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In recent years, athlete monitoring has become increasingly prevalent as professional teams seek to maximize performance and reduce the risk of injury in their athletes (Gabbett, 2016). In soccer, matches normally represent the highest load placed on the athletes, resulting in numerous adverse physiological effects, which can take 72 to 96 hours to fully recover (Dobbin, Lamb, & Twist, 2016; Nédélec et al., 2012). In NCAA Men's soccer, it is common for multiple games to be played in a week, often less than 72 hours apart, which could impair performance due to inadequate recovery. The function of athlete monitoring is to assess the amount of training load (TL) sustained during matches and training and better understand where players may be on the continuum of recovery. Recent developments in technology have enabled objective monitoring of internal TL through heart rate monitoring (Halson, 2014). Additionally, subjective forms of monitoring, such as session rating of perceived exertion (sRPE) (Foster, 1998) and subjective wellness questionnaires (SWQ) (Hooper, Mackinnon, Howard, Gordon, & Bachmann, 1995), have been developed to understand the athletes' perception of TL (sRPE) and overall well-being (SWQ). Web-based athlete monitoring platforms, such as Fit for 90 (FF90), have been developed to improve the efficiency and effectiveness of subjective monitoring (Saw, Main, & Gastin, 2015). While research on athlete monitoring is prevalent at the professional level, few studies have investigated its effectiveness in collegiate soccer, where the playing schedule is highly congested. Thus,

understanding the effectiveness of athlete monitoring in college soccer could optimize recovery strategies and improve overall performance.

Therefore, the purposes of this study were to (1) validate the FF90 sRPE equation, which uses a more intuitive RPE scale than the Borg CR10, with Banister's TRIMP equation, (2) investigate the relationship between internal TL (sRPE and training impulse (TRIMP)) and the FF90 subjective readiness score in NCAA Division I Men's soccer players, (3) investigate the long-term relationship between total number of minutes played on perceived readiness of the athletes across a soccer season. This study was performed with a NCAA Division I Men's soccer team.

The results showed the modified sRPE used by FF90 is significantly correlated to Banister's TRIMP ($r = .857$). Additionally, the FF90 readiness score had a significant inverse relationship to the previous days sRPE ($r = -.296$) and TRIMP ($r = -.333$). When cumulative minutes were accounted for, the strength of the correlations was highest in the players which played the most minutes, suggesting the readiness score was sensitive to spikes in internal TL. The inverse relationship between readiness scores and cumulative minutes played was also significant ($r = -.231$). However, these results need further investigation as the correlations diverged when players were grouped based on minutes played. Overall, this study shows the modified sRPE is a valid measure of internal TL and readiness score is sensitive to fluctuations in internal TL.

EVALUATION OF THE VALIDITY OF THE FIT FOR 90

SUBJECTIVE TRAINING LOAD AND

WELLNESS MEASURES

by

Andrew W. Scheck

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APPROVAL PAGE

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CHAPTER I

INTRODUCTION

Soccer is a complex sport, requiring a combination of well-developed physical qualities, technical skills, and tactical awareness to compete at the highest levels of play (Bangsbo, 2014; Gabbett, Jenkins, & Abernethy, 2009). For professional leagues that follow the Federation of the International Football Association (FIFA) rules, matches consist of two 45 minute halves, with time added on for stoppages in play during each half. Teams are made up of ten field players and one goalkeeper and each team is allowed to make up to three substitutions for any reason (tactical or injury related), though players who are withdrawn from the game cannot re-enter. Because the majority of the field players must play the full match, it is vital that players are prepared to perform at their best, both physically and tactically.

The physical requirements of soccer are demanding, and increase at higher levels of competition (Bangsbo, Mohr, & Krustrup, 2006). At the international level, players cover over 10,000 meters during a match, over 400 meters of which is at a sprint speed, with some players reaching speeds of 32 km/h (Bangsbo et al., 2006). This total distance is made up of 1000-1400 short activities including changes of direction, sprints, tackles, headers, and other soccer specific skills (Stølen, Chamari, Castagna, & Wisløff, 2005). Players also maintain an average heart rate (HR) of 83-87% of their maximal HR (HR_{max}) throughout the match (Alexandre et al., 2012). These facts reflect the myriad of physical attributes needed to play soccer at the highest level, such as speed, agility, muscular strength and power, and aerobic power (Turner & Stewart, 2014). While these physical characteristics are superior in professional and international level soccer players (Bangsbo, 2014; Mohr, Krustrup, & Bangsbo, 2003; Stølen et al., 2005), it follows that teams with a higher level of physical performance are more likely to be successful at sub-elite levels of play.

The physiological demands of competitive soccer described above can disrupt post-match homeostasis by causing muscular soreness, fatigue, and poor sleep quality (Nédélec et al., 2012). These adverse effects following soccer matches place substantial importance on recovery between matches; adequate recovery appears vital to maintain a high level of play throughout a season. Professional seasons often span a 10-month period, beginning in early August and ending in late May, during which teams may play between 40 and 50 games, depending on the results of the matches. It is common for teams, especially those at the highest levels, to compete in multiple matches per week, separated by two to three days, which can impair recovery. Ekstrand, Waldén, and Hägglund (2004) found players who under performed during the 2002 FIFA World Cup had played more (an average of 12.5) matches in the previous ten weeks than those who exceeded expectation (an average of 9 matches). Additionally, it has also been found the injury rate can be significantly higher when players compete in two matches per week (Dupont et al., 2010). This suggests that the number of matches played in a short amount of time can negatively affect performance and potentially lead to injury, however, since teams are often unable to control their competitive match schedule, an emphasis should be placed on recovery between competitions to mitigate the negative symptoms that can follow matches.

The NCAA Division I college soccer schedule has a similar congestion issue to professional soccer. Though the season is much shorter, with only 18 to 20 competitive matches played in a three-month period, teams play multiple matches per week in most weeks of the season, with matches frequently less than 48 hours apart. Such a quick turnover between matches can impair the recovery process, which can take between 72 and 96 hours (Dobbin et al., 2016), resulting in sub-optimal performance and increased risk of injury (Nédélec et al., 2012; Rollo, Impellizzeri, Zago, & Iaia, 2014). Dobbin et al. (Dobbin et al., 2016) found neuromuscular performance (sprint performance and counter movement jump) may still be suppressed more than 72 hours following a soccer match. Additionally, Rollo et al. (Rollo et al., 2014) found decreased functioning on physical performance tests in players who had competed in two matches per week for a six-week period. As the role of sports science in competitive team sports has increased in the last few decades, considerable attention has been paid to monitoring the balance of the physical load placed on athletes during training and matches and the process of recovery (Foster, 1998; Gabbett, 2016; Hooper et al., 1995; Nédélec et al., 2012). The objective of much of this research was to minimize the adverse effects of numerous competitions and allow the coach to select the players needed to be successful for each game.

The rules for NCAA men's soccer are slightly different than the official FIFA rules, with key changes related to tied games and substitutions. Two 10-minute overtime periods are added on to the 90 minutes of regulation play if the score is tied at the end of the match. These extra periods are golden goal, with the first team to score winning. The substitution rules are significantly different than FIFA rules as teams are allowed unlimited substitutions during both halves (and overtime), but players who are removed during the first half are not allowed to re-enter the game until the start of the second half. In the second half, however, players are allowed to enter the game twice. These differences in substitution rules allow coaches to rotate players throughout the game to reduce the accumulation of fatigue, though not all coaches utilize this as a tactic. The increased number of substitutions available may reduce the total number of minutes played and perhaps lessen the length of the recovery process necessary following a match. However, the additional time played for games which end in a draw, or go to overtime, and the quick turn-around of games throughout the season may lead to an accumulation of these and other factors which can impair performance, potentially leading to long term issues such as over-training syndrome, illness, or injury.

Athlete monitoring has become prevalent in many sports and different competition levels over the past few decades. Perhaps the most common form of monitoring is the assessment of training load (TL) players experience during competition and training (Halson, 2014). Coaches and sports scientists use TL data to develop periodization strategies to increase physical performance while decreasing adverse effects such as overtraining, illness, or injury (Foster, 1998; Gabbett, 2016; Moreira et al., 2015; Piggott, 2008). Recently developed methods and technologies, such as individual global-positioning systems (GPS), HR monitors, and session rating of perceived exertion (sRPE), have made it possible to quantify TL in individuals who participate in team sports, which had previously been more difficult (Halson, 2014). These tools help provide insight into specific measures during soccer training and matches, a few of which are the total distance covered during matches, number of changes of directions, running speeds, internal stress response, and global TL, which includes both physiological and psychological factors (Alexandre et al., 2012; Gaudino et al., 2015). In an attempt to optimize match performance, this information is used by coaches and sports scientists to plan training for the team, as well as individual players.

Monitoring the wellbeing, or level of fatigue, of athletes has also been investigated by sports science research, focusing on individual changes or adaptations to training. The methods that have been developed assess physiological factors that can be affected by training such as heart rate variability (HRV), biochemical measures, and neuromuscular function (Halson, 2014). One specific method that has gained increased interest in recent years is subjective wellness questionnaires (SWQ), which assess an individual's perception of wellness or fatigue (Halson, 2014; Saw, Main, & Gastin, 2016). Questionnaires are an inexpensive and non-invasive method that is often easier to implement than many objective measures, and they have been shown to be more sensitive to changes in TL than some objective measures, such as cortisol, testosterone and performance measures (Saw et al., 2016). Often, objective (quantifiable, physiological markers) and subjective (athlete's perception) measures are used in conjunction with one another to reduce bias of the subjective measures as well as assess potential differential changes between the two (Saw et al., 2016). These wellness measures appear to provide greater insight into how well an athlete is adapting to training, which may be helpful for mitigating the risk of long-term issues such as fatigue, illness, or injury (Saw et al., 2016).

Despite a growing amount of research directed towards TL and wellness, the practical application to the management of players needs further investigation, particularly in NCAA Division I men's soccer. Gabbett (2016) discussed the use of the acute:chronic TL ratio and how it can be used to predict risk of injury. While this is a practical use of TL data, it is not an ideal method because it is retroactive, assessing TL after it has taken place rather than allowing for use in a proactive nature that in turn would assist sports scientists and coaches in the prescription of TL. Additionally, much of the recovery or fatigue research examines environments where matches are spread out, occurring once per week or less (Thorpe et al., 2015, 2016), or during non-competitive parts of the season (Buchheit et al., 2013). Gastin, Meyer, and Robinson (2013) examined perceived wellness over an entire Australian Football League (AFL) season, however, the schedule of the AFL is not as congested as that of soccer, especially college soccer.

Recently, athlete monitoring software has been developed to simplify the process of collecting and analyzing data, particularly subjective data submitted by athletes. Fit for 90 (FF90), is one such software program which has been designed with both the athlete and the coach in mind, with the objective of reducing the burden on the athlete while maximizing the quality and analysis of the data (Saw et al., 2015). FF90 is an athlete monitoring platform which can be accessed on multiple devices (smart phones, tablets, or computers) by both the athletes and the coaching staff. Through the FF90 platform, athletes can report their daily readiness (wellness), sRPE, hydration status, weight, injuries or illness, or any other notes they deem relevant to the coach. The daily readiness is a six-item survey which asks the athlete to rate their fatigue, mood, stress, soreness, and sleep quality on a -3 to +3 Likert scale, with zero as a midpoint. The sixth question is simply sleep duration, asking for the total number of hours slept.

1.1 Purposes

Therefore, the purposes of this study were to (1) validate the FF90 sRPE equation, which uses a more intuitive RPE scale than the Borg CR10, with Banister's TRIMP equation, (2) investigate the relationship between internal TL (sRPE and training impulse (TRIMP)) and the Fit for 90 (FF90) subjective readiness score in NCAA Division I Men's soccer players, (3) investigate the long-term relationship between total number of minutes played on perceived readiness of the athletes. The following hypothesis were made based on previous research on the topic:

1.2 Hypotheses

Hypothesis 1: The FF90 sRPE scale will be significantly correlated to Banister's TRIMP equation.

Hypothesis 2: The FF90 readiness score will have a significant inverse relationship to the previous day's internal TL (as assessed by sRPE and TRIMP).

Hypothesis 3: There will be an inverse relationship between cumulative number of minutes played during matches and a decline in readiness scores across the season.

CHAPTER II

REVIEW OF LITERATURE

2.1 Overview

This literature review will briefly discuss the use of athlete monitoring in competitive soccer to determine the effectiveness of monitoring training load and the use of wellness measures to track changes in fatigue over a collegiate season.

2.2 Monitoring Athletes in Collegiate Soccer

The demands of training and competition in high level sport places significant physical stress on athletes. In soccer, the greatest stress is seen during matches, with recovery time being greater than that required from typical training sessions (Dobbin et al., 2016; Impellizzeri, Rampinini, Coutts, Sassi, & Marcora, 2004; Nédélec et al., 2012; Thorpe et al., 2016). Properly monitoring training load (TL) is critical to assist coaches in prescribing suitable loads during training sessions, with the goal of maximizing performance and minimizing the risk of adverse effects such as overtraining and injury (Coutts, Wallace, & Slattery, 2003; Foster, Florhaug, et al., 2001; Gabbett, 2016). In college soccer, it is common for teams to play two or even three matches in a week, at times less than 48 hours apart. Such a quick turnover of competitions does not allow for adequate recovery for athletes who play significant minutes in matches, as the recovery process can take a minimum of 72 hours, with recent research suggesting it may be even longer (Dobbin et al., 2016; Nédélec et al., 2012).

Different methods of athlete monitoring have been developed which utilize TL data to assess changes in fitness, fatigue, and injury risk, such as the monotony (TM), strain (TS) relationship (Foster, 1998) and the acute:chronic (AC) ratio (Gabbett, 2016; Hulin et al., 2014). The former methods, monotony and strain, were designed to evaluate the variability of TL and the overall stress placed on the athletes on a weekly basis, as a lack of fluctuation in daily TL is associated with staleness and illness (Foster, 1998; Piggott, 2008). The AC ratio evaluates the relationship between the accumulation of TL over an extended period (chronic TL) and the previous weeks TL (acute TL) and has become prevalent in professional practice. It has been used to demonstrate how spikes in acute workload, which exceed an athlete's fitness (chronic workload), elevate injury risk in cricket bowlers and rugby players (Gabbett, 2016; Hulin et al., 2014). Additionally, it has been used in return to play research (Blanch & Gabbett, 2016) to assess whether an injured athlete has accumulated a sufficient quantity of training to safely begin team training and competition. A limitation of this method, however, is the amount of time necessary for it to be useful, as several weeks of training are needed before it can be calculated (Gabbett, 2016). This can be problematic during the initial weeks of training, when the athlete has gone through a period of de-training or training load has not been monitored, and in sports with short seasons, such as college soccer, making it a suboptimal form of monitoring,

Monitoring TL alone, however, may not provide all the vital information necessary to evaluate how players are adapting to high TL. Monitoring TL provides information about physical stress, but it offers limited information about psychological or performance related stress—it also does not impart information about the athlete's perceived stress level. Thus, monitoring athletes' subjective wellness, alongside TL, may provide greater insight into the holistic adaptation to stress in soccer athletes (Thorpe et al., 2016). Short SWQ have been developed which allow for assessment of overall wellness and fatigue multiple times per week, if not daily (Saw et al., 2016; Thorpe et al., 2015, 2016). The responses to these surveys are often considered from a retroactive perspective, with a sports scientist examining how the athlete is responding to the training (Saw et al., 2016). While this perspective is useful for assessing an athlete's overall recovery, it is not an optimal method as it often requires an adverse event (illness, injury, or overtraining syndrome) to understand the load which exceeds an athlete's ability to recovery properly. Perhaps a proactive approach, which matches the prescribed daily TL to the athlete's readiness to train, is a more optimal use of wellness data with the goal of maximizing performance. A proactive perspective could be particularly advantageous in collegiate soccer because of the number of matches being played in quick succession. Thus, a holistic approach to athlete monitoring, which examines multiple measurements of TL as well as assessment of an athlete's perceived wellness would be advantageous in maximizing performance in NCAA Division I college soccer.

