Introduction

Readiness is a broad term that simply means the state of being fully prepared for an action or event [1]. We all want to be ready: ready for whatever challenges we face; ready for big events; ready for life. Readiness long term means maintaining good readiness short term, and that's why daily readiness is so important. Strictly speaking, being fully 'ready' means being physically, physiologically and psychologically prepared; perhaps best termed 'whole person readiness'. Unsurprisingly, since this represents so many dimensions of human function, there is no single, stand-alone definitive evidence-based marker for this. Instead, in health and wellness, we typically focus either on psychological readiness (willingness), or on Physiological readiness. It is the latter that is the subject of this paper. Physiological readiness reflects the range of metabolic, hormonal, immunological, inflammatory, haematological, autonomic and cardiovascular responses to loads that significantly influence an individual's performance [2, 3]. It is impossible, and unnecessary, to measure them all. The complexity of readiness and the science behind it supports the integration of a small number of relevant biomarkers that together serve as a readiness tool. The goal is to identify key elements that reflect the multitude of influencing factors, and can be easily measured using a wrist-worn device in an individual way on a continuous and reliable basis. The challenge to achieve this is significant, but the ever improving quality of sensors and machine learning has brought us new opportunities to address this goal.

Readiness to exercise

In those who exercise, the greatest physiological load imposed upon them typically relates to training/exercise sessions. Exercise imposes stresses that, when optimal, result in improvements in fitness, wellbeing and ultimately in good performances, and the use of a readiness tool aims to optimise these benefits. The aim is clear: promote fitness and avoid fatigue. However getting the balance right is challenging. When the loads are too low there is a lack of progress and goals are not achieved. When they are too high the consequences can include underperformance, fatigue, injury, illness and negative psychological consequences.

Optimising training can be likened to balancing on a see-saw: too much tips the individual into the pathway of overtraining, while too little leads to limited training responses. The balance can be very fine: pushing the body to achieve the greatest improvements in fitness can be highly successful but runs the risk of overload, [2, 4-12]. This is manifested as a range of...
symptoms, from fatigue, low mood, sleep disruption, disrupted appetite, and weight changes, to injury and illness.

Physiologically, the numerous changes that occur in response to exercise loads affect autonomic control and cardiovascular responses and hence these are key areas of focus in the evaluation and monitoring of readiness. Whereas in the past, exercise scientists have focused on markers in the saliva and blood (e.g. cortisol levels) in the hope that this would indicate stress responses and influence training recommendations, the results from these approaches have been disappointing. Wearable sensors now allow us to measure stress, autonomic and cardiovascular physiology and other potentially important predictors of readiness (e.g. sleep and circadian influences) that resonate with our understanding of an individual’s readiness state. Wearable sensors also allow us to personalise tools. The susceptibility to ‘overtraining’ differs across individuals, so measurement must be on an individual basis [2-12]. The relative weight of each potential ‘overtraining’ factor may also vary across individuals meaning personalised modelling is the preferred goal of any readiness tool [2-12].

Readiness tools aim to optimise exercise training and performance load management to achieve the following goals:

- **Daily Readiness**: On any given day, defining an individual's readiness for different forms of training. Supporting the best training session(s) to optimise progression towards one or more goals
- **Fitness vs Fatigue**: As part of this optimisation, promoting fitness but minimising fatigue
- **Personalisation**: For a given individual, detecting additional factors, superimposed upon training loads, that are influencing that physiological readiness. Examples include sleep, stress, recovery strategies, nutrition, and health conditions.
- **The Big Picture**: Identifying other behaviours can be supported to promote the effects of the training sessions

To address these aims, when considering the ideal readiness tool and the choice of metrics that define it, the principal questions are:

- What are the key metrics that reflect an individual’s physiological readiness?
- How do they represent the various physiological responses that occur in any individual?
- What other factors should be incorporated that play a significant role in the overall ‘readiness picture’?

