2 Developing athlete monitoring systems

Theoretical basis and practical applications

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Introduction

Athlete monitoring is now common practice in high-performance sport. Fundamentally, athlete monitoring involves quantifying the athlete's training load and their responses to that training. The main reasons for monitoring athletes are that it can provide information to refine the training process, increase athlete performance readiness and reduce risk of injury and illness. Through a systematic approach to athlete monitoring, an improved understanding of the complex relationships between training, performance, and injury can be obtained. The purpose of this chapter is to examine the training theory that underpins athlete monitoring and discuss the key components of an athlete monitoring system. Additionally, a discussion of methods used to analyse and interpret these data will also be provided.

Theoretical basis of athlete monitoring

The main aim of athletic training is to provide a stimulus that is effective in improving physical performance. For positive adaptations to occur, a careful balance between training dose and recovery is required (Matveyev, 1981). At the simplest level, the performance responses can be explained by the fitness-fatigue model. The fitness-fatigue model is a simple approach to quantify a dose-response relationship of training load to fitness, fatigue, and performance. Original work from Banister et al. (1975) used a systems theory to analyse the response of physical training from a function (see Equation 2.1) that comprises both a fitness response to improve performance and a fatigue response that decreases performance.

$$\text{Modelled Performance} = (\text{fitness from training model}) - K\,(\text{fatigue from training model})$$

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Equation 2.1 Banister's original systems theory approach to analyse training. K = The constant that adjusts for the magnitude of the fatigue effect relative to the fitness effect.

The fitness-fatigue model can be used to understand the training-recovery cycle to single and/or multiple bouts of exercise. Figure 2.1A shows the theoretical fitness and fatigue response to a single training bout, whilst Figure 2.1B shows the modelled responses to a series of bouts (i.e., a training program). Figure 2.1B clearly shows that during periods of intensified training, where increased training loads are undertaken in the absence of appropriate recovery, fatigue is increased, having a negative influence upon performance.

Whilst the training-recovery cycle appears simple, a myriad of complex psychobiological adaptations occur which make it difficult to predict the fitness and fatigue effects of training for individual athletes. As a result, it is now common that sport scientists examine these dose-response relationships on a regular basis to inform decisions on training content for individual athletes. Furthermore, despite a growing body of applied work in high-performance sport, there is still a relatively poor understanding of the most appropriate tools and methods that can be used to assess how individuals are coping with training. It is most likely that there are no single criterion measures of training load, fitness, and fatigue that can be applied to all athletes. Therefore, we recommend a multi-dimensional athlete monitoring system that is based on the fitness-fatigue model. It is important that such a system ~~be~~ developed based on established conceptual frameworks and implemented in a manner that accounts for the cultural and logistical limitations that are commonly encountered in high-performance sport (i.e., select input measures feasible to the athlete/sport). Regardless of the environment, the essential components of this system should include quantifying training load measures for each athlete and their fitness and fatigue responses to that training. Figure 2.2 provides a simple model demonstrating the relationships between aspects of training load, fitness, and fatigue

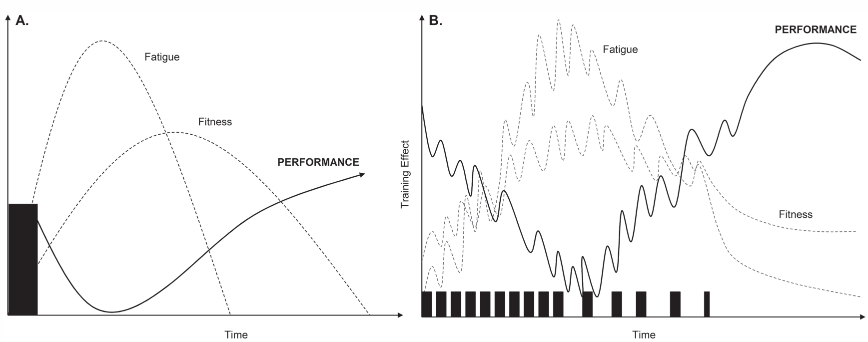

Figure 2.1 The modelled fitness and fatigue responses to (A) a single bout and (B) a sequence of training bouts.