2.3 Training Load Monitoring Methods

Training load (TL) is derived from the assessment of training intensity and volume performed by individual players during a single training session or competition. Often used to monitor athletes' fitness levels, reduce risk of injury, and help coaches develop weekly and long-term periodization, TL has become a primary form of athlete monitoring (Gabbett, 2016; Gaudino et al., 2015; Impellizzeri et al., 2004). There are two distinct divisions of TL, external—the stimulus which drives physiological response, such as running, jumping, or changes of direction, and internal (Viru & Viru, 2000)—the physiological stress response to an external load (Lambert & Borresen, 2010). In continuous exercise or athletics, such as running, swimming, or cycling, external TL is simply measured by taking the total distance covered and the prescribed pace or intensity (i.e. 5x800m in 2 min per set) of training or competition. Measurement of external TL in soccer, however, is difficult due to the intermittent and highly variable nature of the sport. It requires the use specific technological devices such as global positioning systems (GPS), or accelerometers to accurately determine the extent of the external TL of players in training and matches (Halson, 2014). These types of equipment are expensive and require expertise to properly implement the use of the technology and make the information useful for the coaching staff (Halson, 2014). Unfortunately, this level of sport science expertise is beyond the training that most soccer coaches routinely have or are given as part of their coaching credentials. In addition to the difficulty and expense of the instrumentation, measurement of external TL does not provide insight into how athletes adapt to training, making the measurement of internal TL vital to controlling the training process (Impellizzeri et al., 2004).

Since internal TL is the physiological response to the external stimulus, it must be measured indirectly, which can be achieved through both objective and subjective methods. Objective methods are those which can be precisely measured such as heart rate (HR), blood lactate concentrations [La], and hormonal changes, while subjective measures are those which account for the individual's perception of effort or fatigue, such as session rating of perceived exertion (sRPE) or SWQ (Halson, 2014). The most prominent methods for measuring internal TL in soccer are heart rate (HR) response, heart rate variability (HRV) and sRPE (Halson, 2014). HR data obtained during training sessions can be analyzed as a percentage of maximal HR (%HR_{max}), percentage of HR reserve (%HR_{res}), or summated into a training impulse (TRIMP) score, which accounts for changes in HR intensity and the session duration (Alexandre et al., 2012; Halson, 2014). However, like GPS and accelerometer equipment, HR monitoring systems are not always cost effective as the hardware can be expensive and require expertise to interpret the data. Thus, the use of sRPE and SWQ have become common forms of measuring internal TL because of the simplicity of their implementation and the value of the information they provide (Buchheit et al., 2013; Halson, 2014; Thorpe et al., 2015, 2016). The following sections will examine each method of measuring internal TL in greater detail.

2.3.1 Heart Rate Response

Heart rate monitoring is a prevalent method for measuring internal TL, and is based on the linear relationship of HR to oxygen consumption in continuous, progressively intensive exercise (Halson, 2014). The development of HR monitoring systems which can track multiple athletes simultaneously, several of which utilize live-telemetry to collect HR data, allows for the analysis of entire teams at once rather than each athlete separately. These systems express HR data as a % HR_{max} or %HR_{res}, with some able to do both. The %HR_{max} method is calculated by dividing the mean exercise

HR by the athlete's maximal HR. This method does not allow for inter-athlete comparison because of the inter-individual differences in resting and maximal HR (Alexandre et al., 2012). Heart rate reserve, on the other hand, utilizes both values and is calculated using the formula (formula 1):

1) $\%HR_{res} = [(HR_{ex} - HR_{rest})/(HR_{max} - HR_{rest})] \times 100$

where HR_{ex} is the mean HR during exercise and HR_{rest} is the athlete's HR at rest. Because the $\%HR_{res}$ accounts for the variations between athlete's resting and maximal HR, it allows for better inter-individual comparison. Despite evidence to support the use of $\%HR_{res}$ as a more accurate reflection of internal TR, $\%HR_{max}$ is still regularly used in studies which investigate match play (Alexandre et al., 2012).

Whether $\%HR_{max}$ or $\%HR_{res}$ is used to express the HR response, both can be broken down into the amount of time athletes spend in specified zones (Alexandre et al., 2012). Many studies use a zonal breakdown of 10% increments beginning at 50% (zone 1 = 50-60%, zone 2 = 61-70%, zone 3 = 71-80%, zone 4 = 81-90%, zone 5 = 91-100%) (Foster, Florhaug, et al., 2001). However, Alexandre et al. (2012) showed the average HR during soccer matches ranged from 83-87% HR_{max}, which would suggest a need for more specific breakdown of zones than arbitrarily derived 10% intervals. A more precise breakdown used by Helgerud, Engen, Wisløff, and Hoff (2001) placed greater significance on the time spent above 85% HR_{max} (zone 1 = <70%, zone 2 = 70-85%, zone 3 = 85-90%, zone 4 = 90-95%, zone 5 = 95-100%). The authors used this breakdown to assess changes of internal stress during match play, following an aerobic intervention training program. The more precise breakdown of higher intensities was shown to be useful in determining differences between the control group and training group of this study, as the training group spent significantly less time in the two lowest zones (<70% and 70-85%) and significantly more time in the highest three zones (85-90%, 90-95%, and 95-100%) (Helgerud et al., 2001). The traditional 10% increments would likely have still shown a significant difference between the groups, however, the smaller 5% increments for the higher intensities were able to more precisely distinguish between the two groups.

Heart rate variability (HRV) is another form of measuring internal TL which has become more prominent in the past few decades (Alexandre et al., 2012). HRV is commonly used to assess athlete wellness because it is non-invasive and requires minimal expense or expertise if teams already have the tools and personnel in place for HR systems (Flatt, Esco, Nakamura, & Plews, 2016; Thorpe et al., 2015). HRV is an objective measurement of cardiac-autonomic function, which has been shown to be responsive to changes in TL (Flatt et al., 2016). Despite being considered an important aspect of recent research, few studies have had success when using HRV as a monitoring tool in soccer players (Alexandre et al., 2012). HRV is sensitive to psychological factors that are unrelated to training stimulus such as academic workload, travel and social stressors, which may factor into the limited success of the measure from a monitoring perspective (Flatt et al., 2016). In addition, proper assessment of HRV requires a highly standardized protocol to obtain consistent measurements (Thorpe et al., 2015, 2016), including control of variables such as sleep, posture and minimizing the influence of bladder distention (urinary voids should be standard), something that is not always feasible in practical application. Thus, HRV may have less utility in the field than simple assessments of the HR response.

Although the measurement of HR is useful in understanding the internal stress response of athletes to training stimulus, there are several limitations. The intermittent nature of soccer—the numerous brief actions which occur throughout a match—are often too short to elicit a HR response and is therefore not comparable to the continuous, progressively intense exercise used to determine the relationship between HR and oxygen consumption (Alexandre et al., 2012). Environmental factors, such as temperature, humidity, and atmospheric pressure can affect the HR response (Alexandre et al., 2012). Additionally, hormonal effects (i.e. adrenaline) can influence a players HR in competitive play, as the playing environment or scenario can increase stimulation of various hormones. A further limitation of the HR response is that it does not accurately reflect the load of non-aerobic training such as plyometrics, speed and agility, and strength training. Similarly, it is not an effective method of assessing the stress response due to brief activities such as changes of direction, accelerations, repeated sprints, and other aspects that make soccer a highly intermittent sport (Alexandre et al., 2012).

Despite these limitations, HR is considered a useful tool for measuring internal TL because of the relationships between HR, VO_2, and exercise intensity (EI). In continuous exercise, these three components are linearly related; however HR can remain elevated above oxygen consumption during intermittent sports, which can lead to HR overestimating overall intensity (Alexandre et al., 2012). Because of this, Alexandre et al.

describes the relationship between HR and EI as sigmoidal, with HR plateauing at higher intensities. This allows HR to still be useful for understanding the internal stress response in soccer, especially when used alongside other measures of internal TL, such as sRPE, to develop a more global battery of monitoring internal TL. (Alexandre et al., 2012)

2.3.2 Banister's TRIMP

As mentioned above, TRIMP is a summation of an individual's HR response into a single value using arbitrary units (AU), which accounts for changes in intensity and volume of training. First introduced by Edwards (Edwards, 1994), TRIMP is calculated by summing the product of the time (minutes) spent in 5 HR zones and the corresponding multiplier. However, Edward's method uses arbitrary multipliers and HR intensity zones to calculate the TRIMP score, steering researchers to investigate objectively derived equations (Akubat, Patel, Barrett, & Abt, 2012; Banister, 1991). Thus, Banister et al. (1991) sought to develop a TRIMP based on objective relationship of HR and blood lactate concentrations ([La]). They examined the slight increases in HR and [La] during incremental exercise and developed an equation that could weight HR intensities based on experimental data (Akubat et al., 2012) Banister, et al., 1991). The resulting equation generated by the findings from Banister et al. (1991) is as follows (formula 2):

$$\text{2) TRIMP} = T \times \Delta HR \times 0.64e^{1.92(\Delta HR)}$$

where T equals the duration, ΔHR equals $(HR_{ex} - HR_{rest})/(HR_{max} - HR_{rest})$, *e* equals the base of Napierian logarithms (~2.718), and 1.92 is a constant for males. Obtaining individual values of HR_{max} and HR_{rest} for each athlete are important to improve the accuracy of this equation. Another form of TRIMP (Lucia's TRIMP) have been developed to make equations more precise for specific groups of individuals or to be more sensitive to changes in performance (Akubat, 2012), because it was proposed use of the mean HR during exercise may exclude important information which pertains to team sports (Akubat & Abt, 2011). However, these equations require lab based testing for each athlete, which is not always practical in large team settings, especially those that do not have easy access to laboratory based testing equipment.

2.3.3 Session Rating of Perceived Exertion

Session RPE (sRPE) is a simple, non-invasive method of monitoring internal TL (Foster, Florhaug, et al., 2001; Gaudino et al., 2015; Impellizzeri et al., 2004; Thorpe et al., 2016). This method calculates TL by multiplying an athlete's rating of perceived exertion, from the Borg's CR10 (Category Ratio) 0-10 RPE scale, by the duration of the session (RPE 8 x 60 min = 480 AU), providing a single value for the entire session (Foster, Florhaug, et al., 2001). Foster initially validated the sRPE method by correlating it with Edwards TRIMP, in intermittent and continuous exercise, to assess its ability to quantify internal TL.

Since the inception of sRPE, research has expanded to investigate how it relates to other variables to obtain a better understanding of its use in determining TL in soccer players. Impellizzeri et al. (2004) showed sRPE is a valid form of measuring internal TL in soccer players, as it is correlated to Edward's ($r = 0.50–0.77$), Banister's ($r = 0.54–0.78$), and Lucia's ($r = 0.61–0.85$) TRIMP equations. The authors suggested sRPE may be a more valid form of measuring TL when both aerobic and anaerobic energy systems are used, because of the limited ability of HR to account for actions which are predominantly anaerobic. The total number of impacts (r = .729), accelerations (r = .631), and total high-intensity running distance (THIR) (r = .610) (all of which were obtained through GPS/accelerometer devices), were all shown to be significantly ($p < .001$) related to sRPE during training in elite soccer players (Gaudino et al., 2015). While the findings do not suggest that sRPE can estimate these variables, they do show these variables influence an individual's perception of effort throughout a training session. Other research has investigated how the differentiation between aerobic (How hard was the session on your chest/lungs?) and muscular (How hard was the session on your legs?) sRPE can assess changes in performance or fatigue (Gil-Rey, Lezaun, & Los Arcos, 2015; Los Arcos, Martínez-Santos, Yanci, Mendiguchia, & Méndez-Villanueva, 2015). Finally, because sRPE incorporates the individual's perception, there is a psychological component that can affect an athlete's response (Morgan, 1994). Together, these studies have lead researchers to define sRPE as a global form of monitoring TL, as it considers multiple physiological and psychological components which influence an athlete's ability to respond to the demands of training and competition (Gaudino et al., 2015; Impellizzeri et al., 2004; Thorpe et al., 2016). Due to its simplistic, non-invasive nature, sRPE has become a prominent method of monitoring TL in numerous sports, different levels of competition, and multiple modes of exercise (Foster, Florhaug, et al., 2001; Gabbett, 2016; Impellizzeri et al., 2004; Moreira et al., 2015).

The Borg CR10 used in Foster's sRPE has been shown to be significantly correlated with changes in HR and [La] (Borg, Hassmén, & Lagerström, 1987) and has been used in research utilizing graded exercise tests (GXT) for many years. The descriptors for the Borg CR10 follow a similar pattern to the changes in HR and [La] in that the higher values of the scale are given more weight. This creates an exponential effect that is useful in GXT when subjects are asked to work to exhaustion. However, an unevenly weighted scale is less intuitive (the verbal midpoint of “Moderate” does not match the numerical midpoint) and may not be appropriate for team training environments. Athletes would need to be familiarized with the meaning of a maximal effort for an entire training session, which is not realistic in most training environments. A balanced (which equates the verbal and numerical midpoint) scale may allow athletes to be more precise in their assessment of differences in exertion during training sessions and better understand the changes relative to what is considered exhausting.

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

Rating	Descriptor
10	Exhausting
9	
8	Very Hard
7	Hard
6	
5	Moderate
4	
3	Mild
2	Easy
1	
0	Rest

Figure 1. Modified Borg CR10 Scale (left) Versus Modified Perceived Exertion Scale Used by Fit for 90 (right) (Foster, Florhaug, et al., 2001).

2.3.4 Subjective Wellness Questionnaires

Indirect assessment of training load can also be evaluated using perceived physiological and psychological response to training utilizing SWQs. In response to physical stress, athletes' bodies will adapt, either positively or negatively, to the stimulus, moving them along a continuum of physical and psychological wellness (Saw et al., 2016). The purpose of SWQ, also referred to as fatigue or recovery surveys, is to better understand where athletes are on the continuum of recovery, both acutely and chronically (Gastin et al., 2013; Kellmann, 2010). Acutely, insufficient recovery following high TL can lead to fatigue and decreased performance, while the long-term effects can result in overtraining syndrome, injury, or illness (Gabbett, 2016; Hooper et al., 1995; Piggott, 2008). By assessing an athlete's perceived physical and psychological state, SWQ can assist coaches and sports scientist in understanding the impact of their training environment and develop a more individualized approach to athlete monitoring and recovery (Gastin et al., 2013; Kellmann, 2010).

Several types of SWQ have been developed specifically for athletes, such as the Profile of Mood States (POMS) (McNair, Lorr, & Droppleman, 1992), Recovery Stress Questionnaire for Athletes (RESTQ-S) (Kellmann & Kallus, 2001), and Daily Analyses of Life Demands of Athletes (DALDA) (Rushall, 1990; Saw et al., 2016). These specific questionnaires are comprehensive, ranging from 52 to 77 items, and evaluate levels of stress, changes in mood, and perceived fatigue (Saw et al., 2016). In a review by Saw (2016), specific items of these questionnaires have been shown to be associated with objective measures of fatigue, with stress being negatively correlated to cortisol levels, and vigor positively correlated with leukocytes. Subjective measures of well-being were also shown to be more sensitive, consistent, and responsive to changes in acute TL than objective measures. Numerous subjective measures, from several surveys, showed moderate to strong correlation to improved and deteriorated well-being with acute decreases and increases in TL, respectively (Saw et al., 2016). Additionally, responses to stress, fatigue, recovery, physical recovery, general well-being, and being in shape (six specific measures from the RESTQ-S survey) showed moderate to strong responsiveness to acute increase and decrease in TL, as well as chronic TL.