Our ability to address these areas through information derived from sensors on wearable devices is ever increasing. We can now measure many of the markers that play key roles in our daily readiness, and it is now more a matter of carefully selecting the best of those for the job. The strongest contenders are those that indicate how an individual responds to the demands and stresses of daily life: one marker that reflects the response to exercise (training impulse, ‘TRIMP’ described below), one that represents generic health status at any given time (heart rate variability, HRV), and one that reflects our recovery and nighttime health (sleep reservoir and circadian influence).

**Monitoring Load**

A first step towards a measure of readiness involves measuring load, of which there are two types: external load, and internal load. *External load* means the absolute amount of work done, for example weight lifted, total power generated, distance/time/speed travelled. It is independent of the internal characteristics of the person.
Internal load relates to the responses of the individual to imposed stresses - eg a bout of exercise - and is highly variable across individuals. Measures include heart rate (HR), heart rate variability (HRV), rated perceived exertion (RPE), HR/RPE ratio, HR recovery, and training impulse (TRIMP).

### Table 1: Markers of Internal Load

<table>
<thead>
<tr>
<th>Marker</th>
<th>Type</th>
<th>Advantages</th>
<th>Disadvantages</th>
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<tbody>
<tr>
<td>Rated perceived exertion (RPE)</td>
<td>Subjective</td>
<td>Accessible to all; Correlates with steady state HR; Sessional RPE shown to be valid and reliable in reflecting internal load in endurance work; Likely to be of best use when added to other markers</td>
<td>Validity only moderate for HR, VO2max, blood lactate; Takes conscious effort from participant; Some users find it very difficult to use</td>
</tr>
<tr>
<td>Heart rate</td>
<td>Sensor</td>
<td>Accessible measure of internal load Linear relationship with VO2 in steady state exercise</td>
<td>Day to day variation can be high (up to 6.5%), which dilutes it significantly as a sensitive marker; Influenced by environment, hydration, medication, others</td>
</tr>
<tr>
<td>HR/RPE ratio</td>
<td>Subjective &amp; Sensor</td>
<td>May be of use in detecting fatigue</td>
<td>May not offer superiority over HR alone and has same disadvantages as RPE alone</td>
</tr>
<tr>
<td>TRIMP</td>
<td>Sensor</td>
<td>Can be individualised (iTRIMP)</td>
<td>Models have arbitrary basis although ‘real world’ experience is good; limited to aerobic activities</td>
</tr>
<tr>
<td>Blood lactate</td>
<td>Direct blood sampling, procedure dependent</td>
<td>Sensitive to changes in exercise intensity &amp; duration; Good versatile aerobic fitness marker</td>
<td>Regular monitoring difficult, affected by numerous factors including diet, hydration, environment, others</td>
</tr>
<tr>
<td>HR Recovery</td>
<td>Sensor</td>
<td>A marker of autonomic function and relevant to readiness, with potential in susceptibility to errors through the same range of factors that may influence</td>
<td></td>
</tr>
<tr>
<td>HRV</td>
<td>Sensor</td>
<td>A versatile marker that reflects autonomic status and is sensitive to overtraining; Can be personalised, and best if used in longitudinal monitoring; Helpful reflection of overall stress, fatigue, illness and recovery.</td>
<td>No ‘norms’ as wide variation across population; Range of different algorithms to calculate create inaccuracies and confusion; Not solely an indicator of response to exercise loads.</td>
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<td>-------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Psychomotor speed (eg reaction times)</td>
<td>Device</td>
<td>Reflects cognitive slowing. Not exercise specific, highly variable across individuals, multifactorial.</td>
<td>Not a sole indicator of readiness, Affected by many variables</td>
</tr>
<tr>
<td>Sleep</td>
<td>Sensors Logs</td>
<td>Recording changes in sleep metrics allow early detection before performance decrements.</td>
<td>Not a sole indicator of readiness, Affected by many variables</td>
</tr>
</tbody>
</table>

Not all markers of internal load are suitable for monitoring readiness. Some limitations relating to RPE, HR, HR recovery and HR/RPE are described in Table One. Blood lactate changes and psychomotor speed are both potentially useful aspects in the assessment of readiness, and in the future the use of sensors in their assessment will add very useful information to any tool.

