didn't have a session, put 0.

Session 1 RPE *

"How was your workout in this session?" If you didn't have a session, please select "No Session"

Session 2 Type *

Please provide details on your training sessions from yesterday

- ○ School - Technical Training
- ○ School - Strength and Conditioning
- ○ School - Match
- ○ PE Lesson
- ○ Recovery Session
- ○ Club - Technical Training
- ○ Club - Strength and Condtioning
- ○ Club - Match
- ○ Nothing
- ○ Other:

Session 2 Duration *

Please type the duration of this session in minutes. If you didn't have a session, put 0.

Session 2 RPE *

"How was your workout in this session?" If you didn't have a session, please select "No Session".

Session 3 Type *

Please provide details on your training sessions from yesterday

- ○ School - Technical Training
- ○ School - Strength and Conditioning
- ○ School - Match
- ○ PE Lesson
- ○ Recovery Session
- ○ Club - Technical Training
- ○ Club - Strength and Conditioning
- ○ Club - Match
- ○ Nothing
- ○ Other:

Session 3 Duration *

Please type the duration of this session in minutes. If you didn't have a session, put 0.

Session 3 RPE *

"How was your workout in this session?" If you didn't have a session, please select "No Session"

Session 4 Type *

Please provide details on your training sessions from yesterday

- ○ School - Technical Training
- ○ School - Strength and Conditioning
- ○ School - Match
- ○ PE Lesson
- ○ Recovery Session
- ○ Club - Technical Training
- ○ Club - Strength and Condtioning
- ○ Club - Match
- ○ Nothing
- ○ Other:

Session 4 Duration *

Please type the duration of this session in minutes. If you didn't have a session, put 0.

Session 4 RPE *

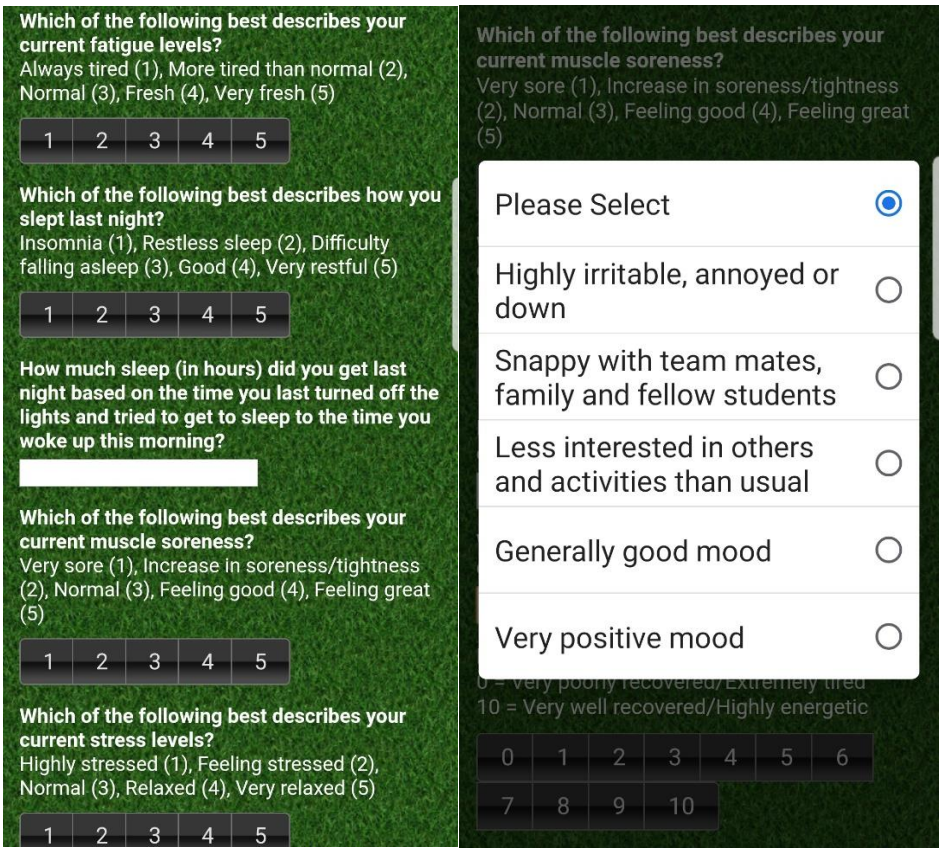
"How was your workout in this session?" If you didn't have a session, please select "No Session".