Shorter SWQ (containing 3-10 items), which can be utilized on multiple days per week, have also shown to be sensitive to changes in TL (Buchheit et al., 2013; Elloumi et al., 2012; Saw et al., 2016; Thorpe et al., 2016). Responses to these shorter SWQs have shown steady improvement in overall well-being following competition in both elite soccer players (Thorpe et al., 2016), rugby sevens players (Elloumi et al., 2012, 2013)and Australian Football (AFL) players (Buchheit et al., 2013; Gastin et al., 2013). The greatest increase in wellness was seen between one and two days after the competition, while the highest overall wellness levels are observed the day preceding a match (rarely assessed on the day of competition). The relationship between objective training load variables, such as HR_{ex}, total distance and high speed running (>14.4 km/h), and different SWQ has also been studied. Thorpe (2015) showed a significant negative correlation between THIR distance (>14.4 km/h) and changes in perceived fatigue ($r = -.51$) in elite soccer players, although there was no significant correlation with the sleep quality or muscle soreness items. Similarly, Buchheit et al. (2013) showed changes in overall perceived wellness (Hooper et al., 1995), YYIR2 performance, total distance, and high speed running were all positively related following a two-week preseason in Australian Football players. These findings suggest SWQs may provide insight into specific external loads during training and positive adaptation that can guide coaches and sports scientist to maximize performance.

Additionally, researchers have begun to question if changes in perceived wellness may be associated with changes in certain TL outcomes in a session. For instance, when a player reports high (negative) levels of fatigue or poor sleep quality in a pretraining SWQ, are performance measures impaired in the session that day? One such study on AFL players showed positive association between wellness Z-scores and two external load measures, player load (algorithm which quantifies overall effect of a session on the athlete) and player load slow (a variable measured in AFL which is thought to assess low speed activity specific to the sport) (Gallo, Cormack, Gabbett, & Lorenzen, 2016). However, Haddad (Haddad et al., 2013) found perceived wellness (Hooper index) had no effect on sRPE in soccer players. It may be possible that sessions can be individually optimized based on perceived well-being, but further research is needed to better understand the influence well-being may have on performance.

For SWQs to provide useful information to the coach and sport scientist, implementation must be well structured. First and foremost, implementation should seek to reduce the burden placed on the athlete to avoid unwanted questionnaire fatigue, which could result in decreases in the validity and reliability of the data (Saw et al., 2015). The original forms of the three sport-specific questionnaires listed above can be lengthy, such as the 52 item RESTQ-S, and are thus implemented infrequently (weekly or monthly) to not be overbearing on the athlete (Laux, Krumm, Diers, & Flor, 2015; Saw et al., 2015). Utilization of these surveys multiple times per week may reduce the athletes' levels of self-efficacy and compliance, which are important for obtaining dependable information (Saw et al., 2015). Only assessing wellness weekly or monthly, however, may not be frequent enough to detect adverse effects prior to their occurrence. To reduce the burden on the athlete, shorter SWQs have been developed which can be used more frequently. Hooper (Hooper et al., 1995) examined the validity of a daily, 4-item questionnaire (sleep, fatigue, stress and muscle soreness; recorded in individual journals) to detect decreases in performance in elite swimmers. For athletes who met the "staleness" criteria, the combination of stress ratings and resting plasma catecholamine levels predicted 74% of variance in performance. These swimmers also reported worse levels of fatigue, muscle soreness, sleep quality, and stress at various points in the season than the "non-stale" swimmers. This was the first study to demonstrate the validity of a short, daily subjective questionnaire to detect decreases in performance.

In addition to reducing the time burden on the athlete, the collection and analysis of data is an important part in proper implementation of SWQs. While the athlete compliance in the Hooper (Hooper et al., 1995) study was high, the wellness journals were collected at 2-week intervals by the coaching staff, limiting their ability to adjust TL prescription based on the information contained in the wellness journals. Current technology, such as smart phone applications and web-based systems, provide platforms that allow for quicker analysis of data, especially in large team settings (Saw et al., 2015).

The ability to analyze data prior to training sessions would allow the implementation of a proactive approach to TL prescription and the individualization of training.

In conclusion, while the association between some objective (HRV, cortisol, leukocytes, etc.) and subjective measures (RESTQ-S, Hooper Index, or modified survey) of adaptation are not strong, it has been recommended that both be used in conjunction with one another when possible (Saw et al., 2016). The recommendation to use a combination of subjective and objective measures is based on the premise that it will help sports scientists better interpret the information obtained and reduce risk of bias or dishonesty in the questionnaire (Saw et al., 2015, 2016). The combination of objective and subjective measures can often help sports scientist to better elucidate if physiological changes are due to improvement in function or a result of overtraining, since many of these changes are similar for both responses in the early stages of overtraining (Hooper et al., 1995). Thus, Saw et al. (Saw et al., 2016) recommends the use of subjective and objective measures together whenever possible. However, given the constraints and feasibility issues related to the proper measurement of HRV in the collegiate setting, we propose the use of other scales in the current study. SWQs are a simple, inexpensive, non-invasive method of measuring TL by assessing changes in an athlete’s physical and psychological response to the load of training and competition.

2.4 Fit for 90 Athlete Monitoring Platform

Fit for 90 (FF90) is an athlete monitoring platform that is designed to meet the needs of both the athlete and the coach. By utilizing a simple web-based platform, which can be accessed on multiple devices by athletes and coaches, FF90 places minimal time burden on the athlete while providing valuable information to the sports scientists and coaching staff (Saw et al., 2015). Through the FF90 web-based platform, athletes are able to self-report their perception for wellness (obtained through a daily readiness survey), training load (sRPE), muscular specific-site soreness (Saw et al., 2015), hydration levels (6 level color scale), as well as illness, injury and body weight. The FF90 readiness survey is a six-item survey that is similar to other short, modified SWQs (Brito, Hertzog, & Nassis, 2016; Buchheit et al., 2013; Hooper et al., 1995; Thorpe et al., 2015, 2016), assessing an athlete's perceived fatigue, stress, mood, overall soreness, sleep quality, and sleep duration. Each question is scored on a 7 point Likert scale, with the range being from -3 to +3, allowing for a neutral score of zero. A key difference in the FF90 readiness survey from other SWQs (Buchheit et al., 2013; Hooper et al., 1995; Thorpe et al., 2015, 2016) is the differential weightings for the survey questions, which are then summated into an overall readiness score from 0% to 100%. This difference in presentation of the athlete's perceived wellness allows for the coach or sports scientist to easily identify changes in well-being that may merit closer examination. Overall, FF90 is science-driven athlete monitoring platform that seeks to maximize the quality of information derived from the athlete while presenting the information to the coaching staff in a simple useable format.

CHAPTER III

METHODS

3.1 Experimental Design

This study used a retrospective, longitudinal research design with data being collected from the beginning of the 2016 NCAA Men's Soccer preseason through the completion of the final competitive match. A total of 13 weeks were included in the study. Data was collected during all team training sessions and matches.

3.2 Subject Characteristics

Twenty-two players from an NCAA Division I team in the Atlantic Coast Conference were used in the study (mean ± standard deviation; age 20.5 ± 1.5 years; height 70.3 ± 1.8 in; weight 160.4 ± 16.3 lbs; body composition 11.8 ± 2.8% fat mass). All athletes had multiple years of experience playing soccer at the highest youth level of their respective country. In regards to NCAA Division I college soccer experience, 11 were playing their first season, six their second season, two their third season, and three their fourth season. All goalkeepers were excluded from this study due to the different physical demands of the position.

3.3 Testing Procedures

The athletes performed a series of physical performance tests prior to the start of preseason training. These tests evaluated the power, strength, agility, speed, and fitness of each of the athletes and will serve as potential moderating variables to changes in readiness, as previous research has suggested faster players experience greater levels of soreness (Gastin et al., 2013). There was no post-test following the season.

The field-based speed and power tests were performed on an outdoor artificial turf surface with players wearing cleats. The tests consisted of a static, single-leg hop for distance (unilateral concentric power), countermovement broad jump (bilateral power), single-leg triple-hop (unilateral stretch-shortening cycle), 10 and 20 meter sprints (speed), the 505-agility test (unilateral agility), and the Yo-Yo Intermittent Recovery Test Level 1 (YYIRL1) (Cone, 2012).

In the single-leg hop for distance, the athlete began standing on one leg with his heel flush with the front of the starting line. The other leg was slightly elevated off the ground. The player then squatted to 90 degrees of flexion in the knee, holding that position for three seconds before jumping for maximal distance. The athlete landed on their non-jumping leg and the distance was taken from the front of the starting line to the heel of the landing leg.

The counter movement broad jump began with the athlete standing on both legs, heels flush with the starting line. From the standing position, the athlete quickly dropped down to a self-selected depth before jumping for maximal distance, landing on both feet. The distance was measured from the front of the starting line to the heel of the closest foot.

For the single-leg triple hop, the test began with the same starting foot position as the single-leg hop for distance. The athlete then performed three successive jumps, the first from a standing position, with the intent of covering as much distance as possible. Upon landing from the final jump, the athletes were instructed to land on their jumping leg and place their other leg out in front to maintain balance. The distance was measured from the front of the starting line to the heel of the jumping leg. All distances for the jumping tests were measured to the closest whole centimeter.

The 10- and 20-meter sprint test and 505-agility test are designed to assess acceleration, speed and unilateral agility, respectively. The sprint test was setup with three timing gates (Brower TC Timing System, Utah, USA) placed at 0, 10, and 20 meters. Each gate was elevated 45 centimeters above the ground. A starting cone was placed 50 centimeters behind the starting gate and a cone gate was placed at 25 meters to encourage the athletes to continue to accelerate the full 20 meters. Athletes were instructed to place front foot at the starting cone and to begin the test when desired. Each player was given two attempts, with the better overall 20-meter time being recorded.

The setup for the 505-agility test included a starting cone 50 centimeters behind the first gate, two gates placed at 0 and 10 meters, and an outbound line at 15 meters. The test involves the athlete sprinting 15 meters to the outbound line, turning and sprinting back through the gate. Two attempts were given, with the athlete cutting to their right on the first attempt (only the left foot crosses the outbound line) and their left on the second attempt. The test began with player placing the foot which would cross the outbound line just behind the starting cone. Times were recorded from 10-, 20- (10-meter change of direction), and 30-meters for both trials.

The final test performed was the YYIRL1, which was performed on a separate day to maximize performance. This was the only test performed on a well-ventilated, indoor artificial turf surface (due to weather restrictions). The test consists of repeated 20-meter shuttle runs (20-meter run to outbound line and 20-meter run returning to the start) separated by 10 second rest intervals (Krustrup et al., 2003). Audio bleeps controlled the pacing of the test, signaling the start, mid-point, and end of each shuttle. The test was considered complete when the athlete failed to complete the entire shuttle in the specified time on two occasions. The final completed stage was recorded as the athlete's score. Returning athletes had been familiarized with all the tests above as they were standard tests performed by the team, and all incoming freshman were given the opportunity to practice each test following the standardized warm-up.

In addition to these performance and fitness tests, the athletes completed a movement assessment (Functional Movement Screen (FMS)) and unilateral strength test (Y-balance test) (Cone, 2012). Athletes performed these tests in small groups due to the time constraints of the tests. For the FMS test, athletes performed the following exercises while being assessed by the strength and conditioning coach: deep squat, hurdle step, inline lunge, active straight leg raise, shoulder mobility, trunk stability push-up, and rotary stability test. Proper protocol as specified by the FMS was followed for each test.

The Y-balance test (a derivation of the Star Excursion Balance Test) is an assessment of unilateral, lower limb strength and dynamic balance (Gribble, Hertel, & Plisky, 2012). For the test, participants performed maximal reach with non-standing leg in the anterior, posterior lateral, and posterior medial directions. The athlete performed a total of 4 trials in each direction on each limb, with the average of the final two attempts being taken as their score. Proper testing protocol for the Y-balance test was followed and athletes performed the test either barefoot or in socks.

3.4 Readiness Monitoring

Utilizing the Fit for 90 (FF90) athlete monitoring platform (web-based software which can be used on multiple devices), players were required to submit their daily readiness score prior to 9 o'clock in the morning on each day, including competition and rest days. The readiness questionnaire is a 6-item survey asking the athlete for their perceived fatigue, mood, stress, soreness, sleep quality, and sleep duration. (It is important to note, the specific-site muscular soreness portion of the FF90 monitoring platform is separate from the readiness survey and does not factor into the overall readiness score). The first five questions were scored on -3 to +3 Likert scale, while the sleep duration question asks the athlete to report estimated hours of sleep to the nearest half-hour. The responses to the readiness questionnaire were then aggregated into a single readiness score, with each question being weighted differently in the overall score. This readiness score was only viewable on the coaching platform (see Appendix D) of the FF90 software to ensure athletes were unable to see their own responses, and minimize the chance that previous responses would alter future responses. See appendix A for screenshot of the players' readiness survey on FF90 platform.

3.5 Session RPE Monitoring

Following each session, athletes submitted their individual session-RPE (sRPE) score on the FF90 platform. Approximately 30 minutes after the conclusion of each session, players accessed the FF90 website where they were asked to rate the intensity of the session on a zero (rest) to ten (exhausting) scale and submit the training time. The RPE scale used was different from Borg's CR10 scale in that the verbal descriptors were equated with the numerical (five was described as moderate) and the highest rating was "Exhausting" rather than "Maximal". The duration of each training session was taken from the start of the warm-up through the end of the final training exercise. For matches, only the minutes played by the athlete was submitted for the duration (Gil-Rey et al., 2015). Athletes were responsible for submitting sRPE following each team organized session including team training, strength training, and matches. See appendix B for screenshot of players' sRPE form on FF90 platform.

3.6 Additional FF90 Monitoring

In addition to assessment of readiness and sRPE, FF90 also allows the athletes to report specific-site muscular soreness, weight, hydration status, illness, and injury. These portions of the platform were all optional for the athlete to submit, and do not factor in the readiness score calculation. See appendix C for screenshot of the players' additional monitoring on FF90 platform.

3.7 Monitoring Training Load through Heart Rate Monitors

For every team training session, game, and fitness test each player wore a heart rate (HR) monitor (Firstbeat Sports, Finland). Maximal heart rates were recorded during the YYIRL1 fitness test, however, if a player reached a higher HR during training or match play, the maximal HR (HR_{max}) was readjusted with the new value. The data retrieved from the HR monitors was assessed in two ways, as a percentage of HR_{max} and summated into a single value using Banister's TRIMP (Banister, 1991). The intensity zones for the HR data were broken down into five zones: zone 1 = <70%, zone 2 = 70-85%, zone 3 = 85-90%, zone 4 = 90-95%, and zone 5 = 95-100% (Helgerud et al., 2001).

For each session of HR data recorded from the players, the Firstbeat Sports software provides a value for measurement error that is calculated for the entire session. Accurate recording of HR during the session is dependent on the athlete wearing the HR strap properly and the transmission of the HR signal from the strap to the computer. Gaps in transmission of the HR data can also occur, resulting in periods of lost data. To minimize the use of data that contained high measurement error or had large gaps in the data (for a variety of reasons), the following criteria were used to assess whether the HR sessions were included in the overall analysis: 1) all data with a measurement error of less than 35% and containing no gaps in transmission were included, 2) data with measurement error greater than 35% without gaps in the data were assessed on a case-by-case basis for inclusion, 3) data with less than 35% measurement error containing gaps in the data were considered on a case-by-case basis to determine at what points in the session the gaps occurred (e.g. during half-time of match, while not active), 4) data exceeding 40% measurement error was excluded from analysis, and 5) data containing gaps which exceeded 15% of the overall session were excluded from analysis.