**TRIMP**

The TRaining IMPulse model (TRIMP) is a popular expression of aerobic training load that is amenable to measurement by wearables, quantified as exercise duration multiplied by exercise intensity, estimated using HR reserve (HRR) and a “weighting” factor (y) that adjusts the intensity to make long-duration low-intensity activities produce a similar training load score to that induced by shorter, high-intensity training activities [13-17].

\[
\text{TRIMP} = \text{Time (mins)} \times \% \text{HRR} \times \text{weighting factor (y)}
\]

Where \( \% \text{HRR} = (\text{mean HR during session} - \text{HR}_{\text{rest}}) / (\text{HR}_{\text{max}} - \text{HR}_{\text{rest}}) \) and \( y \) is a nonlinear coefficient that models the relationship between the rise in blood lactate during exercise and the fractional elevation in HR during exercise above resting HR. [14].

TRIMP-based models are now widely used in load management and monitoring. Various modifications of this model have been made over time focusing on the balance between fitness and fatigue, which allow for time spent in specific heart rate zones, improving sensitivity to more intensive exercise and interval training and to promote applicability across different sports [17-19]. Individualisation of the measure

*Readiness: Getting the Balance Right*
(iTRIMP) reduces issues relating to the arbitrary nature of zones and generic weightings, and may be more responsive as a measure [20]. Notably, the 'dose response' relationships between exercise and fitness vs fatigue are not linear, but rather they are complex and vary across time with cumulative periods of training and fatigue. However, mathematical modelling allows differentiation between the influence of fatigue and positive adaptations on performance, and the effects of tapering and overtraining [21-25]. Such modelling allows predictions of fitness and fatigue over extended periods of time and hence translation to a readiness tool [21,26,27].

Measuring internal load beyond responses during exercise

While TRIMP and fitness-fatigue modelling are established tools to assess readiness in those who train regularly, they are much less tested in those who do not exercise. Furthermore, in any individual, the evaluation of internal loads beyond those specifically related to exercise should also be considered as part of any comprehensive readiness tool.

HRV

Heart rate variability (HRV), the fluctuation in the time intervals between adjacent heartbeats, is a valid metric in this context. The variability of our heart rates allows us to adapt to physiological, environmental and psychological challenges [28,29]. HRV is largely considered to reflect the highly complex dynamics of the autonomic nervous system (ANS) and specifically the relative balance between the parasympathetic and sympathetic nervous systems, although non-ANS factors also can influence HRV [30].

HRV is sensitive to factors such as health status, hydration, nutrition, and sleep, that can affect functional capacity of an individual. In general, people who have an active lifestyle and maintain a good or high level of physical fitness can achieve an increase in their basic parasympathetic activity and thus an increase in their time domain measured HRV [31-37]. In contrast, cumulative or too intensive sporting activity (e.g. competition series, overtraining syndrome), brings about a decrease in HRV [38,39] and indeed time domain measurements mostly decline with decreased health status [40,41]. These features of HRV have largely driven the support for its use in readiness assessment.

The challenge in using HRV as an indicator of readiness lies not in its validity as a health metric, but in the pitfalls in the assumption that it fully reflects readiness status. There remains much to be understood about this metric and there are hazards in overestimating its reliability. These hazards can be divided into (i) those relating to measurement of HRV itself and (ii) to human factors that can result in HRV being unreliable.

Methodologies used in determining HRV

There are multiple methodologies used in HRV measurement, with variables including the accuracy of sensors used for signal detection, sampling time frames, methods of signal analysis and algorithms used [28-30,39,42]. A detailed discussion is beyond the scope of this text but there are several reviews of this topic [e.g. 28-30]. Note that a plethora of different metrics can be generated, all called HRV, but it is important to note that different variables are not interchangeable. It is likely that these indices reflect different physiological phenomena, and the specific indices chosen depends on the context, but there is much that is yet not understood in this respect. Furthermore, some indices are less stable than others [43].
RMSSD\(^1\), generated from time domain analysis, is sensitive, stable and a generally accepted better method of HRV calculation than others and is applicable to the field of readiness [44]. Measurement when still and in particular during deep sleep is preferred [44].