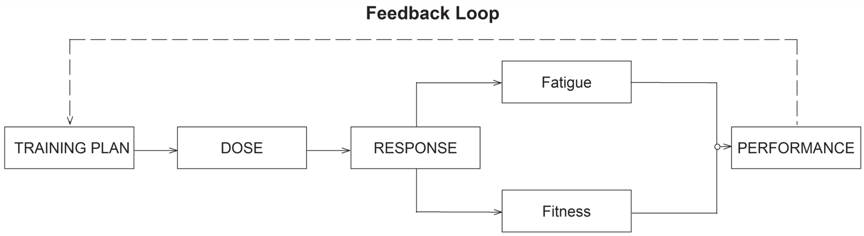

Figure 2.2 Conceptual model for developing athlete monitoring systems.

that combine to provide an iterative monitoring system that can apply to most athletes. For a more detailed discussion of the conceptual framework that underpins this simplified model, readers should refer to Jeffries et al. (2021).

Fundamental components of an athlete monitoring system

Training load

Training load is the input variable in a training system that coaches and scientists most commonly manipulate to elicit the desired training response. As such, quantifying and monitoring training load should form the foundation of any athlete monitoring system. The following sections provide an overview of various constructs of training load and how they may be integrated into athlete monitoring.

Physical training is typically quantified with reference to the type, frequency, duration, and intensity of each exercise bout. Traditionally, training load has been described as a measure of *external load* (e.g., work or speed and distance covered) (Impellizzeri, Rampinini, et al., 2005). Recently, microtechnologies such as global positioning system (GPS) and micro electrical mechanical system (MEMS) components have allowed for increasingly detailed information on the external loads completed by the athlete (Malone et al., 2017). These advances have led to the widespread use of external load measures for quantifying training in both endurance and team sports. Indeed, these devices now provide detailed information on various aspects of external load such as distance travelled above specified speeds, the number of accelerations/decelerations, as well as the body loads experienced in three dimensions. With the data available from the microsensors in these devices, it is also possible to count discrete activities such as collisions, tackles, changes of direction, and/or twisting activities (Gastin, McLean, et al., 2013; Hulin et al., 2017; Keaney et al., 2016). Collectively, these data can provide detailed information to scientists and coaches on the loads completed by athletes. However, despite the large amount of information provided, there are cases where the associated cost, time-intensive data analysis, and measurement precision issues have limited the effective use of such devices (Coutts, 2014).

Importantly, the external load measures provided from these devices may not accurately depict the psychophysiological stress imposed on individual athletes, as other factors such as current fitness level or training environment may play a role. Accordingly, it is the relative psychophysiological stress imposed on the athlete known as the *internal training load* that provides the signal for adaptation (Viru & Viru, 2000). The relationship between internal and external training load measures and training outcome is shown in Figure 2.3.

Many researchers have attempted to develop practical methods for quantifying internal training load that incorporates both training duration and individual training intensity. Historically, heart rate (HR) has been the most common method for assessing internal load. However, with intermittent activity – which is common to many sports – HR may not reflect both the aerobic and anaerobic contributions to energy provision, or accurately compare stress from different modes of training (e.g., skills training vs. resistance training) (Coutts et al., 2009). Fortunately, Carl Foster developed the session-RPE method as a global rating of session intensity (Foster et al., 1996, 2001). The session-RPE method of monitoring training load in team players requires each athlete to provide a rating of perceived exertion (RPE) for each exercise session along with a measure of training time (Foster et al., 2001). To calculate a measure of session