3.8 Submaximal Fitness Test

To assess possible changes in fitness over the season, the players' HR was analyzed following a submaximal fitness test. Shortened versions of the YYIRL1 which last at least six minutes have been shown to inversely correlate to performance on the maximal version of the test (Bangsbo, Iaia, & Krustrup, 2008). This submaximal test was performed on three separate occasions throughout the season, each on the Wednesday morning training session during a week, which only contained one match. Due to the lack of control over the game schedule, the tests occurred at different intervals with the first test coming after three weeks of training, the second test five weeks later, and the final test three weeks after the second. The submaximal fitness test began with a shortened warm-up before the players were asked to run the YYIRL1 up through stage 14-8 (the first running speed with a complete set of eight shuttles and a total running time of roughly six minutes and twenty seconds) . A marker was set on the HR monitoring software (Firstbeat Sports) at the completion of this stage to allow for a precise assessment of the athlete's HR at the end of the final shuttle. The YYIRL1 was used as a submaximal fitness test due to the athletes' familiarity with the test and its ability to serve as a thorough warm-up for the training session to follow.

3.9 Statistical Analysis

All descriptive data analyzed in the study will be presented as mean ± SD. The statistics for each of the hypotheses in this study will be described separately below. In addition, training session data will be presented for the entire season (mean± SD). The following verbal descriptors will be used in relation to correlation values: very weak (r = .00 - .19), weak (r = .20 - .39), moderate (r = .40 - .59), strong (r = .60 - .79), and very strong (r = .80 - 1.00). *A priori* statistical significance is set at $p<0.05$.

To answer the first aim of this study, a correlation analysis was run to determine the relationship between the FF90 sRPE and Banister's TRIMP for each training session and match.

The second aim was answered using a correlation analysis between the daily readiness score and the internal TL, as assessed by sRPE and TRIMP obtained from each training session and match. A separate correlation analysis was run for sRPE and TRIMP. The correlation will be run between a single readiness score and the internal TL from the previous day.

The third, and final, aim of this study examines how readiness changes over the course of the entire season. To perform this statistical analysis, the readiness score submitted on each Monday morning during the season was used for analysis. Monday is chosen as the comparison day because it normally followed an off day (Sunday) and was often more than 48 hours after a match, but not a match-day. Similar to the first part of this hypothesis, a correlation statistic will be used to compare the readiness score on each Monday and cumulative minutes played to that point in time.

CHAPTER IV

RESULTS

A total of 25 players began the study at the start of the season, however, four of the players arrived on campus after the body composition and performance testing had been completed and these individuals were unable to complete the testing prior to the start of the season and thus, no performance data is available for these players. The anthropometric data is listed in Table 1 and the mean and standard deviations for the performance testing is presented in Table 2. These values are used to present the overall fitness levels of the participants, and were not used in any of the hypothesis testing. The descriptive results for the submaximal fitness test are presented in Table 3. The values represent the player's $\%HR_{max}$ at the completion of stage 14-8 on the YYIRL1 test. A repeat measures ANOVA was used to analyze results from this test. A significant decrease in $\%HR_{max}$ was observed between the initial running of the full YYIRL1 test before preseason and the first submaximal test during the season. However, the increased stress players may have experienced during the full YYIRL1 may have caused HR values to be inflated earlier in the test and not necessarily a sign of improved aerobic fitness, particularly since none of the other tests were significantly different.

Table 1. Demographic Statistics

	N	Mean	Std. Deviation
Playing Year	23	1.9	1.1
Age	23	20.5	1.5
Height (in)	23	70.3	1.8
Weight (lb)	23	161.3	15.9
% Body Fat	21	11.8	2.8
BMI	23	22.9	1.4

Over the course of the collegiate soccer season, 2095 readiness survey entries were made, with 1553 sRPE and 1865 TRIMP data points collected. The sRPE data entries include both training session and lifting sessions. However, HR data was not recorded for the lifting sessions because it is a poor indicator of internal stress response for this activity. Therefore, the sRPE values submitted for lifting session were excluded from the statistical analysis for continuity of data used in the first two hypotheses. All HR data from one player was removed from analysis, since over half of the HR sessions were not usable. After the removal of lifting sRPE data and HR data based on the described criteria, a total 1465 and 1755 data points remained for sRPE and HR, respectively. All data entries for a single day were summated for analysis, as matches often included two or three separate HR data points but only one sRPE data point, resulting in 1419 sRPE and 1413 HR data points during the season.

Table 2. Performance Testing Results

Test	N	Mean	Std. Deviation
YYIR1 (m)	21	2182.9	224.7
Triple Hop – Left (cm)	21	714.5	50.5
Triple Hop – Right (cm)	21	712.0	43.3
Static Broad – Left (cm)	21	231.9	12.7
Static Broad – Right (cm)	21	228.4	12.8
Broad Jump (cm)	21	268.6	15.8
505 Agility – Left (s)	21	5.48	.15
505 Agility – Right (s)	21	5.48	.13
0-10 m sprint (s)	21	1.73	.06
0-20 m sprint (s)	21	2.99	.10
FMS	20	15.3	1.8
Y-Balance anterior - Left (cm)	20	58.9	5.2
Y-Balance anterior – Right (cm)	20	58.7	5.7
Y-Balance posterior-medial – Left (cm)	20	102.5	4.7
Y-Balance posterior-medial – Right (cm)	20	103.2	4.1
Y-Balance posterior-lateral – Left (cm)	20	97.2	4.0
Y-Balance posterior-lateral – Right (cm)	20	97.9	4.7

Table 3. Descriptive Statistics for Sub-maximal YYIR1 Stage 14-8.

	Mean	Std. Deviation	N
Submax Test 1	92.2%	2.7%	17
Submax Test 2	87.1%	2.7%	17
Submax Test 3	86.5%	2.8%	17
Submax Test 4	87.2%	3.6%	17

The average amount of time spent active during either training or matches was 66.3 minutes (SD ± 28.5 minutes), and the mean readiness score over the season was 80.3% (SD ± 12.6%). The means for sRPE, and TRIMP for each day of training or matches were, 382.5 arbitrary units (AU) (SD ± 249.0), and 115.6 AU (SD ± 63.9), respectively.

For the first hypothesis, the sRPE scores were found to be significantly correlated to TRIMP scores for the same day of training or games (r = .857, p = .00) (Figure 2). This confirms the validity of the modified sRPE scale used by FF90 for soccer players, returning a higher correlation than previously found between Foster's sRPE and Banister's TRIMP (r = .50 to .77) (Impellizzeri et al., 2004). The individual player correlations ranged from r = .795 to .925 (p = .00 for all players). The variance for this results was r^2 = .735. Figure 3 is a sample graph of one athlete's sRPE and TRIMP values for a three-week period.

For the second hypothesis, the readiness scores had a significant, inverse relationship with both sRPE (r = -.296, $p < .01$; Figure 4) and TRIMP (r = -.333, p = .00; Figure 5). The variance for this result, however, was weak, being $r^{2 =}$ .088 and r^2 = .111 for sRPE and TRIMP, respectively. Because games represent the highest internal TL players experience, individuals who played a greater number of minutes are exposed to higher internal TL than individuals who played fewer minutes or not at all. Since it was hypothesized the readiness score would be negatively related to the previous days internal TL, it would follow that the higher the TL the greater the corresponding decrease in readiness score. Therefore the data was split into the following groups based on cumulative minutes played during the season: group 1 = <10 minutes (n = 4), group 2 = 10 – 500 minutes (n = 7), group 3 = 500 minutes – 900 minutes (n = 6), group 4 = > 900 minutes (n = 8).

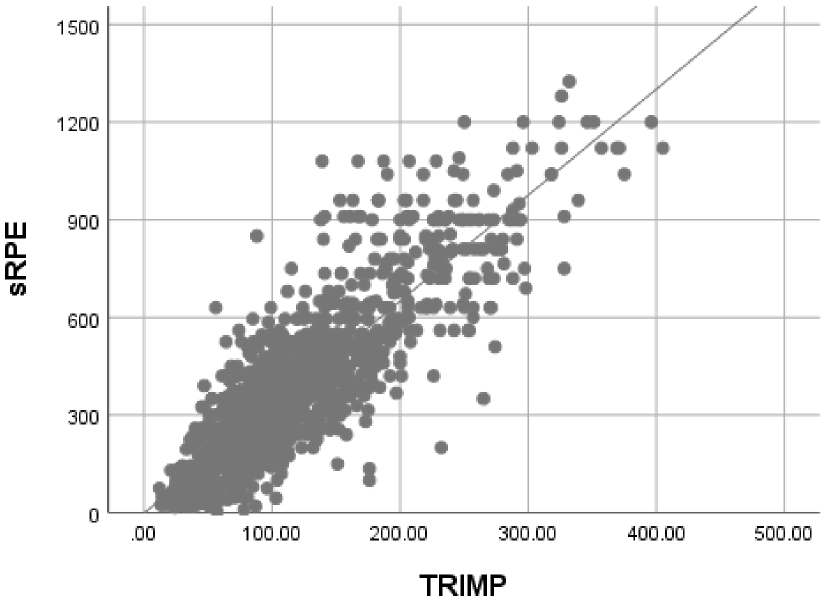

Figure 2. Scatter Plot with Slope for sRPE (AU) and TRIMP (AU).

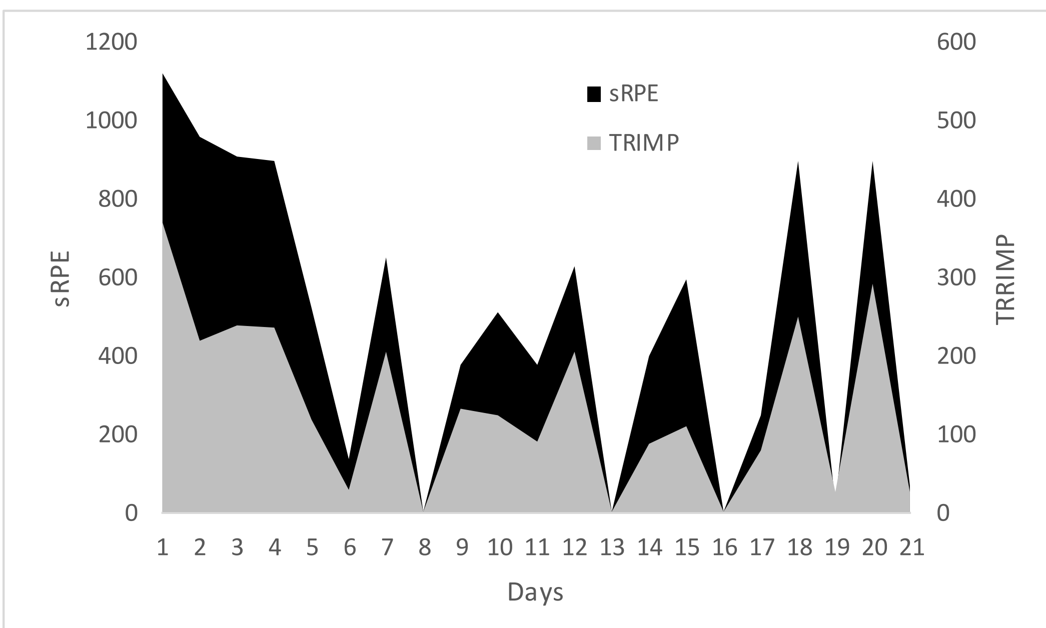

Figure 3. Pattern of sRPE (AU) and TRIMP (AU) for an Individual Athlete.

The correlation between the readiness score and internal TL varied by group, but in all cases, the variables were inversely correlated with readiness score (Table 4). Figure 6 provides a visual of the correlation between the readiness score and TRIMP based on groups. Fisher's z-score transformation was used to determine differences between correlations of each group. Group 4 is significantly different from each of the other groups for the correlation between readiness and sRPE and readiness and TRIMP, but no other groups were significantly different from one another.

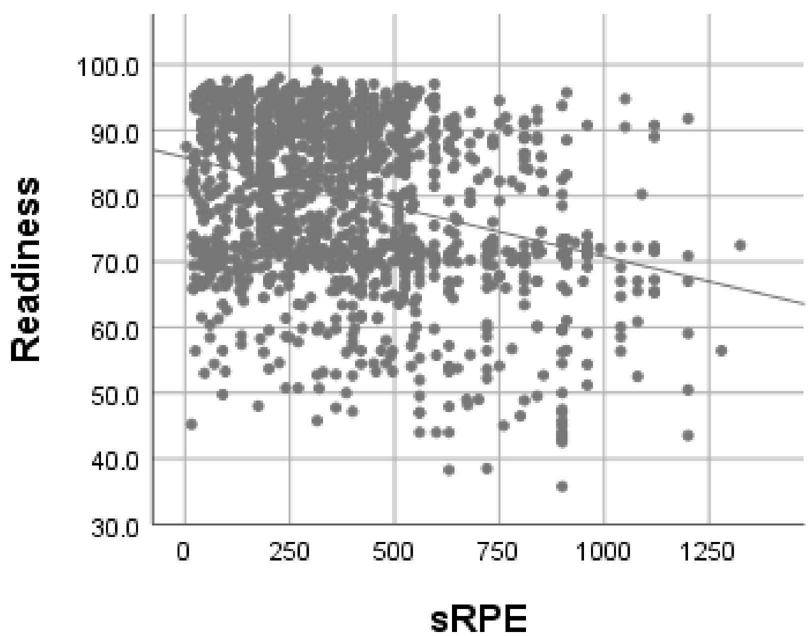

Figure 4. Scatter Plot with Slope for Readiness (%) and sRPE (AU).

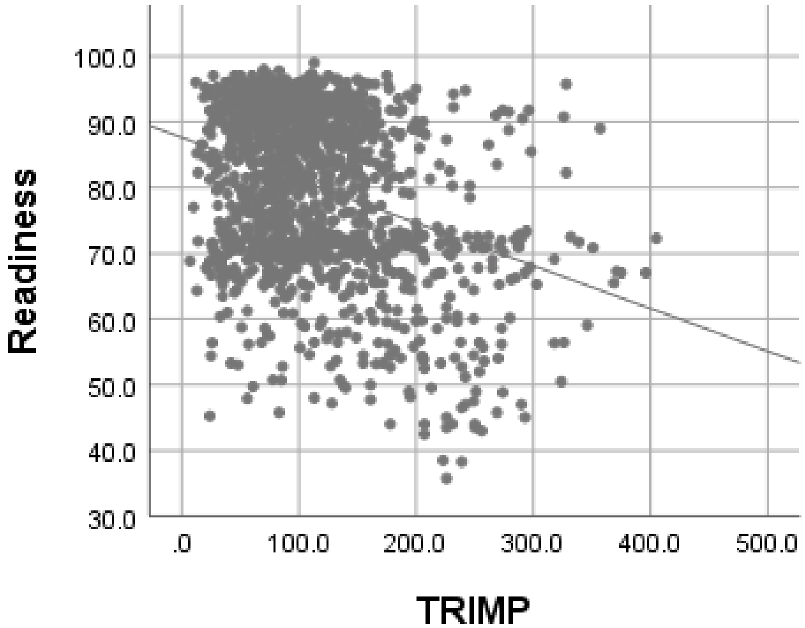

Figure 5. Scatter Plot with Slope for Readiness (%) and TRIMP (AU).

Table 4. Correlation Between Readiness & Internal TL by Group.

Group			sRPE	TRIMP
1	Readiness	Pearson Correlation	-.178*	-.124
		Sig. (2-tailed)	.019	.064
		N	175	225
2	Readiness	Pearson Correlation	-.211**	-.188**
		Sig. (2-tailed)	.000	.000
		N	330	354
3	Readiness	Pearson Correlation	-.186**	-.279**
		Sig. (2-tailed)	.000	.000
		N	379	380
4	Readiness	Pearson Correlation	-.400**	-.469**
		Sig. (2-tailed)	.000	.000
		N	523	442

*Correlation is significant at the 0.05 level (2-tailed).

