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MONITORING RECOVERY IN AMERICAN FOOTBALL

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KEY POINTS

- Athlete monitoring can be a tool used to gauge and elevate players' responses to training to help the maintenance of maximal performance and minimize injury and/or illness risk.
- There are many tools for both internal and external load monitoring, however little research has been performed within the context of American football.
- Given that American football is a team sport made up of different positions requiring unique skillsets and game demands, the individualization of monitoring tools and/or techniques is critical.
- Data analysis and interpretation needs context, both in terms of training phase (e.g., preseason vs. in-season) and in determining meaningful changes in selected monitoring tools.
- When implemented effectively and with proper communication between players and performance staff, athlete monitoring may assist in maintaining season-long football player readiness.

INTRODUCTION

In an ideal world, American football (herein referenced as football) players arrive at each day of practice and competition feeling rested, powerful and ready to compete at their best. In reality, players exhibit both highs and lows in terms of psychological and physiological levels of preparedness, both for training and games. The purpose of this Sports Science Exchange (SSE) article is to define player monitoring by first discussing the different parameters associated with external and internal load assessments in football, and then discussing tools to monitor the player's recovery. Key applications specific to the football player will be shared with the aim of optimizing both their health and performance.

RESEARCH REVIEW

Athlete Monitoring

Monitoring and Recovery Landscape.

Load during activity may be defined as a stimulus experienced and responded to by an individual before, during or after participation in exercise (Herring et al., 2019). Football training load can be described as the input variable that is manipulated to elicit a desired training response and level of preparedness for the rigors of the competitive season (Gabbett et al., 2017; Halson, 2014a; Impellizzeri et al., 2005, 2019). External load is the prescribed work the player completes during training, practice and games while internal load is the player's psychological and physiological responses that occur while completing the external load. Typically, both psychological and physiological fatigue associated with the stressors of training, practice and competition can be compensated with recovery. Although the term "recovery" is often used in football, identifying a common consensus or appropriate integration of the term is often elusive.

Recovery is defined by the Oxford dictionary as 'a return to a normal state of health, mind or strength.' Therefore, recovery is a multifaceted restorative process necessary to return a player to physiological and psychological balance. In football, recovery can be used as an umbrella term referring to different behaviors (i.e., sleep and nutrition) and modalities (i.e., hydrotherapy, compression, massage, neuromuscular stimulation and many more) to restore/enhance player 'readiness' before training sessions and/or games.

For example, the time course of neuromuscular function and perceptual assessments varies considerably between 24 – 120 h post-game depending on the sport (rugby, Australian football and soccer), position and competitive level of the athlete (Cormack et al., 2008; Thorpe, 2018; Twist & Highton, 2013). Following a football game, players experience muscle damage (as measured by creatine kinase (CK) levels in the blood) (Kraemer et al., 2009), stress (as indicated by plasma cortisol concentrations) (Hoffman et al., 2002) and perceptual fatigue (Fullagar et al., 2017). Additionally, perceptions of wellness, including soreness, sleep and energy, have been shown to take longer than four days to return to pre-game levels in Division1 NCAA football players (Fullagar et al., 2017). Although the specific time course of neuromuscular function recovery following a football game has not been established to date, it is reasonable to assume this will be influenced by playing position, playing time and number of impacts experienced.

The practical implementation of player monitoring poses a challenge in football due to the multidimensional and complex structure of training and the game, the busy training (strength and conditioning as well as practice) and competition schedules, along with logistical issues such as the substantial number of players on the roster. Currently, there is very little sport science research and knowledge dissemination in football, especially compared to global sports such as soccer (i.e., global football) and basketball. Current available knowledge is skewed towards technical and tactical domains, leaving plenty of opportunity to better understand knowledge related to the sport science and sport medicine relationships to athletic performance and health (Gleason et al., 2023). The current literature that has assessed psychological and physiological responses to football has focused primarily on college players (Fullagar et al., 2017; Hoffman et al., 2002; Kraemer et al., 2009, 2013; Sterczala et al., 2014), with no research to date on professional football players. Our hypothesis is that mitigating psychophysiological disturbances is also relevant during the professional season, in maintaining performance, health and general player wellbeing.