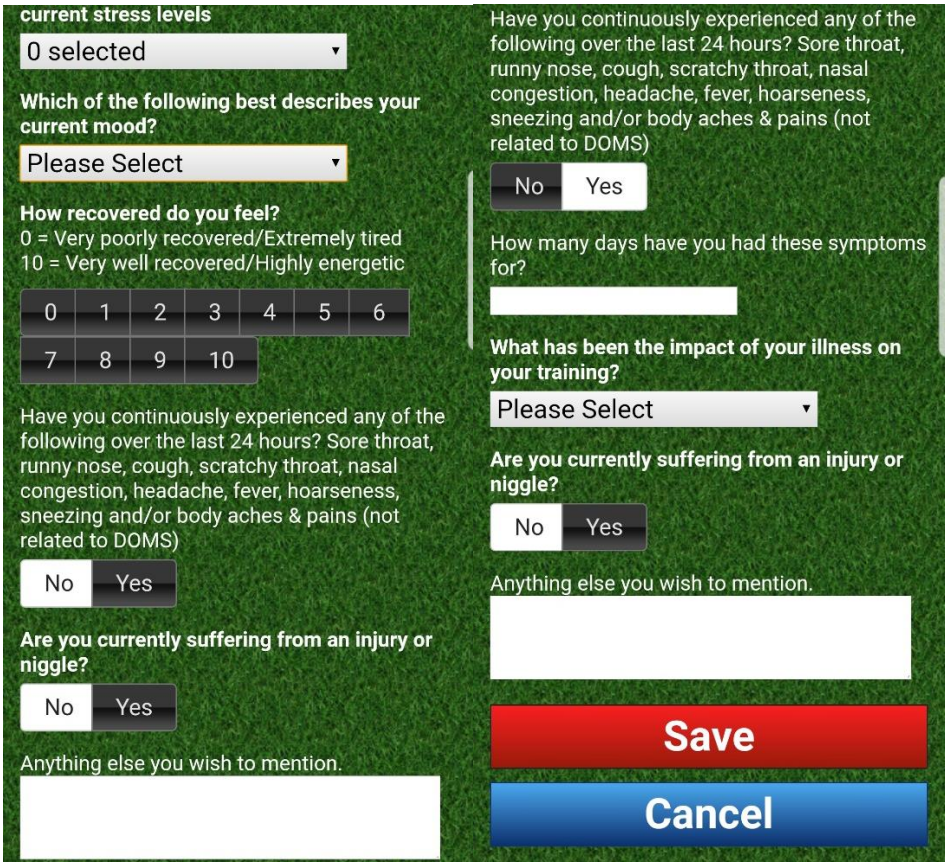
Rest Days *

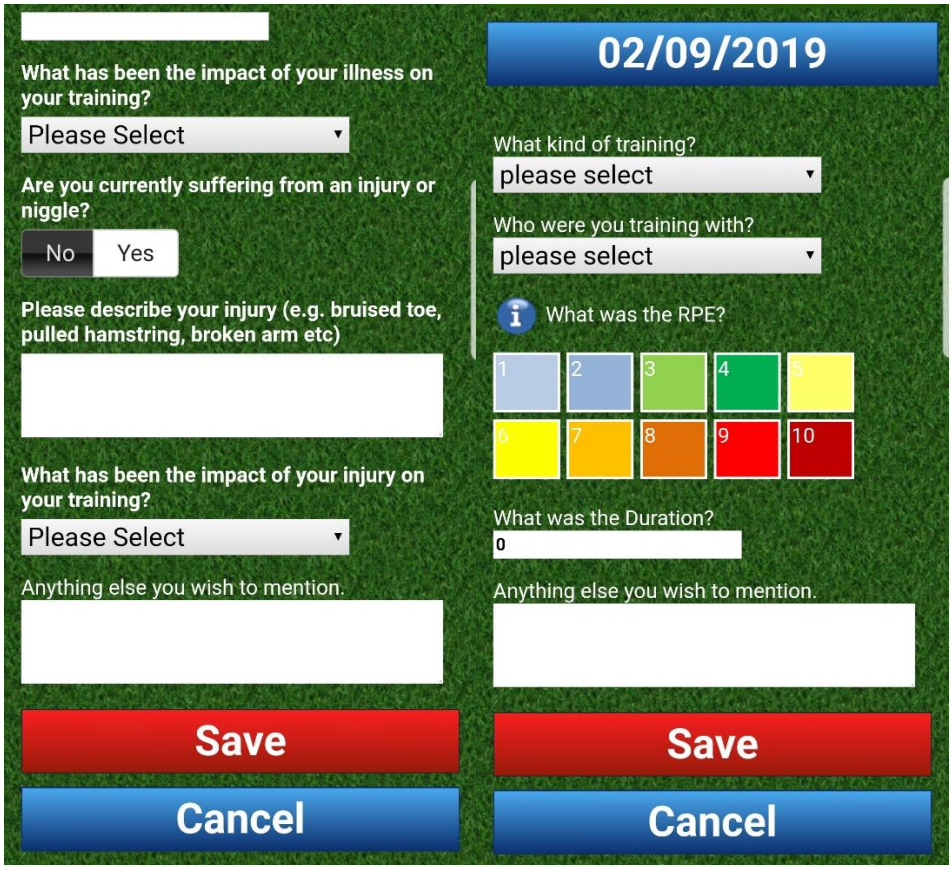
Please tick one or more of the following times when you rested yesterday.Use your discretion - e.g. if you had a session that started at 4.30pm til 7pm, but nothing before it, this would still count as morning and afternoon rest periods

- ☐ Morning (9am-1pm-ish)
- ☐ Afternoon (1pm-5pm-ish)
- ☐ Evening (5pm onwards)
- ☐ None

11.3.2 Appendix 3B: Web-based application questionnaire used for study 5







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