**Correlation is significant at the 0.01 level (2-tailed).

For the final hypothesis, a significant, inverse relationship was found between readiness scores and the cumulative minutes played over the season (r = -.231, *p* = .00) (Figure 7), but the variance explained by this relation was weak (^{r2} = .053). When the data was split by groups, the results diverge. Some groups show a positive relation (Group 1: r = .491, *p* = .00; Group 3: r = .014, *p* = .91) and others negative (Group 2: r = -.328, *p* = .00; Group 4: r = -.178, *p* = .08).

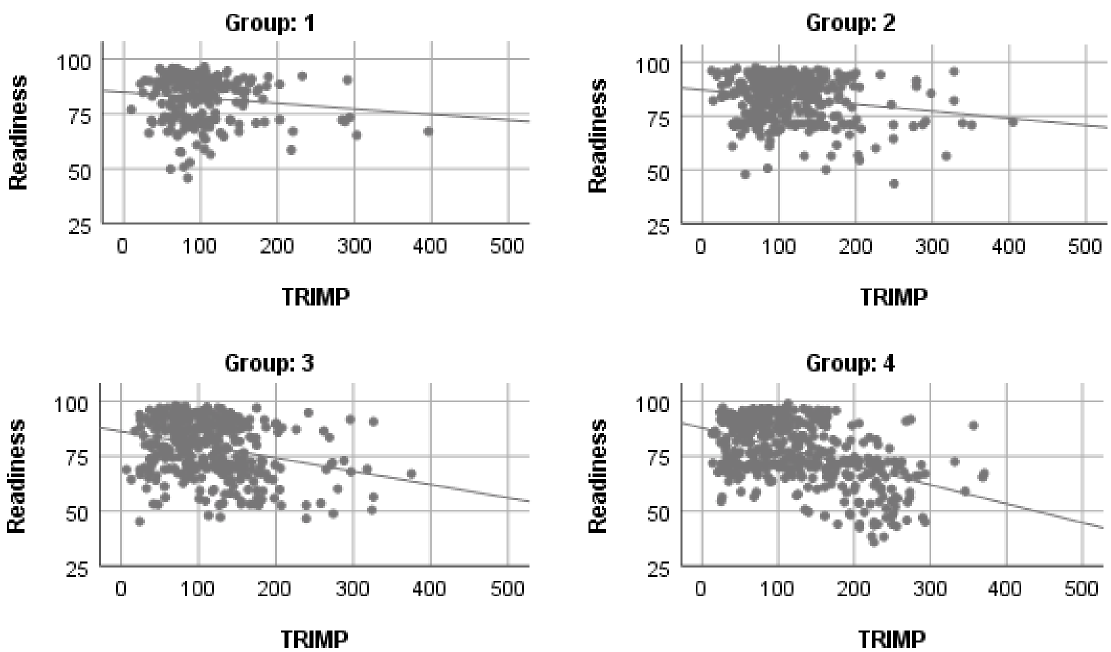

Figure 6. Scatter Plot with Slope for Readiness (%) and TRIMP (AU) by Group.

After determining correlation statistics for each purpose for the entire season, the data was split at the mid-point of the season to analyze potential differences between the first and second half of the season. The descriptive statistics for both halves of the season are presented in Table 5.

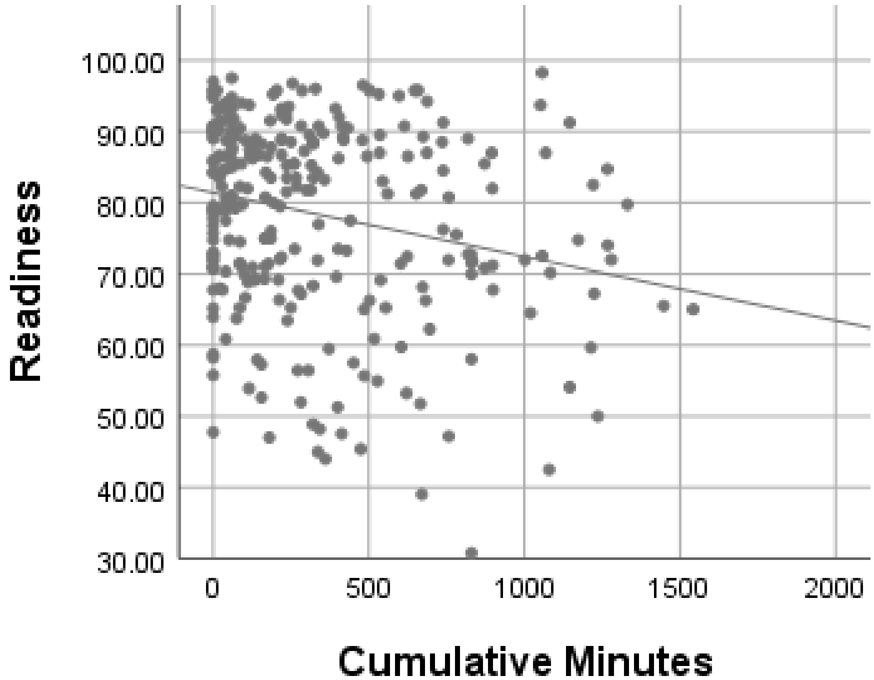

Figure 7. Scatter Plot with Slope for Readiness (%) and Cumulative Minutes Played (min).

The correlation between sRPE and TRIMP was slightly lower in the first half of the season than the second (r = .855, *p* = .00; r = .867, *p* = .00), but this was not significant. The readiness had a similar correlation with sRPE (readiness to sRPE, r = -.319, *p* = .00, and r = -.278, *p* = .00) and TRIMP (readiness to TRIMP, r = -.313, *p* = .00, and r = -.374, *p* = .00) in both halves of the season. For the final hypothesis, there was a slight decrease in the correlation between readiness and cumulative minutes played from the first half (r = -.357, *p* = .00) to the second half (r = -.285, *p* = .00) of the season.

Table 5. Mean & SD for Measures for Split Season

Season		N	Mean	Std. Deviation
1st Half	Duration (minutes)	818	73.1	31.9
	Readiness (%)	1109	80.4	12.5
	sRPE (AU)	818	423.6	262.9
	TRIMP (AU)	819	121.6	68.4
2nd Half	Duration (minutes)	601	57.1	19.6
	Readiness (%)	986	80.1	12.8
	sRPE (AU)	601	326.5	216.7
	TRIMP (AU)	594	107.4	56.1

CHAPTER V

DISCUSSION

The purpose of this study was to investigate the use of an athlete monitoring platform in a NCAA Division I Men's soccer program. Fit for 90 is a web-based athlete monitoring platform, which allows players to easily submit their subjective responses to a daily readiness survey, sRPE, specific-site soreness, and several other components that can give coaches insight into the overall well-being of the athletes. There were three results from this study, all of which were significant. First, the modified sRPE used by FF90 was positively related to Banister's TRIMP (r = .857, p = .000) for measurements from the same session. Second, the FF90 readiness score had an inverse relationship with the previous day's internal TL, having a slightly stronger correlation to TRIMP (r = -.333, p = .000) than to sRPE (r = -.296, p = .000). Finally, the readiness score was negatively related to the cumulative minutes played over the course of the season (r = -.231, p = .000). This final result needs more investigation as the direction and level of correlation varied when the subjects were grouped based on total minutes played.

5.1 Session-RPE and Banister's TRIMP

The correlation observed between the FF90 sRPE and TRIMP (r = .857) has the strongest correlation of all the hypotheses tested in the current study. This result demonstrates the ability of individuals to subjectively account for internal TL and the effectiveness of the modified scale used by FF90. The strength of the relation between the FF90 sRPE and Banister's TRIMP for individual players in this study ranged from r = .795 to .952, which exceeds that observed in previous research (Impellizzeri et al., 2004; Kelly, Strudwick, Atkinson, Drust, & Gregson, 2016). This suggests that perhaps the modified FF90 sRPE may be a more effective form of assessing internal TL than Foster's (1998) original sRPE formula.

The original sRPE formula was developed by Foster (1998), utilizing the Borg CR10 scale to determine the perceived exertion, which was multiplied by the duration of the session. The difference between the FF90 sRPE and the original formula is the RPE scale. The Borg CR10 scale was developed on the non-linear relationship between HR and [La], which created an exponential relationship between verbal and numerical descriptors. However, the relationship between HR and [La] does not reflect the linear relationship between exercise intensity and HR. The scale used by FF90 has two distinct differences from the Borg CR10 scale that may lead to it being a more effective indicator of internal TL. First, it equates the numerical and verbal descriptors, making if more intuitive and maintaining a linear relationship between the descriptors. Second, the descriptors ask the players to consider their *state of fatigue* following a session rather than the *level of intensity* at which they worked during the session or game, which may be a more accurate representation of overall exertion for the bout of exercise.

Impellizzeri et al. (2004), was one of the first to investigate the effectiveness of Foster's sRPE in soccer, comparing it with Banister's, Edward's, and Lucia's TRIMP equations. The correlation between sRPE and TRIMP from this study ranged from r = .50 to .85 for all three equations, but Banister's TRIMP had the lowest range (r = .50 to .77).

This range was below that found by Foster for sRPE and Edward's TRIMP ($r = .75$ to $.90$) (1998); however, speed skaters were the primary athletes included in Foster's research. The difference in athletes led Impellizzeri et al. (2004) to concluded the lower correlation seen in soccer players was due to the increased influence of anaerobic actions to the overall load, which HR does not effectively measure. Though the range of correlation between Foster's sRPE and Banister's TRIMP was the lowest of the equations, the authors did not suggest there was a significant difference between the equations, thus Banister's TRIMP is a valid form of assessing internal TL in soccer players. The range of correlation in the current study was similar to that observed by Foster, actually, being slightly higher. The improved correlation could be related to the difference in descriptors used by the FF90 RPE scale. The highest rating on the FF90 scale is "Exhausting," which asks the individuals to consider their level of exertion across the entire bout of exercise. The highest rating on the Borg CR10 scale, however, is "Maximal" (Foster, Florhaug, et al., 2001), which can direct an athlete towards considering how hard they worked during the exercise bout. For example, an athlete could play 15 minutes in a match, and work as hard as possible and the player could report a 10 on the Borg CR10 scale. For the 15 minutes played, this would be a total sRPE of 150 AU. However, the player may not be exhausted after only 15 minutes of playing and report a 6 on the FF90 sRPE scale, yielding an overall score of 90 AU. Thus, while this may not be the definitive or sole cause of the higher correlation, it is likely a potential factor in the higher correlation found in this study.

The strength of correlation between the FF90 sRPE and Banister's TRIMP suggests the comparison between the two is an effective form of monitoring athletes. The findings of this study suggest sRPE is an adequate alternative to assess internal TL when HR monitoring is not feasible due to expense or lack of expertise. However, Halson (2014) recommends the use of both when possible, because the nature in each measure can account for inconsistencies of the other. For example, a player in this study did not participate in training for two consecutive days before a game due to illness, which he reported through the FF90 platform. During the game, the athlete played the entire 90 minutes of the match and submitted a 10 on the RPE scale, resulting in a sRPE of 900 AU. However, the player's TRIMP was roughly half (138 AU) of his average over the course of the season (258 AU), which was likely due to the remaining effects of the illness the athlete experienced on the previous two days. This is one specific example of the benefit of monitoring sRPE and TRIMP together, as a ratio between the two can give insight into potential adverse factors. Conversely, a player may submit a lower sRPE for a session or match in which they record a higher TRIMP score, potentially indicating that they have attained a higher level of fitness. However, proper interpretation of changes in HR in relation to changes in fitness is challenging and contested (Alexandre et al., 2012; Buchheit, Simpson, Al Haddad, Bourdon, & Mendez-Villanueva, 2012), as players with higher levels of fitness can often maintain a higher HR during training compared to less fit players (Helgerud et al., 2001). These are just a few examples which demonstrate the challenge of interpreting HR data alone, and support the notion that systematic monitoring should include assessment of both sRPE and HR (Alexandre et al., 2012).

5.2 Fit for 90 Readiness Score and Internal TL

The results for the correlation between the FF90 readiness score and both measures of internal TL confirm the second hypothesis. The inverse correlation between readiness and TRIMP ($r = -.333$) was slightly higher than that for readiness and sRPE ($r = -.296$), though they were not significantly different. When players were split into groups based on cumulative minutes played over the season, the strongest correlation for both sRPE ($r = -.400$) and TRIMP ($r = -.469$) was found in the group that played the most minutes. Since the readiness score assesses the response to the load experienced previously, it follows that the players who experienced these spikes in TL would have had the greatest fluctuation in readiness scores. Overall, the results for the second hypothesis confirm the FF90 readiness score is sensitive to fluctuations in internal TL.

The higher correlation observed between readiness and TRIMP, compared to readiness and sRPE, could be due to both the readiness survey and sRPE being subjective measures. While the results of the first hypothesis test validated the FF90 sRPE as a measure of internal TL, there are still non-training related factors which can impact sRPE. Session-RPE is a global measure of TL (Gaudino et al., 2015; Impellizzeri et al., 2004) which accounts for physiological and psychological factors, thus a player's sRPE may be different based on their mood or level of stress outside of training (e.g. academic test, personal confrontation), which could cause it to differentiate from the TRIMP. Heart rate, on the other hand, is an objective measurement and is more likely to be affected by external variables such as temperature and humidity, which can be taken into consideration and assessed objectively, compared to psychological stress. While the differences in correlations between sRPE and TRIMP with readiness were negligible, the total variance explained by either was minimal ($r^2 = .088$ and .111, respectively). This suggests that while the correlations were significant, there are many other factors influencing the readiness score in these athletes.

The strongest negative correlation was observed in group 4, which played the most minutes during the season, and suggests the readiness score is more sensitive to spikes in internal TL. Games often account for the greatest internal TL for those who play the majority of the minutes (Thorpe et al., 2015, 2016), and can result in an extended recovery process, which can take more than 72 hours (Dobbin et al., 2016; Nédélec et al., 2012). Thorpe et al. (2016) found soccer player’s subjective ratings of fatigue, sleep quality, and soreness decreased between 35-40% between the day before a match to the day after. Each day following the match showed slight incremental increases, with the largest being between one and two days post-match. In a separate study by Thorpe et al. (2015), subjective fatigue had a large correlation ($r = -.51$) with total high intensity distance (an external TL measure obtained through GPS units), during training and match play. Both of these studies reported the match day as the highest TL experienced by the players, followed by the worst perceptions of fatigue. While the subjective measure in this study was a single score comprised of six sub-scales (fatigue, soreness, stress, mood, sleep quality, and sleep duration), the correlations between the readiness score and internal TL for the players in group 4 reflect those found in these two previous studies. This would also explain the weaker correlation observed in the groups which did not accumulate as many minutes over the course of the season. A recent study by Pelka, Schneider, and Kellmann (2017) had similar findings to the present study, with players who played more than 60 minutes during matches experiencing greater fluctuations in subjective physical measures and psychological measures than players who played less than 60 minutes, providing further support for the results of the present study.

In addition to the number of minutes played, the amount of experience using subjective forms of monitoring may impact the relationship between readiness and internal TL. Many athletes have limited experience with athlete monitoring programs, particularly SWQs, as they have become prevalent in professional practice in recent years (Buchheit et al., 2013; Thorpe et al., 2015, 2016). Anecdotally, this learning curve was observed in the current study between two freshman players. The correlation between readiness and internal TL for one athlete was r = -.578 (p = .000) for sRPE and -.570 (p = .000) for TRIMP, while the other athlete had a correlation of r = .095 (p = .507) and .096 (p = .447) for sRPE and TRIMP, respectively. The first athlete was familiar with the FF90 athlete monitoring platform, having used it at his youth club for the previous two years. The second athlete, however, had not participated in any form of athlete monitoring prior to the start of his freshman season. While these two examples are extremes, and not necessarily indicative of all cases, it does emphasize the importance of clearly explaining the proper use of subjective measures and the potential for a period of adjustment to the subjective forms of monitoring. Similarly, the majority of the players in group 4 were either returning players or older, which could also affect the strength of correlation seen in this group. Inclusion of an acclimation period to the subjective monitoring prior to the start of the season would have been ideal, however this is not always feasible in college soccer because freshman and transfer athletes often do not participate in formal training prior to the start of preseason.