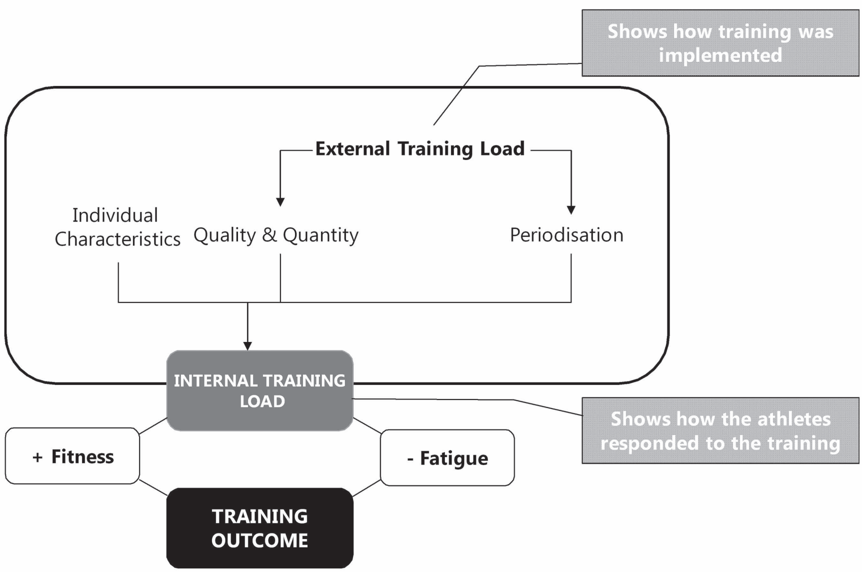

Figure 2.3 The relationship between internal and external training load on training outcomes.

Source: Adapted from Impellizzeri, Rampinini, et al. (2005).

intensity, athletes are asked a simple question: 'How intense was your workout?' (usually within 30 minutes of finishing their workout). A single value representing the magnitude of training load for each session is then calculated by the multiplication of training intensity – determined from Borg's RPE scales (Borg, 1998) – by the training session duration. Compared to alternative measures of internal load (i.e., HR or blood lactate measures) the session-RPE method enables coaches to combine training load from different training modalities in the same units for an accurate reflection of total training load.

There are now numerous measures of training load that can be used in athlete monitoring. The various constructs of external and internal load should be used by scientists and coaches for different purposes. The external load is used to prescribe and quantify training the stimulus, and the internal load is used to measure how the athletes respond to the training dose. Whilst each of these measures helps to understand the training process for athletes, the value of load monitoring is increased when these measures are contextualised against each other and against the athlete's fitness and fatigue responses to training.

Fitness

Measuring changes in fitness is a fundamental component of an athlete monitoring system that can be used to interpret whether the prescribed training has been appropriate for individual athletes. Without regular fitness measures, it is difficult to accurately determine if athletes are positively responding to training, and/or if the athlete's fitness status has been adequately developed. Anecdotally, it is often questioned after poor performance if the result was due to lack of fitness or other physical capacities. Assessing fitness has been a difficult task for applied sport scientists, as most gold-standard assessment procedures require expensive laboratory equipment, maximal effort exercise, and interruptions to the training program.

Criteria for a fitness test that can be included in a monitoring system are that it should be valid and reliable, able to accurately reflect training status, cost effective, and easy to implement with minimal disruption to normal training. Accordingly, studies have aimed to develop non-fatiguing fitness tests that assess physiological responses (i.e., HR, blood lactate, and RPE) to standardised submaximal work (Buchheit, 2014, 2015; Buchheit et al., 2011, 2013; Crowcroft et al., 2015; Impellizzeri, Mognoni, et al., 2005; Lamberts et al., 2010). This research has resulted in the development of simple field tests assessing HR responses to standard bouts of exercise to monitor athletes' acute and chronic fitness adaptations to training (Buchheit, 2014).