The external load applied to a player during training and throughout the season is designed to elicit a desired effect on player performance and well-being, culminating in high-level athletic performances across the season. The external load the player has completed (i.e., strength and conditioning, practice, training and games) induces varying degrees of physiological and psychological fatigue. In general, the greater the fatigue experienced, the greater the "recovery" required. This load and recovery continuum will depend on the activity and the individual responses. Therefore, characterizing the external load imposed on a player is important to understand the stressors of the season while monitoring the individual internal load helps identify how an athlete is coping with those stressors. Improper recovery may lead to reduced performance and impaired player health. Performance, physiological, biochemical and subjective measures are all options for player monitoring. Nevertheless, understanding which measures are most appropriate in any given football-specific circumstance remains to be determined (Coutts & Cormack, 2014; Saw et al., 2016).

External Load Monitoring.

External loads are those factors that cause a player physical stress. From a football perspective, these are activities performed during training and games. There are two types of physical stressors, external load and internal load. External load can be divided into controllable (training, practice, etc.) and uncontrollable (games) variables. This measurement is the foundation of any player monitoring program and should be conducted independently of the players internal load characteristics and performance/subjective assessments (Halson, 2014a).

In principle, for a coach to prescribe an appropriate external load, they should understand the current workload the player is exposed to during practice and games (Gabbett et al., 2017). The type of external load measurement chosen needs to be specific to the individual as certain measurements may not apply to every position on the football field. For instance, monitoring the throw count would not be appropriate for a lineman considering their position does not require that type of movement or workload. Instead, choosing position-specific metrics for the lineman, such as contacts (hits) and/or contact load (G-forces (Gs)), will provide more appropriate and meaningful information. It is important to note that markers of external load should be monitored against position-specific and individual performance indicators. This will allow the evaluation of how the "load" is impacting performance, which can then be modified accordingly. How the load is managed will depend on many factors including the players individual goals, injury history and time of the season. The following section will discuss internal load variables that are applicable to football.

Time. The total amount of time an athlete spends training, practicing and competing can be captured across days, weeks and months to illustrate total physical exertion. If possible, it is important to capture all training sessions, whether in the weight room or on the practice/ game field, and to be as exact as possible. The time spent training can also be utilized to support capturing session ratings of perceived exertion (RPE) (see below in internal load for more information). Time is a low-cost, reliable and accurate assessment of training stressors that is easily interpreted by all parties. During periods of big changes in training principles, such as frequency and total time, such as the beginning of training camp, it is important to consider the previous training load implications of the players to determine their training load readiness and time can be a relatively easy metric to gauge total training hours without advanced technology.

Training Frequency. Similar to time, training frequency can be a low-cost, easily implemented assessment of an athlete's external training load. Training frequency can be captured by assessing the number of sessions where an athlete physically exerted themselves, including strength training, speed training, plyometrics, skill training, practice and competition. As with time, understanding the implications of large increases in training frequency for athlete adaptations, health and performance is an important consideration for programming training stimulus.

Global Positioning Systems (GPS) Metrics. The use of micro technologies such as accelerometers, global positioning systems (GPS) and radio-frequency identification (RFID) chips and the associated commercialization of the hardware and software necessary to support tracking sport specific training, have increased the ability to describe activity profiles of various multi-dimensional field sports, including football. The use of these technologies provides greater insight into the sport-specific requirements and can aid in the design of specific training programs (Torres-Ronda et al., 2016). However, careful consideration should be applied when utilizing GPS metrics as the demands of the game vary greatly across positions. Currently, only one GPS research study has been performed in the NFL, albeit during training camp (Ward et al., 2018), and a few others have been conducted at the collegiate level (Bayliff et al., 2019; Flatt et al., 2020; Sanders et al., 2017; Wellman et al., 2016) Below, we discuss a few of the key metrics that can be captured utilizing GPS technologies and their implications for monitoring football players.

Total distance is a relatively easy to interpret metric and can be utilized as a measure of training volume in field-based team sports (Akenhead & Nassis, 2016). However, capturing this data in the context of football requires GPS or RFID technology. Differences in total distance covered and high-speed running distance (HSD: defined as distances run above 70% of the maximum speed for the respective position group and typically established using all available training data from previous training sessions) between positions has been well documented (Ward et al., 2018). However, to date, there remains to be well established normative data for the volume of distance covered to optimize football performance for any position. As would be expected, skill positions such as wide receiver and defensive back, who typically play in the open spaces of the football field, have been observed to have a higher amount of running distance and sprints during a season compared with all other positions, and non-linemen have a greater amount of running distance compared to lineman (Wellman et al., 2016). Although non-linemen travel greater distance than lineman during a game, the responsibility of linemen creates a more static stance at the beginning of the play. The shorter starting difference between defensive and offensive linemen results in greater and more frequent impact forces than non-linemen (Ward et al. 2018). These starting points allow for shorter running distances with greater acceleration and deceleration followed by quick change of direction (Wellman et al., 2016). The volume of HSD across position groups will vary based on training and tactical decisions across teams and organizations, such as tempo and style of play (Ward et al., 2018). Quantifying and prescribing training demands specific to the team dynamics is an important consideration when applying these advanced technologies and capabilities in any sport organization.