5.3 Fit for 90 Readiness Score and Cumulative Minutes Played

The FF90 readiness score had a slightly negative correlation with cumulative minutes played (r = -.231) calculated each Monday over the season. This result confirms the hypothesis and suggests that as a player accumulated more minutes throughout the season their readiness score was slightly suppressed each subsequent week. This result may be misleading, because the results are inconsistent when data are split into groups based on total minutes played. Group 1 had a positive correlation (r = .491, *p* = .00), which would be appropriate as these players played less than 10 minutes during the season. However, almost no correlation was observed in group 3 (r = .014, *p* = .91) who played the second most minutes of the four groups, ranging from 500 and 900 minutes during the season. The results for group 2 and 4 both showed negative correlations, but were similarly confusing, since group 2 (r = -.328, *p* = .00) had a stronger correlation, which was significant, than group 4 (r = -.178, *p* = .08).

This is one of the first studies to examine the longer-term effects of minutes played and changes in response to a SWQ, and the first to examine it in NCAA Division I men's soccer. As discussed previously, the collegiate season has a congested game schedule, playing between 18 to 20 games in a period of 12 to 13 weeks, which may potentially lead to injury (Dupont et al., 2010). Research in the AFL has investigated the use of SWQ over an entire season (Gastin et al., 2013), but only examining the sensitivity of the SWQ to daily and weekly loads, and not potential changes over the entire season.

The most similar research to the current study was by Rollo et al (Rollo et al., 2014), which examined changes in physical performance and subjective wellness measures over a six week period. However, the two groups used in this study were comprised of 15 total players, meaning that most of the participants played a significant portion of the game minutes. The lack of research relating specifically to this hypothesis made it difficult to choose the best way to proceed with the analysis, which may be one potential cause of the inconsistent findings. Other causes could be the day chosen for analysis between weeks and the individual differences in approach to the readiness score.

There were three main reasons for choosing Monday as the day for comparison of cumulative minutes and readiness score, 1) no games were scheduled for Mondays, 2) it was most often preceded by an off day on Sunday (except for two weeks), and 3) it was normally the third day after game and readiness scores would have been less affected by potential acute effects of a game. Retrospectively, this may not have been the best method of assessing changes throughout the season, since some weeks included only a single game while others included multiple games. While Rollo et al. (2014) found subjective wellness measures were unaffected by multiple games per week over an extended period of time, the days on which games were played was consistent throughout the study (Wednesday and Saturday) and the subjective survey used (REST-Q) was implemented each Monday over a six week period.

The use of cumulative minutes played may also have been a contributing factor to the inconsistent results because of significant fluctuations in playing time throughout the season for some players. For example, some players in group 3 could have played significant minutes for the first 3 or 4 weeks and then gone several weeks without playing at all due to injury or poor form which could have caused the variable results observed in this group. Use of the cumulative internal TL on each Monday would have been a better measure to compare to the readiness score. Using the cumulative internal TL may have been a more consistent measure across the season, or provided greater insight into weekly variations (Gastin et al., 2013).

Finally, the differences in approach between individuals could have affected the relationship between the readiness score and cumulative minutes. Not only might there be a learning curve to using subjective forms of monitoring, but athletes may have different approaches to using the survey. Some individuals may utilize the full range of the -3 to +3 scale for the readiness questions, which would lead to a greater range of overall readiness scores, while others may be less prone to submit extreme responses. Some research has standardized SWQ responses into z-scores to account for these differences between individuals (Gallo et al., 2016), however, the use of z-scores did not seem appropriate since the subscales involved in determining the readiness score were not individually investigated. While there are several potential flaws in the analysis worth noting, the results of the correlation did support the hypothesis. More research is needed on the long-term changes in readiness and how they relate to changes in performance, but the current results suggest players' perceived readiness decreased as they played a greater number of minutes.

5.4 Limitations

As with all research, there are limitations to the current study. The subjective nature of the sRPE and readiness monitoring is a limitation because responses may be biased. Most players' primary concern is whether they are playing in matches, and this could lead some athletes to respond to the subjective measures in a way they may think makes them look more favorable for selection in the game. Particularly for the wellness survey, athletes may feel as though submitting a high level of soreness or fatigue may affect the coach's decision to select that player for the game. Individuals may also seek to make themselves look more fit by submitting a lower sRPE for a training session or match, even though this may suggest to the coach the individual was not working hard enough. Additionally, the subjects included in this study were college athletes with academic obligations that could have impacted several of these factors. High academic stress has been shown to be related to increased injury and it is possible reduced sleep and increased stress were some of the causes for the increased injury rate during this period (Mann, Bryant, Johnstone, Ivey, & Sayers, 2016). These limitations suggest the importance of understanding the personalities of the players, and reminding the athletes to submit honest responses to all subjective monitoring. In addition, it is important for athletes to understand that these subjective measures are only tools that can guide decisions, but no strict rules exist for using them.

The study did not account for uncontrollable factors that may have affected the relationship between sRPE and TRIMP over the season. External variables such as the temperature, humidity, or weather conditions could have altered the HR response during the season. Changes in fitness may have also occurred, which may have impacted the sRPE and TRIMP relationship. An increase in fitness may allow a player to work at a higher HR for a longer period of time, which would result in a higher TRIMP score, but the athlete may not report an increased sRPE. Also, match related variables have been shown to affect TL in soccer players, thus the result of the games (win vs. loss) could have impacted the players perception of effort for the match and training the following week (Brito et al., 2016).

Another limitation is sRPE was only correlated to one TRIMP equation, instead of using multiple TRIMP equations. To confirm the findings in the current study, sRPE from the FF90 program should be assessed against other TRIMP equations. As discussed earlier, Banister's TRIMP equation was experimentally derived based on the HR and [La] relationship, however, Akubat and Abt (2011) contend this method of calculating TRIMP may underestimate the overall internal TL because it utilizes the average HR for an entire session, and does not account for spikes in intensity. These authors suggest that Edward's TRIMP equation is more reliable because it is not based on blood [La], despite the fact that the zonal weightings were arbitrarily assigned. Some researchers argue for the use of [La] monitoring in soccer (Eniseler, 2005; Impellizzeri, Rampinini, & Marcora, 2005), yet several of the studies utilized as evidence for this argument have not examined the changes in [La] during intermittent sports (Akubat & Abt, 2011) or have concluded HR and [La] should be measured in conjunction with one another for optimal effectiveness of [La] information (Coutts, Rampinini, Marcora, Castagna, & Impellizzeri, 2009).

The lack of external TL measures, such as THIR or accelerations, is also a limitation of the current study. Recently, measurement of external TL has become more prevalent in professional practice because of the development of wearable devices such as GPS and/or accelerometer instruments. These devices can easily provide information for numerous external TL measures, such as total distance, running speeds, impacts, accelerations, decelerations, and several others which can help coaches and sports scientists analyze the impact of games and training on athletes (Buchheit et al., 2013; Gaudino et al., 2015; Thorpe et al., 2015). Recent research has investigated the relationship between some of these external TL measures and both Foster's sRPE and SWQs. The addition of some of the external TL measures, particularly total distance, THIR, accelerations, and impacts, in the first and second hypotheses could have improved the generalizability of the findings of the present study.

The external TL measure could also be used to assess the potential match related changes in performance over the course of the season. As discussed previously, assessing potential changes in fitness levels through analysis of HR information is challenging because several variables must be taken into account (Buchheit et al., 2012), especially across the course of a season when temperature and humidity levels may be significantly different (Alexandre et al., 2012). The external TL measures are more easily interpreted and less sensitive to environmental changes, making them a more effective measure of changes in performance (Buchheit et al., 2013). Unfortunately, these devices were not available for inclusion in this study, because the team could not afford the units for the entire team.

Finally, the present study did not investigate the relation of the subscales of the readiness score with either internal TL or cumulative minute played. Most research to this point has examined the relationship between TL and subscales of wellness such as soreness, fatigue, stress or mood (Saw et al., 2016; Thorpe et al., 2015). Research has investigated the summation of wellness subscales (Buchheit et al., 2013), but it is possible the one of the subscales of the readiness score had a stronger correlations with internal TL or minutes played.

5.5 Practical Applications

The findings of the present study show the FF90 athlete monitoring platform is an effective form of subjective monitoring for team environments. Key benefits to subjective monitoring are its non-invasive nature, minimal expense, and limited expertise needed to understand the information (Impellizzeri et al., 2004; Saw et al., 2015, 2016; Thorpe et al., 2015, 2016). The modified sRPE used in the current study appears to be a reliable and valid form of tracking global TL and can be used in isolation, or alongside an objective form of monitoring such as HR. The use of HR may take additional expertise beyond that needed to interpret sRPE data, but it can be a useful tool when used in conjunction with sRPE (Alexandre et al., 2012). The TL data obtained from either sRPE or HR can be used by coaches and sports scientists to; 1) understand the impact of training on players (Foster, Carl, Kara, Esten, & Brice, 2001; Little & Williams, 2007), 2) periodize training methods (Moreira et al., 2015; Suzuki, Sato, Maeda, & Takahashi, 2006; Thorpe et al., 2015, 2016), 3) monitor an individual’s level of fitness or overtraining (Foster, 1998;

Foster, Florhaug, et al., 2001; Gabbett, 2016), 4) and develop return to play strategies (Blanch & Gabbett, 2016).

The FF90 readiness score can also be used to assess overall well-being of the athletes and how they respond to training methods and other external variables which may not be readily considered, particularly sleeping habits. Several sport-related factors and academic obligations may impact an individual's sleep which can negatively impact the recovery process (Fullagar et al., 2016; Mann et al., 2016). The readiness score can provide coaches additional insight into sleep habits, which may guide conversations with players to improve the quality of recovery. It is possible that the readiness score could provide insight to improvements in fitness levels, or potentially negative effects such as over-training; however, more research is needed to investigate these applications.

5.6 Future Research

Future research can build on the topics in the present study, particularly the practical application of the readiness score. A few simple directions for future research would be the examination of the relationship between the FF90 sRPE and Edward's TRIMP, because it may account for the intermittent nature of soccer better than Banister's TRIMP (Akubat & Abt, 2011). Also, the data could be split between training sessions and games to determine if the strength of the correlation between sRPE and TRIMP, or readiness and internal TL, is different between the two settings.

Two future topics of research on the use of the readiness score could be determining if there is a threshold in a player's readiness that increases risk of injury and the proactive use of the readiness score. Changes in the variability of a player's readiness score could signify a change in their adaptability to the load. Additionally, proactive use of the readiness score could improve the individualization of TLs for athletes. The findings of Gallo et al. (2016) suggest there is a correlation between perceived wellness and performance in training on the same day, thus it may be appropriate to alter TL for athletes based on their readiness score. This would be a favorable alternative to the reactive approach of the acute:chronic ratio (Hulin et al., 2014) and training monotony and strain (Foster, 1998).

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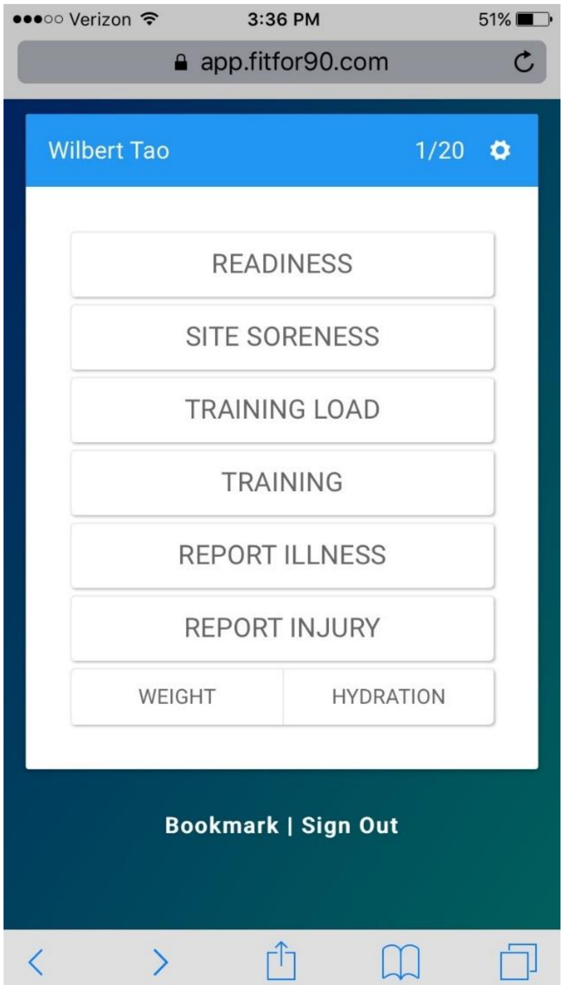
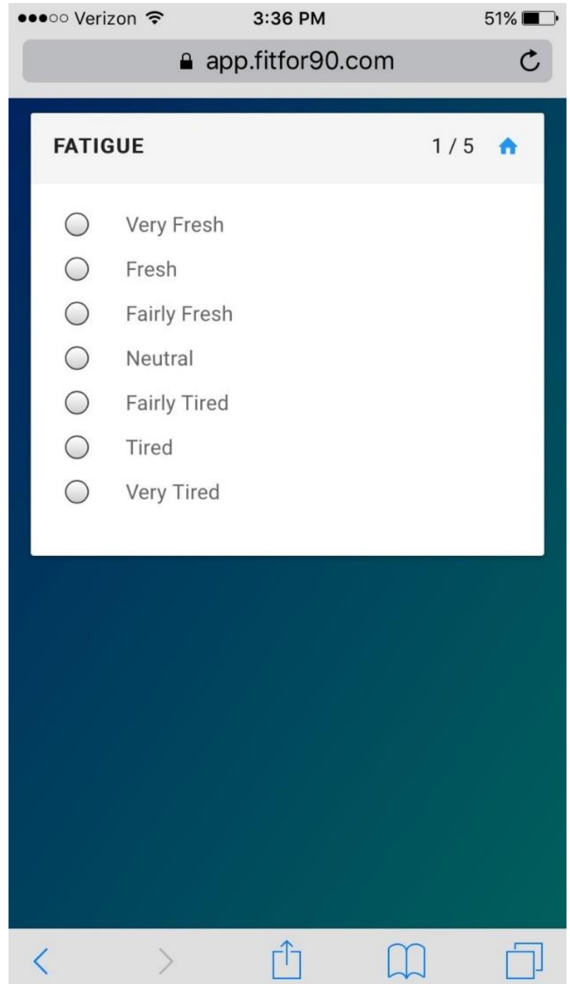
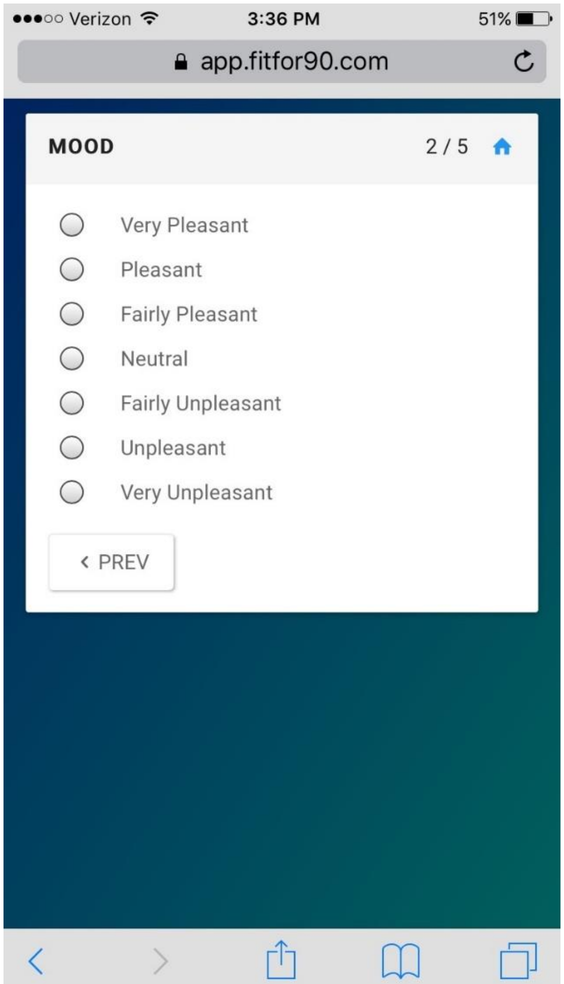
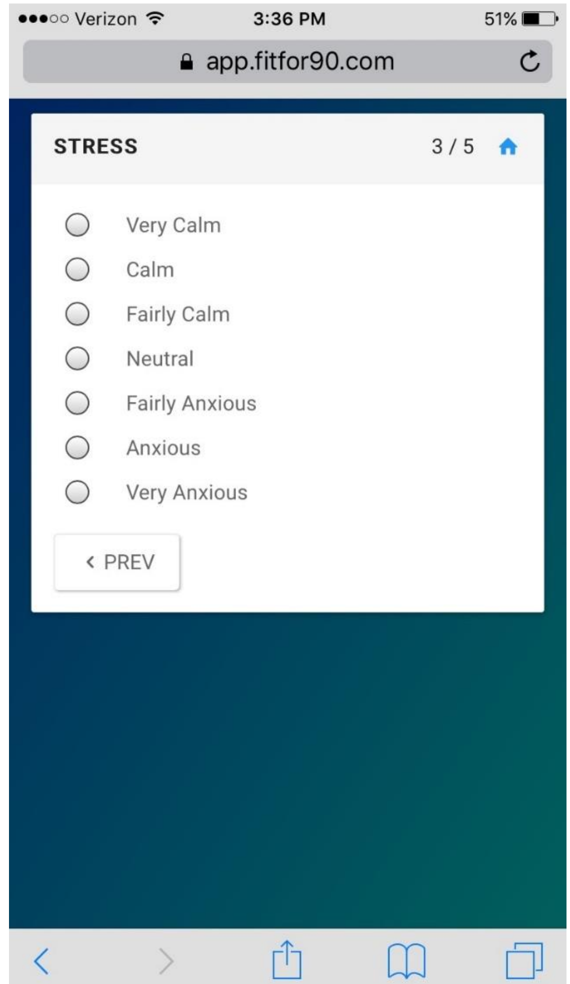
APPENDIX A