Resting HR, HR response to exercise (HR_{ex}), and HR recovery (HRR) following exercise are simple measures that can be collected from athletes in the training setting – and have been reported to have some utility for assessing athlete fitness. For example, as HR is closely related to oxygen uptake during continuous exercise, a lower HR_{ex} provides a good marker of an athlete's aerobic fitness level that can be collected from a brief standardised submaximal exercise bout. However, since recent research has shown that lower submaximal HR can also be associated with overreaching (Aubry et al., 2015), it is critical that HR responses be interpreted in the context of other factors such as the training load, fatigue status, and non-training stressors. Similarly, short-duration measurements of resting heart rate variability (HRV) indices have been shown to reflect parasympathetic modulation and as a useful non-invasive longitudinal monitoring tool for athletes (Buchheit et al., 2014; Plews et al., 2013). Previous studies have related changes in HRV-derived indices to positive or negative training adaptations and to reflect the acute training response (Bellenger, Fuller, et al., 2016; Buchheit et al., 2014). However, the interpretation of directional changes in HRV-derived measures should also be contextualised with consideration to an athlete's training history, training intensity distribution, phase of the season, and acute psychological state (amongst other factors) (Buchheit, 2014). The main practical utility of HR measures is that they are non-invasive and time efficient, ~~are~~ relatively cheap, and can be routinely applied to many athletes. However, despite its common implementation in the field, HR monitoring is still not accepted as a gold-standard fitness test. This is likely due to the lack of consistency in methods of application and/or interpretation of changes in these variables. Nonetheless, despite these limitations, simple HR measures may provide useful insight into the fitness-related changes to training – especially if they are interpreted in the context of other important aspects such as training load and athlete fatigue status.

Fatigue

Athlete fatigue is a difficult concept to define, thus making its precise measurement problematic. Due to its multifactorial genesis, there is no commonly agreed-on definition of fatigue. However, it is generally accepted that athlete fatigue is a psychobiological state associated with an inability to complete a physical task that was once achievable within a recent time frame and is usually associated with altered perceptions of effort, along with feelings of tiredness and/or exhaustion. Whilst the physiological and psychological mechanisms underlying subjective fatigue are not yet fully understood, there is consensus that measurements of subjective fatigue are an essential aspect of athlete monitoring.

There are many psychometric tools, commonly termed athlete-reported outcome measures (AROMs) that can be used to assess various aspects of subjective fatigue (and other subjective responses), including the Profile of Mood States (McNair et al., 1971), Daily Analysis of Life Demands for Athletes (Rushall, 1990), Total Quality of Recovery (Kenttä & Hassmén, 1998), Recovery-Stress Questionnaire for Athletes (Kellmann & Kallus, 2016), Acute Recovery and Stress Scale (Kellmann & Kölling, 2019, 2020; Kölling et al., 2020), and the Short Recovery and Stress Scale (Kellmann & Kölling, 2019, 2020; Kölling et al., 2020). Many of the questionnaires used to assess AROMs are extensive and take longer than a few minutes to complete, which limits their routine use for monitoring athletes. Therefore, short customised questionnaires which can be administered on a regular basis have become commonplace (Taylor et al., 2012). Notably, it has recently been shown that various customised single-item AROMs – such as perceptions of fatigue, mood, and soreness – have greater sensitivity to acute and chronic training loads than commonly used objective measures (Saw et al., 2016). For example, recent studies from professional rugby league (McLean et al., 2010), soccer (Thorpe et al., 2015, 2017), and Australian football (Buchheit et al., 2013) have shown that these custom-designed AROMs are sensitive to daily, within-weekly, and seasonal changes in training load. However, despite their convenience and the observed relationships with training load, it is concerning that most of the commonly used items/tools in both research and practice to assess AROMs (including fatigue) have not been validated using established clinimetric methods (Jeffries et al., 2020).