Internal Load Monitoring.

The internal load represents the relative physiological and psychological stress experienced as a result of practice and games (Halson, 2014a). This measurement is important in order to understand how the player responds to the external load as well as training load and subsequent adaptation (Halson, 2014a). Therefore, internal load is most valuable when it is paired with external load. This allows staff to accurately recognize and intervene when players are fatigued or not coping with the demands of training and games. Monitoring both the internal and external load between players also makes it possible to separate the fresh versus fatigued football players on a team (Halson, 2014a). For example, identical external training loads could elicit different internal loads in two different players even with similar physical characteristics. The following section will discuss internal load variables that are applicable to football.

Rating of Perceived Exertion (RPE). The RPE, initially created by Gunnar Borg (Borg, 1962), can be used to determine the perceived effort during or after training, based on the notion that the player can monitor their own physiological stress due to afferent and efferent sensory signals. Foster and colleagues (2001) proposed a method to monitor training load through a combined subjective and objective methodology, known as session rating of perceived exertion (sRPE). The sRPE assesses the internal load of the player by subjectively classifying the intensity of the entire training session or practice. Thus, following the completion of training, practice or a game, a player can rate 'how hard the session was' on a scale from 0-10 (Borg CR-10 scale). This value is then multiplied by the duration of the session in minutes. For example, if practice was 120 min in duration and the player rated the practice a 5, the sRPE training load is calculated as:

$$\text{Training Load (Arbitrary Units, A.U.)} = 5 \text{ (sRPE)} \times 120 \text{ (duration)} = 600 \text{ A.U.}$$

Two recent reviews sought to determine the validity and ecological validity of utilizing sRPE to monitor training load (Haddad et al., 2017; McLaren et al., 2018). The reviews confirmed the validity, reliability and internal consistency of sRPE across several sport domains and populations (men, women, children, adolescents, adults, elite athletes, etc.). A meta-analysis by McLaren et al. (2018) identified 10,418 individual session observations across varying team-sports and found correlation coefficients between sRPE and total distance, accelerometer load and collision impacts to be r = 0.79, 0.63 and 0.57, respectively. The validity of sRPE as a monitoring tool has also been established in soccer (Alexiou & Coutts, 2008; Impellizzeri et al., 2004), rugby (Lovell et al., 2013), Canadian football (Clarke et al., 2013), Australian Rules football (Scott et al., 2013), resistance training (Day et al., 2004), interval training (Minganti et al., 2011) and conditioning (Alexiou & Coutts, 2008; Lovell et al., 2013). However, to date, the validity and reliability of sRPE has not been established in football.

Given the low cost, ease of administration, lack of time commitment from individual players and previously established validity and reliability across sports and training domains, it is reasonable to suggest that sRPE would be a reliable internal load monitoring tool for football and further research should aim to confirm this. Until this research is completed, sRPE could be paired with other physiological parameters, such as heart rate, to provide a well-rounded internal training load monitoring program for football.

Heart Rate.

Monitoring heart rate (HR) is one of the most common methods of assessing the internal load in athletes. A linear relationship between HR and the rate of oxygen consumption during steady-state exercise provides the basis for utilizing HR as a valid means to understand the cardiovascular stress (i.e., internal load) endured by the athlete during exercise (Hopkins, 1991). Specifically, the HR response is directly associated with exercise intensity. It is important to consider and control for factors such as hydration, environment and medication when using HR as a means of monitoring internal load (Bagger et al., 2003). Nevertheless, through consistent measurement, a player's HR can provide insight into their training status. For example, during standardized exercise protocols an "uncharacteristically" high HR may indicate an impaired training status or a state of under-recovery. Therefore, obtaining and understanding the baseline HR profile of the player is critical for subsequent internal load interpretation, as is annual measurement of a true HR maximum (versus prediction from 220-age). As with all monitoring, athlete context is an important consideration and emotional excitability related to practice or competition may independently elevate HR.