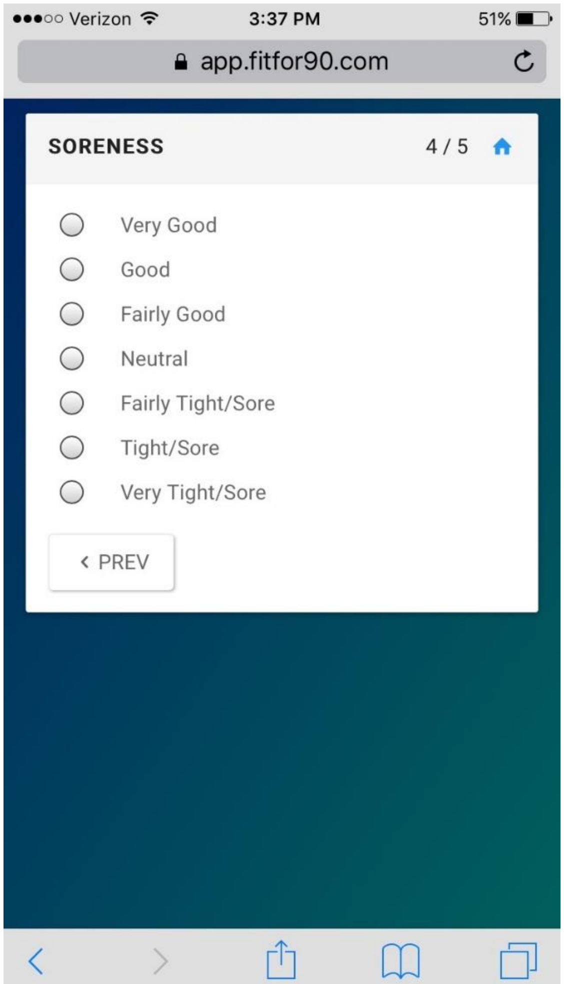
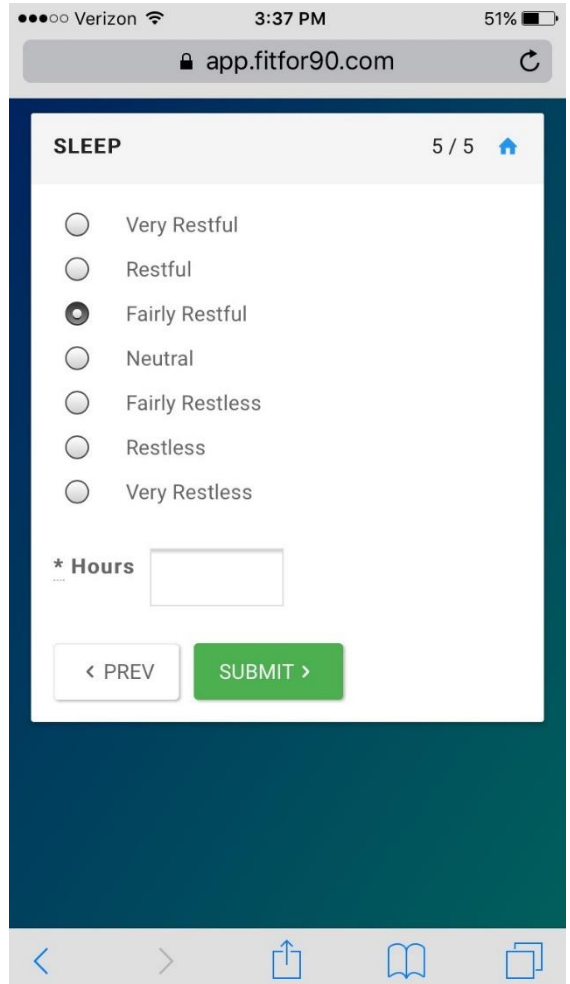
FIT FOR 90 READINESS SURVEY SCREENSHOTS


●●●○○ Verizon
3:36 PM
51%
app.fitfor90.com
Wilbert Tao
1/20
READINESS
SITE SORENESS
TRAINING LOAD
TRAINING
REPORT ILLNESS
REPORT INJURY
WEIGHT
HYDRATION
Bookmark | Sign Out


●●●○○ Verizon
3:36 PM
51%
app.fitfor90.com
FATIGUE
1 / 5
Very Fresh
Fresh
Fairly Fresh
Neutral
Fairly Tired
Tired
Very Tired

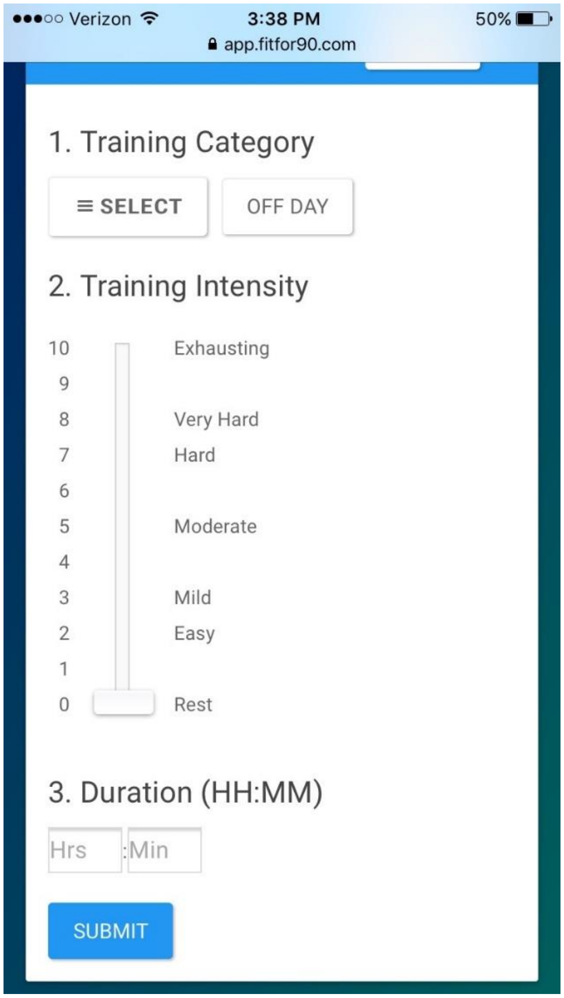

●●●○○ Verizon
3:36 PM
51%
app.fitfor90.com
MOOD
2 / 5
Very Pleasant
Pleasant
Fairly Pleasant
Neutral
Fairly Unpleasant
Unpleasant
Very Unpleasant
PREV


●●●○○ Verizon
3:36 PM
51%
app.fitfor90.com
STRESS
3 / 5
Very Calm
Calm
Fairly Calm
Neutral
Fairly Anxious
Anxious
Very Anxious
PREV


●●●○○ Verizon
3:37 PM
51%
app.fitfor90.com
SORENESS
4 / 5
Very Good
Good
Fairly Good
Neutral
Fairly Tight/Sore
Tight/Sore
Very Tight/Sore
PREV

●●●○○ Verizon
3:37 PM
51%
app.fitfor90.com
SLEEP
5 / 5
Very Restful
Restful
Fairly Restful
Neutral
Fairly Restless
Restless
Very Restless
* Hours
PREV
SUBMIT

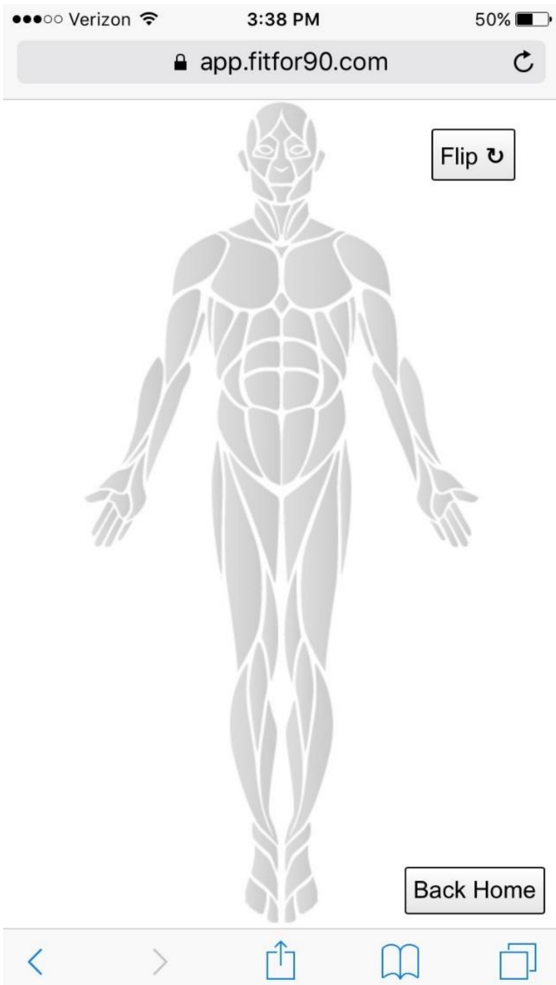
APPENDIX B

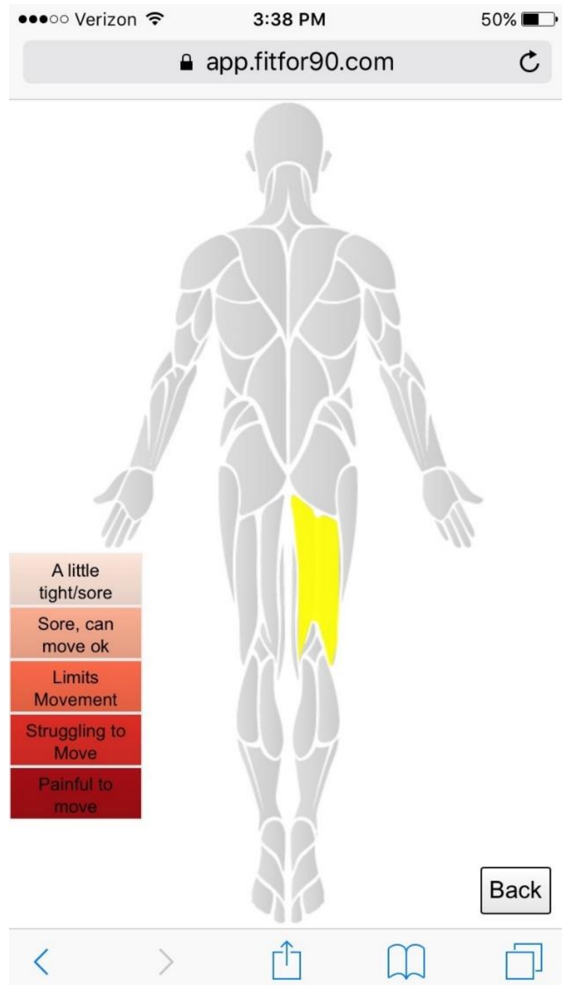
FIT FOR 90 SESSION-RPE SCREENSHOT

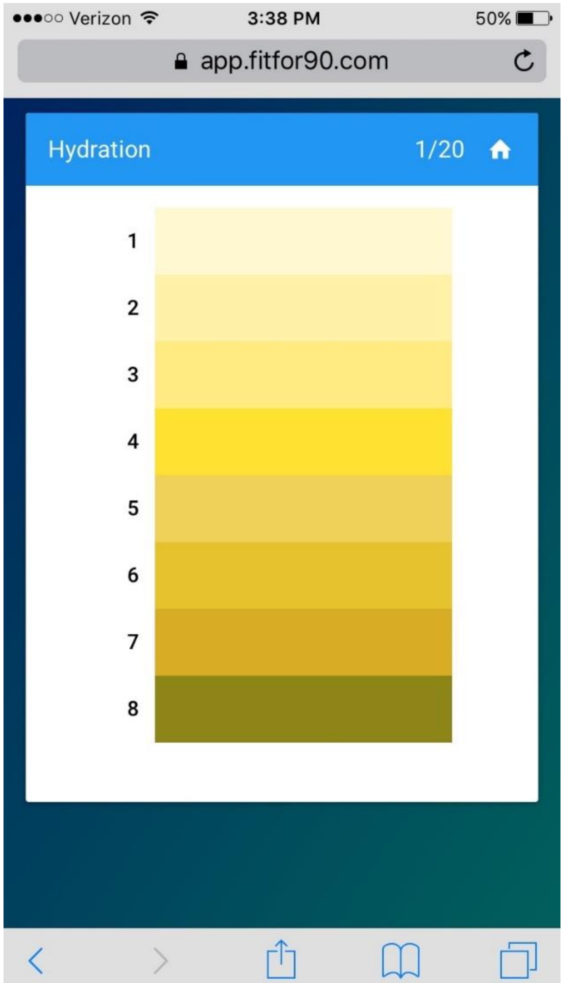

●●●○○ Verizon
3:38 PM
50%
app.fitfor90.com
1. Training Category
≡ SELECT
OFF DAY
2. Training Intensity
10 Exhausting
9
8 Very Hard
7 Hard
6
5 Moderate
4
3 Mild
2 Easy
1
0 Rest
3. Duration (HH:MM)
Hrs
:Min
SUBMIT