Whilst longer questionnaires that include multi-dimensional assessment of factors surrounding fatigue (and recovery) status of athletes have strong empirical support, in the practical setting, specific single-item questionnaires may be attractive as they are time efficient and offer ease of interpretation (Bowling, 2005). While there appears to be support for the use of short or single-item questionnaires for assessing subjective fatigue, it remains a concern that the popular single-item scales used with athletes have not undergone rigorous validation for their psychometric properties (Jeffries et al., 2020). Accordingly, future research is still required to develop valid athlete-specific monitoring tools and also to assess the efficacy of using single-item scales compared to the validated but longer multi-dimensional tools (Saw et al., 2017).

Other components

Various biochemical markers have also been suggested as useful components of athlete monitoring systems (Urhausen & Kindermann, 1992). Specifically, markers of muscle damage, hormonal, and immune measures have shown to respond to changes in training intensity and dose and have been associated with overreaching in a variety of athletes (Coutts et al., 2007; Halson et al., 2002). However, due to logistical issues such as drawing blood or obtaining saliva samples from athletes, along with the costs and time for analysis, these measures are not usually suitable for daily monitoring. Nonetheless, these measures may be useful for investigating athletes already showing signs or symptoms of overtraining.

Regular assessments of the neuromuscular system, such as countermovement jumps, range of motion, muscle strength imbalances, and clinical assessments, have been used to identify injury risk factors and therefore are often incorporated into athlete monitoring systems. However, whilst a complete review of these monitoring tools is beyond the scope of this chapter, we recommend that these be included if they are implemented by skilled clinicians who understand the noise in these tests and the importance of standardised test procedures. The benefit of using these measures in monitoring is that they can assist in understanding how individual athletes may be coping with training and can be used to monitor and manage an individual athlete's musculoskeletal health.

Analysing data

Whilst it is essential that athlete monitoring systems are based on established conceptual frameworks (Jeffries et al., 2021) and consist of valid and reliable measures, the effectiveness of the system is dependent on how well the data can be used to inform coaching and training decisions. In high-performance sport, decisions around manipulating training need to be relayed to the coach within a brief period prior to training commencing. Traditionally, a heavy reliance has been placed upon identifying trends in monitoring data visually; however, with the development of integrated monitoring systems, there is a need for stronger evidence to highlight the likelihood of a particular outcome (i.e., injury, illness, or change in performance) (Taylor et al., 2012). Therefore, the purpose of the following section is to address several key concepts used to develop evidence-informed monitoring systems to assist in decision-making around a training prescription.

Contextualising training load

Understanding the non-linear individual athlete dose-response relationships between training on performance, fitness, and fatigue is a major challenge in athlete monitoring. An increasing number of scientific reports use various analysis methods of monitoring data to suggest readiness to perform, the likelihood of illness or injury risk, and methods to estimate performance outcomes (Crowcroft et al., 2020; Foster et al., 1996; Gabbett, 2016; Ryan et al., 2021). The following section will aim to describe some of the commonly used methods to contextualise training load data.

The fitness-fatigue model is a simple approach to quantify a dose-response relationship of training load to performance. Although this method has previously been used to predict performance, fitness, and fatigue measures, the overly simplistic nature of what is a complex non-linear dose-response relationship in highly trained athletes limits its efficacy when applied in practice. Indeed, large variability in the predicted compared to actual responses (i.e., performance, fitness, and fatigue) from these models has identified limitations in the application of this model in the development of training plans for elite athletes (Hellard et al., 2006). This may be due to the many different constructs that influence performance outcomes which may be oversimplified in these mathematical models. Furthermore, this approach assumes that a single measure can quantify sports performance. As such, the application of this approach may be limited in sports where performance is dependent upon a combination of physical, technical, and tactical skills (as these structures cannot be integrated into a single measure). Nonetheless, the benefit of using the fitness-fatigue model is that it provides a theoretical foundation for planning future training, and it may assist in reducing training errors.