Heart Rate Variability. Resting heart rate variability (HRV) is a metric that has gained popularity to monitor recovery status in team sports. Resting HRV is a noninvasive indicator of autonomic modulation of the heart, reflecting cardiovascular recovery after a training session (Stanley et al., 2013) and has been suggested to indicate both positive and negative adaptations to training (Plews et al., 2013). Appropriate methodological approaches to monitoring, including longitudinal tracking of responses to training, taper and competition, are critical (Halson, 2014a) due to the high day-to-day variability caused by environmental and homeostatic factors. While studies have interpreted HRV data differently, Plews et al. (2013) suggest the use of the natural logarithm of the square root of the mean sum of the squared differences between R-R intervals (ln rMSSD). In addition, weekly averages can be used to improve validity in comparison to single-day measurements (Plews et al., 2012).

Flatt et al. (2018) utilized HRV to determine positional differences in recovery from consecutive-day training sessions in elite NCAA football players. In this study it was concluded that ~20-hour recovery time between the end of training session 1 and the onset of training session 2 was not sufficient for cardiac-parasympathetic activity to return to baseline in linemen. However, receivers, defensive backs, linebackers, running backs and tight ends had all recovered to near baseline values. This finding aligns with a systematic review that determined the HRV recovery from exercise is slower in individuals with lower aerobic fitness and is attenuated for longer durations after high-intensity, anaerobic exercise (Stanley et al., 2013). The combination of higher cardiac strain, lower aerobic fitness and increased anaerobic workload (e.g., repeated blocking, tackling and short sprints) for linemen increase the possibility of reduced cardiac-parasympathetic recovery following training sessions (Deren et al., 2012, 2014).

Measuring HRV should be completed in a rested state either at the training facility prior to training or at home. Measurements obtained at home after waking can be more challenging but may be mitigated by utilizing inexpensive smartphone applications that have been validated (Esco et al., 2017; Flatt & Esco, 2013). However, further research is required to determine specific guidelines for football players.

Muscle Damage.

Football players experience skeletal muscle damage due to high-velocity eccentric loading, rapid acceleration and deceleration forces and blunt force trauma (Dick et al., 2007; Feeley et al., 2008; Shankar et al., 2007). Muscle damage results in elevations of CK (Kraemer et al., 1990, 2013; Malm, 2001). In football, changes in CK over the course of a season are minimal, yet large individual variations can be observed (Kraemer et al., 2013). The individual variation is likely to be due to "starters" versus "non-starters" (Stone et al., 2019). Starters will experience more game time and consequently more muscle damage over the season. Of interest is that monitoring CK can also inform strength and conditioning programs (Kraemer et al., 2013). Therefore, monitoring CK may be a valuable internal load measure in football to inform players recovery strategies and "readiness" to perform.

At present, CK should be measured in serum, however, future research is needed to determine if saliva is a truly valid alternative. Much of the research in salivary-CK is clinical in nature, focusing primarily on patients with myocardial infarctions (Mirzaii-Dizgah et al., 2012). Although this may transfer to monitoring post exercise, further research is required before applying in football settings (Barranco et al., 2018). Of course, measuring CK is only a qualitative measure of membrane damage and does not indicate specifics of the actual contractile muscle damage. Other blood measurements such as troponin may be more useful and warrant additional research.

Neuromuscular Fatigue.

The result of football-specific fatigue on neuromuscular performance and the time course of recovery has received very little attention in the literature. Although data are limited in football, there are simple, practical, and reliable measures of lower body power that can be used to monitor neuromuscular fatigue, including the countermovement jump (CMJ) and isometric-midthigh pull (IMTP) (Hughes et al., 2019).

The CMJ provides single-point concentric variables, such as peak power, force and height and has been reported to be a suitable athlete-monitoring method for neuromuscular fatigue (Gathercole et al., 2015). Moreover, this assessment has been shown to be the most reliable measure of lower-body power in comparison to other popular jump tests (Markovic et al., 2004). The IMTP is a reliable and valid test for measuring maximum strength, providing practitioners valuable information on peak force (McGuigan & Winchester, 2008) and rate of force development as well as fatigue in football players (De Witt et al., 2018).