Wearable sensors are now the most commonly used measurement tools in HRV assessment through analysis of photoplethysmography (PPG). These systems are particularly accurate during sleep, which strengthens their use in this phase [44].

The human factor
At any one time, a number of ANS and non-ANS related factors influence HRV, including age, race, gender, genetics, circadian rhythm, environment, nutrition, infections, noise, sleep, smoking, fitness, alcohol, most diseases and a variety of medications [28-31, 41, 47]. Elevated body weight or elevated fat-free mass are also associated with a decrease in HRV [45]. Such factors can influence not only HRV itself but also accuracy of its measurement. For example, even in more reliable devices, greater errors are seen in certain populations including males, individuals with greater body mass index, and those with darker skin [44].

When HRV is used to indicate readiness, it is the changes and trends in HRV that are taken as the key indicators, but there can be significant inter-individual variation in this respect. The relative sensitivity to change is potentially affected by the factors described in Table Two, and this is a critical consideration in readiness assessment. Some individuals have blunted HRV responses due to health conditions, medications or inherent factors, which make HRV a less reliable tool [48,49]. Furthermore, intra-individual variation is also an issue; the sensitivity of HRV to stressors over time may be variable and unpredictable. While this does not exclude HRV in readiness assessment, it indicates that it should not be used alone.

Table 2: Factors influencing HRV

<table>
<thead>
<tr>
<th>Physiological</th>
<th>Age, gender, circadian rhythm, physical stress, mental stress, genetics, race, most diseases, body composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifestyle behaviours</td>
<td>Alcohol intake, fitness, nutrition, sleep, smoking</td>
</tr>
<tr>
<td>External factors</td>
<td>Heat/cold, noise, pain, circadian disruption</td>
</tr>
</tbody>
</table>

Sleep
While the usefulness of fitness fatigue models and HRV has been established, it is also clear that other metrics must be considered as part of reliable readiness assessment. There is a risk, though, that the desire to incorporate other markers will dilute the effectiveness of the tool by introducing error. The variability of heart rate as a metric in this respect has been highlighted earlier, and the use of resting heart rate, and / or rate of heart rate stabilisation overnight potentially adds error, rather than strengthens, any readiness tool. The value of the use of body temperature in readiness assessment, though commonly proposed, is also equivocal since fluctuations around the norm are physiologically acceptable in healthy people.

One metric that is indubitably important in readiness is sleep. Sleep science is complex...
and we still do not have a full understanding of all of its elements. While we consider sleep duration, latency, efficiency, consistency, and perceived quality as important dimensions, and we recognise the value of measuring HRV during deep sleep, we also recognise that it is in essence cumulative sleep deprivation that strongly influences a lack of readiness, both cognitively and physically [50-52]. Sleep quality is linked to sleep regulation which in turn is the result of our duration of sleep bouts and awakenings and sleep debt (our ‘sleep reservoir’) and the influence of the individual’s circadian rhythm superimposed upon this. One population in whom this has been researched most effectively is the military, and modelling tools utilising sleep reservoir and circadian variation have been established to regulate working behaviours to avoid fatigue, with good effects. Such tools are promising in the assessment of readiness across wider populations [50-52].

Summary

Readiness is a complex concept that is not indicated by a single metric. Assessing daily readiness to exercise in a balanced and comprehensive way necessitates consideration of internal responses to training loads in addition to wider biomarkers that indicate health state and recovery. With respect to the former, the fitness-fatigue model is already well established in assessing internal loads. As to the latter, when incorporating wider indicators of readiness there is a risk in attempting to incorporate too many overlapping and potentially unreliable biomarkers that do not strengthen the tool. HRV and sleep are both such strong indicators of health, wellbeing and performance that they warrant inclusion in any readiness model. Downward trends in HRV signal the individual is not ready to train intensively. Furthermore, utilising our understanding of the sleep reservoir and circadian effects acts as a safety net to avoid overtraining in those with significant cumulative sleep deprivation. Modelling readiness based on these three critical areas - HRV, sleep and internal loads - provides an excellent, scientifically credible basis for balanced, progressive and successful training, and the benefits that follow.

REFERENCES

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