The acute-to-chronic workload ratio (ACWR) is based on the crude rearrangement of the fitness-fatigue model, where fitness is comparable to that of chronic workload (e.g., 28 days rolling average workload) and fatigue is comparable to an acute workload (e.g., 7 days rolling average workload). Although initial use of this model was to plan and predict performance, recently this simplified approach has been suggested as an approach to predict and/or monitor injury, particularly within team sports (Gabbett, 2016; Hulin et al., 2016). Indeed, a large body of evidence has reported that large spikes in acute workloads are associated with a substantial increase in injury risk (Griffin et al., 2020). Unfortunately, however, these associations have been shown to be statistical artefacts related to the use of the ratio score (i.e., the ratio score which rescales the explanatory variable and magnifying its effect estimates) (Impellizzeri et al., 2021). Rather than directly applying a metric such as the ACWR to guide training load decisions, we recommend that ~~that~~ care be taken with overloading athletes, particularly during periods of re-loading after long layoffs or during periods of heavy training.

Undoubtably, the athlete's training load is one of the most important aspects to control when preparing athletes ~~from~~ competition. At present, when making decisions about future training, practitioners should avoid using a blind metrics-driven approach. Rather, combining information relating the athlete's training history and their responses to that load from a variety of objective and subjective sources, along with the other important contextual information from performance (e.g., training goals/history), medical (e.g., medical history)~~,~~ and coaching (e.g., performance goals) staff when making decisions about future training is considered best practice.

Contextualising the training response with monitoring tools

The purpose of monitoring an athlete's training response is to assess if an athlete is tolerating the demands of training. Whilst many observational studies have shown that monitoring tools are responsive to changes in training load, injury, and illness, the magnitude of change from baseline values required to influence performance outcomes is not yet fully understood. Currently, few studies have attempted to determine the 'meaningful change' required for a monitoring variable to have an impact upon important training outcomes. The following section will aim to address some of the considerations around inferring outcomes from athlete monitoring variables.

Smallest meaningful change

For any monitoring variable to be practically useful, sport scientists must first understand the 'true' or meaningful change required for it to be an important practical consideration (i.e., level of change in a variable that is beyond its normal day-to-day variation). A common method used to determine if each athlete monitoring tool is appropriate for implementation is through analysis of the signal-to-noise ratio (SNR) (Ryan et al., 2019). The 'signal' could be referred to as the typical change observed in response to a training or competition stimulus, whereas the 'noise' is determined from the typical error in measurement (from test-retest reliability analysis). By using the co-efficient of variance (CV) of both assessments, the responsiveness of athlete monitoring tools can be established via the signal-to-noise ratio (SNR) analysis (Ryan et al., 2019).

When quantifying the smallest meaningful change in performance and real data relating the monitoring variable to the outcome score are not available, an approach based upon Cohen's effect size principle is recommended. The measure is calculated as a change in performance outcome that is greater or less than 0.2 (small effect) multiplied by the between/or individual athlete CV. However, as many monitoring variables (e.g., physiological or perceptual measures) are indirectly related to changes in performance, using a larger fraction of CV may be more appropriate (e.g., 0.5, or 1 × CV) (Buchheit, 2014). The fraction of the CV selected to identify a meaningful change is highly dependent upon the sport (i.e., the nature of the performance requirements), the type of training being completed, and how the monitoring variables are collected. For example, the CV of the same subjective wellness questionnaire have ranged from ~5% in highly trained swimmers to between 12% and 32% in Australian football players (Crowcroft et al., 2017; Gastin, Meyer, et al., 2013). These findings demonstrate that monitoring tools need to be assessed relevant to the sport or the way they are being implemented (Saw et al., 2017). Additionally, it is also important to assess the specificity and sensitivity of measures to the likelihood of important outcome measures (i.e., performance, injury, illness, etc.) (Buchheit, 2014).