For both the CMJ and IMTP, practitioners should be consistent in their methods to avoid error and reliability issues. In our experience, standardizing warmups, hand placement, squat depth, timing of assessment (pre/post-game/exercise, days following games, etc.) and encouraging/ensuring maximal player effort will improve the quality of the results. Establishing a protocol at the beginning of the season will reduce the variability in the data and allow for better interpretation and identification of neuromuscular fatigue.

INTERPRETING MONITORING TOOLS

Data Analysis

While selection of the appropriate load measure (internal and external) is critical to athlete monitoring and the fine tuning of training or recovery, the usefulness of a program also relies heavily on how well the resulting data are used to inform decisions. It is clear that an individualized approach is needed in monitoring (Thornton et al., 2019), particularly in a team sport setting where group averages and results likely do not reflect individual responses. Similarly, when monitoring an athlete, the magnitude of change from baseline for either performance or recovery is not yet fully understood and there are various ways to determine what represents a meaningful change in relevant athlete monitoring data. This dictates careful consideration of how to analyze, interpret and present any collected data (Thornton et al., 2019).

As mentioned earlier, load data is of particular interest as it is difficult to make decisions regarding readiness to perform without first understanding how much work an athlete is being subjected to and how they are responding to it. There are multiple methods of calculating load and any changes and responses to it including the original fitness-fatigue model (Banister et al., 1975), acute to chronic workload ratio (ACWR) (Gabbett, 2016), an alternative exponentially weighted moving average of ACWR (EWMA) (Murray et al., 2017a), using standardized scoring (z scores) and standard tens scores. The original Bannister fitness-fatigue model provides a theoretical establishment for planning future training, however due to the many differing systems that affect performance outcomes its efficacy may be limited (Hellard et al., 2006). ACWR is similarly based on a fitness-fatigue model whereby acute loading represents fatigue and chronic loads fitness. Predefined periods of time are often used (e.g., acute 7 d, chronic 28 d) on a rolling basis which are then used to create a ratio (Gabbett, 2016). This method has been investigated in many team sports and has even been suggested as an approach to monitor injury risk (Hulin et al., 2016; Murray et al., 2017b). However, to the authors' knowledge there are no investigations into football. Similarly, there has been some disagreement in using such a simple rolling average approach (Williams et al., 2017).

Thus, the EWMA method was developed. This approach utilizes a weighting structure to place a greater impact on more recent external loads. A decreasing weighting factor is often assigned based on a chosen time decay constant, which frequently still follows a similar time frame (e.g., acute 7 d, chronic 28 d) (Williams et al., 2017). These EWMA loads are then used to create the ratio. It has been suggested this may be more sensitive in identifying injury risk (Murray et al., 2017b), however this too has not been investigated in football. Potential limitations to utilizing the ACWR or EWMA approaches include the variation in the fitness of players across a season, the inability to collect consistent data (e.g., missing due to injury or missed measurements), misjudgment of appropriate individual thresholds and potential issues pertaining to its calculation such as mathematical coupling (Lolli et al., 2019). Although a recent investigation has proposed a formula to uncouple the ratio, there is limited evidence regarding its relation to injury risk (Windt & Gabbett, 2019).

Z scores are often used in normally distributed data and represents how many standard deviations (σ, SD) an observation is from the mean (μ) and in which direction (Moore et al., 2009). Therefore, to calculate this value a few computations must be performed and at least one assumption met. It is beyond the scope of this article to discuss this process, but the data should be tested for normality to meet the assumption and allow for proper interpretation. This approach may allow for an understanding of variation across a season. Practitioners may be able to choose set periods of data (e.g., preseason) to calculate the mean and standard deviation and utilize the resulting values as a marker of change in fitness over the course of a season. Utilizing z scores also enables a practitioner to 'set the sensitivity' of their assessment by adjusting what z score corresponds to an athlete response needing attention. For example, a z score of -1 to -1.49 (SD) may be inherent to the athlete or assessment, whereas a z score of $\leq$ -1.5 (SD) would be worth noting and indicate further investigation. Limitations to utilizing z scores include collecting enough data, determining the best z score thresholds for each measure, the necessity for normally distributed data, and interpretation without proper explanation. The difficulty in interpreting z scores may lead practitioners to normalize to a base 10 system (e.g., 1-10 scale), often called standard tens (STEN). This normalization has the benefit of enabling multiple measures to exist within the same scale, which may have implications when communicating results. Methods to normalize z scores and even EWMA are explained in research (Thornton et al., 2019).