APPENDIX C

FIT FOR 90 ADDITIONAL MONITORING SCREENSHOTS

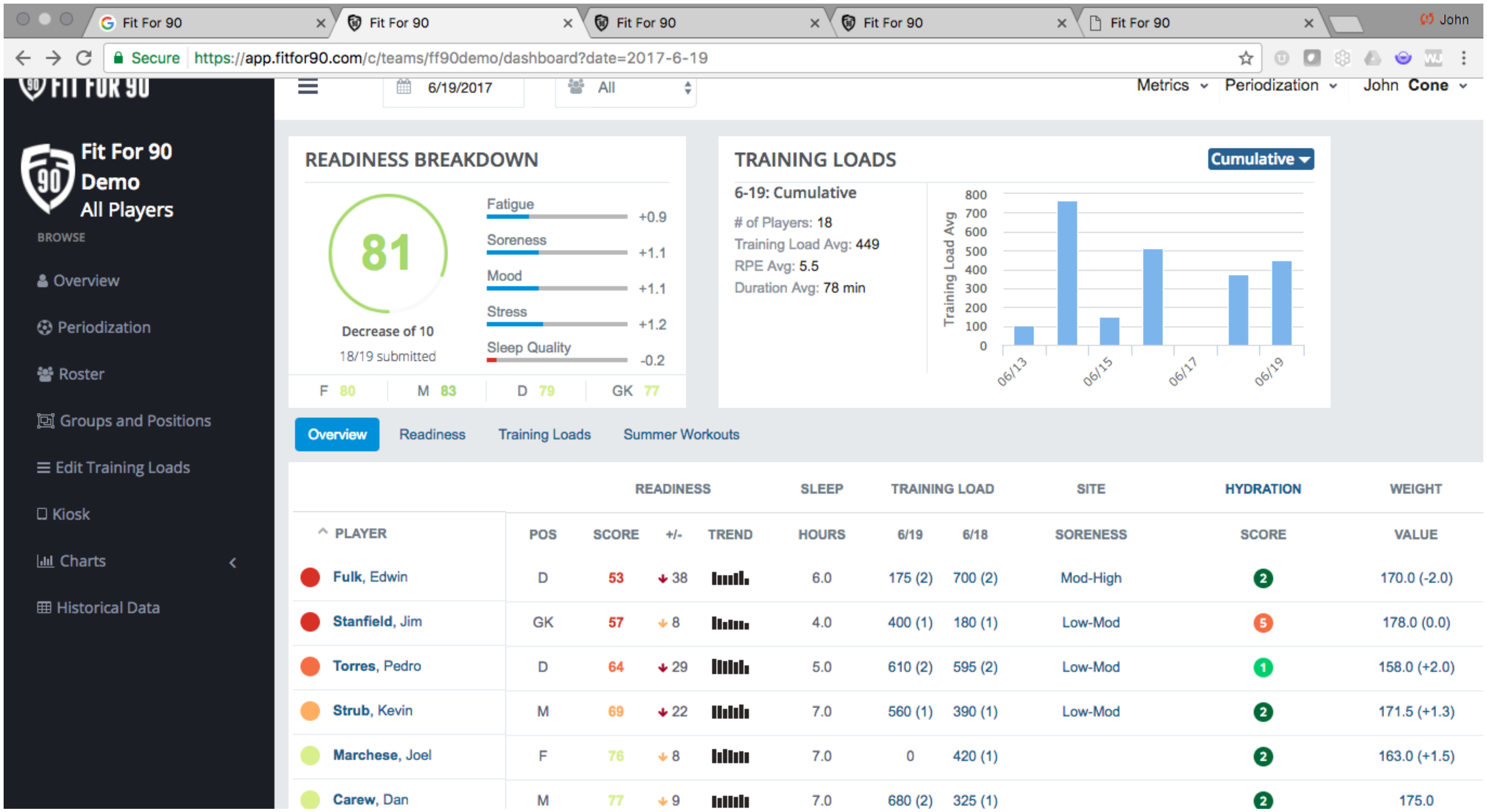

●●●○○ Verizon
3:38 PM
50%
app.fitfor90.com
Flip ↻
Back Home

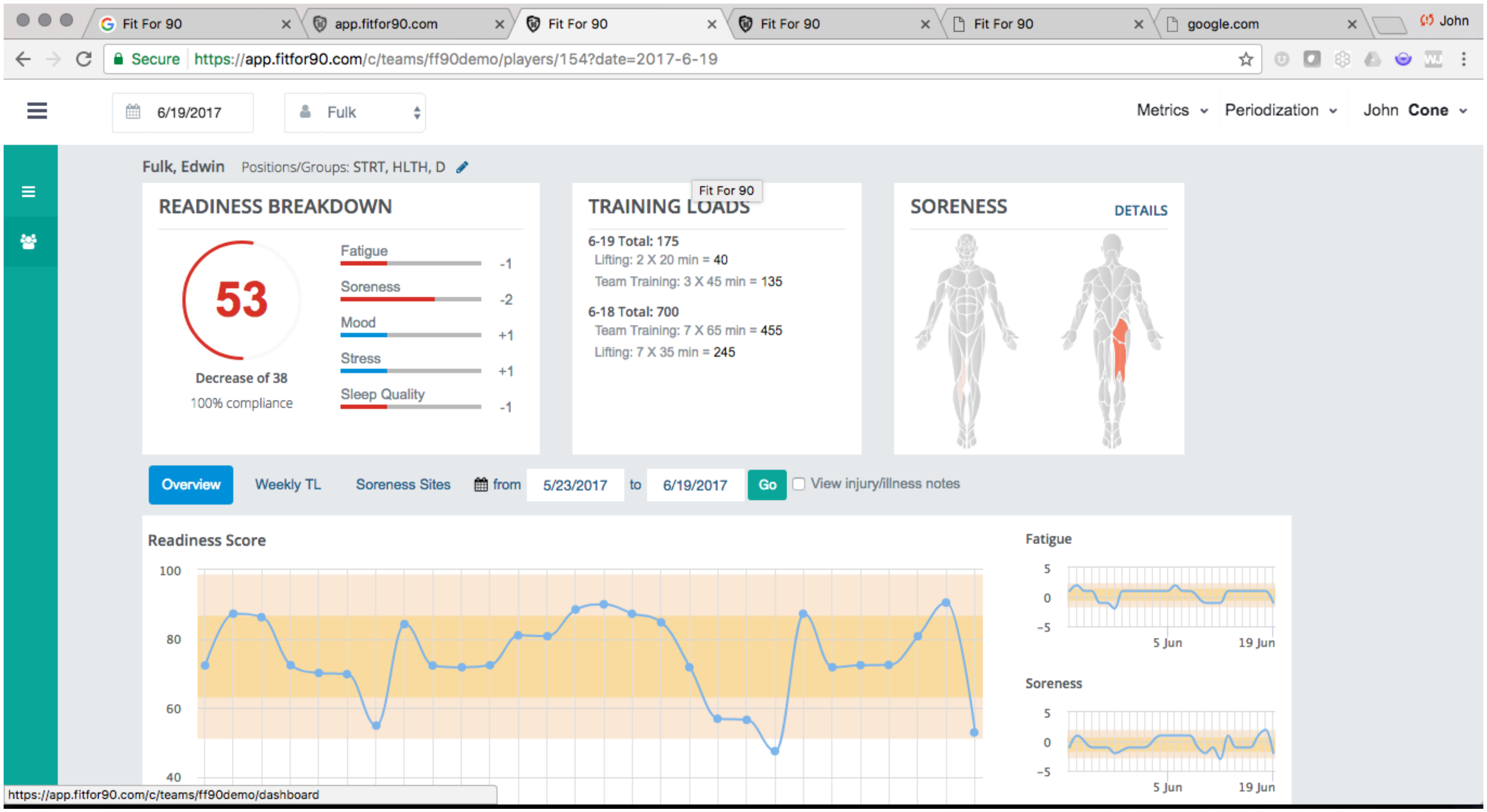

●●●○○ Verizon
3:38 PM
50%
app.fitfor90.com
A little tight/sore
Sore, can move ok
Limits Movement
Struggling to Move
Painful to move
Back

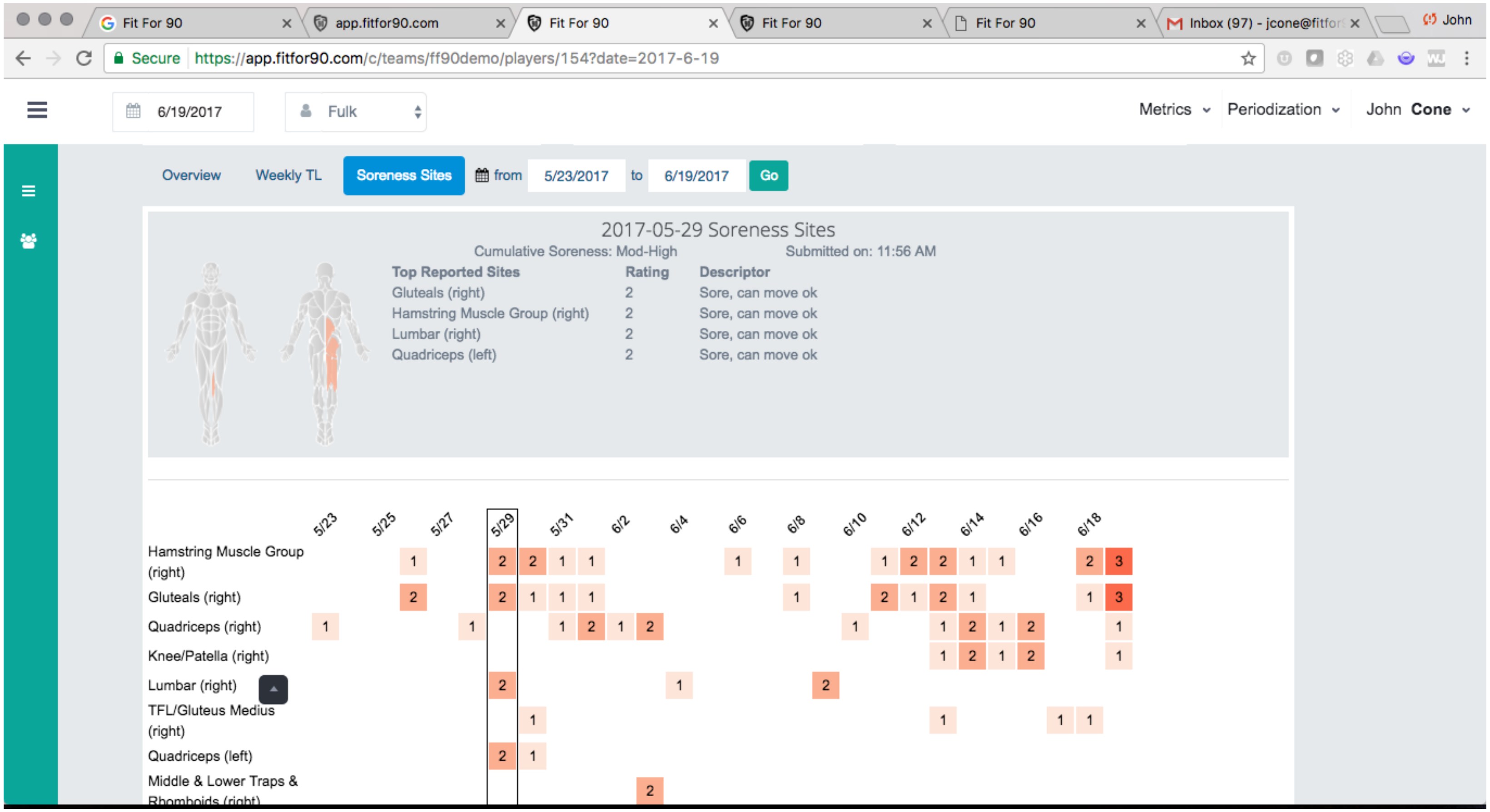

●●●○○ Verizon
3:38 PM
50%
app.fitfor90.com
Hydration
1/20
1
2
3
4
5
6
7
8

APPENDIX D

FIT FOR 90 COACHING DASHBOARD SCREENSHOTS


Fit For 90
Secure https://app.fitfor90.com/c/teams/ff90demo/dashboard?date=2017-6-19
6/19/2017
All
Metrics
Periodization
John Cone
Fit For 90 Demo All Players
BROWSE
Overview
Periodization
Roster
Groups and Positions
Edit Training Loads
Kiosk
Charts
Historical Data
READINESS BREAKDOWN
81
Decrease of 10
18/19 submitted
Fatigue +0.9
Soreness +1.1
Mood +1.1
Stress +1.2
Sleep Quality -0.2
F 80
M 83
D 79
GK 77
TRAINING LOADS
Cumulative
6-19: Cumulative
# of Players: 18
Training Load Avg: 449
RPE Avg: 5.5
Duration Avg: 78 min
Training Load Avg
06/13
06/15
06/17
06/19
Overview
Readiness
Training Loads
Summer Workouts
READINESS
SLEEP
TRAINING LOAD
SITE
HYDRATION
WEIGHT
PLAYER
POS
SCORE
+/-
TREND
HOURS
6/19
6/18
SORENESS
SCORE
VALUE
Fulk, Edwin D 53 38 6.0 175 (2) 700 (2) Mod-High 2 170.0 (-2.0)
Stanfield, Jim GK 57 8 4.0 400 (1) 180 (1) Low-Mod 5 178.0 (0.0)
Torres, Pedro D 64 29 5.0 610 (2) 595 (2) Low-Mod 1 158.0 (+2.0)
Strub, Kevin M 69 22 7.0 560 (1) 390 (1) Low-Mod 2 171.5 (+1.3)
Marchese, Joel F 76 8 7.0 0 420 (1) 2 163.0 (+1.5)
Carew, Dan M 77 9 7.0 680 (2) 325 (1) 2 175.0


Fit For 90
app.fitfor90.com
Fit For 90
Fit For 90
Fit For 90
google.com
John
Secure
https://app.fitfor90.com/c/teams/ff90demo/players/154?date=2017-6-19
6/19/2017
Fulk
Metrics
Periodization
John Cone
Fulk, Edwin
Positions/Groups: STRT, HLTH, D
READINESS BREAKDOWN
53
Decrease of 38
100% compliance
Fatigue -1
Soreness -2
Mood +1
Stress +1
Sleep Quality -1
TRAINING LOADS
Fit For 90
6-19 Total: 175
Lifting: 2 X 20 min = 40
Team Training: 3 X 45 min = 135
6-18 Total: 700
Team Training: 7 X 65 min = 455
Lifting: 7 X 35 min = 245
SORENESS
DETAILS
Overview
Weekly TL
Soreness Sites
from
5/23/2017
to
6/19/2017
Go
View injury/illness notes
Readiness Score
100
80
60
40
Fatigue
5
0
-5
5 Jun
19 Jun
Soreness
5
0
-5
5 Jun
19 Jun
https://app.fitfor90.com/c/teams/ff90demo/dashboard


Fit For 90
app.fitfor90.com
Fit For 90
Fit For 90
Fit For 90
Inbox (97) - jcone@fitfor
John
Secure
https://app.fitfor90.com/c/teams/ff90demo/players/154?date=2017-6-19
6/19/2017
Fulk
Metrics
Periodization
John Cone
Overview
Weekly TL
Soreness Sites
from
5/23/2017
to
6/19/2017
Go
2017-05-29 Soreness Sites
Cumulative Soreness: Mod-High
Submitted on: 11:56 AM
Top Reported Sites
Rating
Descriptor
Gluteals (right) 2 Sore, can move ok
Hamstring Muscle Group (right) 2 Sore, can move ok
Lumbar (right) 2 Sore, can move ok
Quadriceps (left) 2 Sore, can move ok
5/23
5/25
5/27
5/29
5/31
6/2
6/4
6/6
6/8
6/10
6/12
6/14
6/16
6/18
Hamstring Muscle Group (right)
Gluteals (right)
Quadriceps (right)
Knee/Patella (right)
Lumbar (right)
TFL/Gluteus Medius (right)
Quadriceps (left)
Middle & Lower Traps & Rhomboids (right)