Highlighting 'red flags' with sensitivity and specificity

A simple reporting method used to demonstrate a change in monitoring variables is through a traffic light alert system to identify 'red flags' (potential risks to inhibit training quality, elevated risk of injury or illness) (Robertson et al., 2017). When managing many athletes, this method may be useful as a 'lead generator' for sport science or coaching staff to start a discussion as to how the athlete is tolerating training demands. However, very few scientific reports have attempted to assess the efficacy of an alert system to highlight the increased likelihood of an outcome when monitoring the training response.

A common analytical approach used to assess if monitoring variables are effective to identify an outcome (e.g., performance change, injury, or illness), is to compare the accuracy of a monitoring cut-off value against a binary outcome (e.g., Did performance improve? – yes or no). These values can then be applied to quantify the accuracy and optimal cut-off values to inform decision-makers of the likelihood of an outcome (Fawcett, 2006). For example, Buchheit et al. (2014) compared the use of an intra-individual CV and the between-athlete standard deviation at different cut-off values to assess change in HR and

RPE following a standard warm-up to changes in running performance. This analysis identified that variations in HR outside of the intra-individual CV could improve the predictive accuracy in highlighting individual performance change. However, developments on this analysis have since shown that the use of any single monitoring variable has poor discriminatory ability to highlight performance changes (Crowcroft et al., 2017). As such, the need for a multi-dimensional monitoring system could be required to improve the diagnostic accuracy of athlete monitoring systems.

Developing multi-dimensional monitoring systems

The interpretation of any monitoring variable must be interpreted in the context of the athletes' training phase and training load. Several studies have identified the importance of contextualising physiological and perceptual measures with training load, particularly during intensified training periods (Aubry et al., 2015; Bellenger, Karavirta, et al., 2016; Hug et al., 2014). A heuristic derived from these studies identified that attenuated performance would see a noticeable shift in physiological measures and a large negative change in subjective measures during increased training load. However, the same change in the absence of negative subjective measures may indicate positive training adaptations and a likely improvement in performance. These findings highlight the need to contextualise changes in training load, fitness, and fatigue measures with each other to gain a comprehensive understanding of how athletes are responding to training.

To overcome some of the limitations in interpreting data from multi-dimensional monitoring systems (i.e., predicting outcome measures), advanced data analytic techniques such as neural networks or machine learning have been proposed. Indeed, a case study reported a high prediction accuracy of the performance of an elite swimmer using a neural network model using training monitoring data (Edelmann-Nusser et al., 2002). However, since these modelling techniques require large data sets over extended periods to 'train' the predictive accuracy, its practical usefulness may be limited. Furthermore, due to the 'black box' functioning where the outcomes don't explicitly explain causal relationships of each input variable to the outcomes, some have urged caution in blindly adopting neural networks to model athlete training responses (Hellard et al., 2006). Therefore, while the use of advanced modelling techniques may provide an attractive analysis method for predicting performance outcomes from athlete monitoring data, the practical utility in the daily training environment is not yet established.

Conclusion and recommendations for practice

Athlete monitoring systems are now commonplace in high-performance sports. The goal of these systems is to monitor how individual athletes are responding to training and help ~~inform~~ decisions about future training. Due to the perceived benefits of these systems, many high-performance organisations make significant financial and human resource investments in this area. Whilst there is no criterion structure, an athlete monitoring system should be based on sound conceptual framework, should be developed to the resources available, and should fit the culture of organisation. Fundamental measures that should be incorporated in these systems include quantifying training load, and proxy measures of athlete 'fitness' and 'fatigue'. Following this, correct interpretation of the data requires that all changes be contextualised in relation to the actual training load completed by the athlete, whilst accounting for the magnitude of change required for practical importance in monitoring the training response. In practice, the information provided by these measures may be used to develop heuristics that can inform coaches and sport science staff on all aspects of an athlete status (i.e., fitness, injury risk, readiness to perform, well-being, etc.). When these systems are implemented effectively, important feedback can then be provided to athletes and coaches that assist in improving the training process and result in enhanced readiness to perform and reduced injury risk.

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