Decision Making

After obtaining and determining if any further analyses need to be performed, the next practical step is understanding what designates a meaningful change in serial measures of an assessment (i.e., change needed beyond day-to-day or biological variability). To date there are several ways that have been suggested to accomplish that task in monitoring data. Mathematical processes that are often considered include effect sizes (Cohen, 1988), SD (Moore et al., 2009), smallest worthwhile change (SWC) (Buchheit, 2014), magnitude-based decision/inference (MDB/MBI) (Batterham & Hopkins, 2006), Bayesian estimation (Mengersen et al., 2016), critical difference values (CDV) (Lewis et al., 2016) and two one-sided test procedure (TOST) or equivalence testing (Lakens, 2017). For brevity, each of these procedures will not be discussed, however each has their benefits and limitations with some potentially better suited to particular measures or assessments.

Of note is the importance of determining the sensitivity and specificity of available assessments to their outcome of interest (Buchheit, 2014). Many of the aforementioned monitoring tools are indirectly related to performance and/or recovery, therefore understanding meaningful change may be dependent upon many variables including position of the player, measurement error and method of collection, among other things (Thornton et al., 2019). Subjective wellness questionnaires have been shown to have large coefficient of variation differences when comparing between sports (Coutts et al., 2021), demonstrating the need for understanding each assessment's relevant implementation within a football monitoring program. Even as these statistical methods are used to generate thresholds, it can still be too difficult describing their consequence to coaches or players. Therefore, a traffic light-based system has often been implemented and even described within the literature (Robertson et al., 2017). Not only does this serve as an easy, quick-look indicator, it can act as a gauge to start discussions with team staff or players as to how they are tolerating training or game demands, or if outside factors may be implicated. However, there are limited investigations as to how effective this red-yellow-green light method is in highlighting outcomes in monitoring training responses. However, there are reports suggesting individualization of these thresholds may be more accurate when highlighting performance change (Hecksteden et al., 2018). A potential limitation to this approach may be that it is unlikely a single monitoring assessment or variable can holistically capture performance changes on the field of play (Crowcroft et al., 2017) and multiple 'traffic lights' may be needed. This too may introduce difficulty in decision making as all 'traffic lights' may not indicate the same directional change.

It is also critical to consider the context of the time period in which the data are being collected (e.g., preseason vs. in season). The load imposed upon players often changes throughout the course of a competitive year and studies have shown the importance of contextualizing monitoring measures (Aubry et al., 2015), particularly when there are planned or known increases in training volume. A large jump in external load in combination with a large decrease in perceptual measures may indicate or precede a dip in performance or recovery, whereas that same increase in external load without a concomitant decrease in perceptual measures may indicate appropriate recovery, an adaptation or improved tolerance to training. Nevertheless, data itself cannot make decisions, rather these measures and further analysis may help inform practitioners of athlete fitness, readiness or wellbeing status and prompt action. It is the action of practitioners following data collection, analysis and interpretation that dictates the success of the program.

PRACTICAL APPLICATIONS

- The goal of an athlete monitoring system is to monitor how each individual player is responding to training and game demands. However, there are many factors that practitioners should consider prior to implementing monitoring within a football program such as cost, staff resources and logistics, among others.
- There are many different methods that can be utilized for determining internal and external loads. It is key that the methods chosen are valid, specific and sensitive to the outcome variable(s) of interest, whether that is change in performance, recovery and wellbeing or injury risk.
- Once data has been collected, appropriate processing needs to be completed to ensure all assumptions are met before further analysis and interpretation takes place. In some instances, the determination of what constitutes meaningful change may need to first take place before making any decisions.
- Data alone does not change athlete behavior, and communication between the players and the performance team is critical to ensuring an effective athlete monitoring system and any enhanced athlete readiness that may follow its use.

SUMMARY

In summary, football load during training and throughout the season is designed to elicit a desired training response on player performance, well-being and level of preparedness for the rigors of the season. An appropriate player monitoring strategy aims to elevate the player's responses to training and practice to elicit performance maintenance across the season. Identifying an appropriate player monitoring strategy may help optimize external load prescription and/or moderate player recovery behaviors which may lead to sustained performance, reduced injuries and a more successful player. Alignment and effective communication between the players and the interdisciplinary sports performance team is paramount in successfully executing a player monitoring program.

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