Readiness: Getting the Balance Right

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October 2021

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

Marker	Type	Advantages	Disadvantages
Rated perceived exertion (RPE)	Subjective	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	Validity only moderate for HR, VO2max, blood lactate; Takes conscious effort from participant; Some users find it very difficult to use
Heart rate	Sensor	Accessible measure of internal load Linear relationship with VO2 in steady state exercise	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
HR/RPE ratio	Subjective & Sensor	May be of use in detecting fatigue	May not offer superiority over HR alone and has same disadvantages as RPE alone
TRIMP	Sensor	Can be individualised (iTRIMP)	Models have arbitrary basis although ‘real world’ experience is good; limited to aerobic activities
Blood lactate	Direct blood sampling, procedure dependent	Sensitive to changes in exercise intensity & duration; Good versatile aerobic fitness marker	Regular monitoring difficult, affected by numerous factors including diet, hydration, environment, others
HR Recovery	Sensor	A marker of autonomic function and relevant to readiness, with potential in	Susceptibility to errors through the same range of factors that may influence

		monitoring the accumulation of fatigue.	HR.
HRV	Sensor	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	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
Psychomotor speed (eg reaction times)	Device based	Reflects cognitive slowing	Not exercise specific, highly variable across individuals, multifactorial
Sleep	Sensors Logs	Recording changes in sleep metrics allow early detection before performance decrements	Not a sole indicator of readiness, Affected by many variables

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].

TRIMP=Time (mins)×%HRR×weighting factor (y)

Where %HRR = (mean HR during session − HR_{rest}) ÷ (HR_{max} − HR_{rest}), and *y* = 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 (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

Physiological	Age, gender, circadian rhythm, physical stress, mental stress, genetics, race, most diseases, body composition
Lifestyle behaviours	Alcohol intake, fitness, nutrition, sleep, smoking
External factors	Heat/cold, noise, pain, circadian disruption

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

[1] root mean square of successive differences between normal heartbeats

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

1. https://languages.oup.com/google-dictionary-en/
2. Saw A et al. Monitoring athlete training response. Br J Sports med 201 50: 281-291.
3. Coutts A, Cormack SJ. Monitoring the training response. In: Joyce D, Lewindon D, eds. High-performance training for sports. Champaign, IL: Human Kinetics Publishers, 2014:71–84.
4. Meeusen R, Duclos M, Foster C, et al. Prevention, diagnosis and treatment of the overtraining syndrome: joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). Eur J Sport Sci 2013;13:1–24.
5. Kuipers H, Keizer H. Overtraining in elite athletes. Sports Med 1988;6:79–92.
6. Armstrong LE, VanHeest JL. The unknown mechanism of the overtraining syndrome: clues from depression and psychoneuroimmunology. Sports Med 2002;32:185–209.
7. Kenttä G, Hassmén P. Overtraining and recovery: a conceptual model. Sports Med 1998;26:1–16.
8. Urhausen A, Kindermann W. Diagnosis of overtraining: what tools do we have? Sports Med 2002;32:95–102.

9. Hooper SL, Mackinnon LT. Monitoring overtraining in athletes. Sports Med 1995;20:321–7.
10. Hug M, Mullis PE, Vogt M, et al. Training modalities: over-reaching and over-training in athletes, including a study of the role of hormones. Best Pract Res Clin Endocrinol Metab 2003;17:191–209.
11. Lehmann M, Foster C, Dickhuth H-H, et al. Autonomic imbalance hypothesis and overtraining syndrome. Med Sci Sports Exerc 1998;30:1140–5.
12. Petibois C, Cazorla G, Poortmans J-R, et al. Biochemical aspects of overtraining in endurance sports. Sports Med 2003;33:83–94.
13. Bannister, E.W. Modeling elite athletic performance. In: *Phys- iological Testing of the High- Performance Athlete.* J.D. Mac- Dougall, H.A. Wenger, and H.J. Green, eds. Champaign, IL: Human Kinetics, 1991. pp. 403–424.
14. Banister EW, Morton RH, and Fitz-Clarke JR. Modeling human performance in running.
J Appl Physiol 69: 1171–1177, 1990.
15. Lucia A, Hoyos J, Perez M, et al. Heart rate and performance parameters in elite cyclists: a longitudinal study. Med Sci Sports Exerc. 2000;32:1777–82.
16. Edwards S. High performance training and racing. In: Edwards S, editor. The heart rate monitor book. Sacramento: Feet Fleet Press; 1993. p. 113–23.
17. Halson S. Monitoring training load to understand fatigue in athletes.Sports Med (2014) 44 (Suppl 2):S139–S147
18. Amador García-Ramos, Belén Feriche, Carmen Calderón, Xavier Iglesias, Anna Barrero, Diego Chaverri, Thorsten Schuller & Ferran A. Rodríguez (2015) Training load quantification in elite swimmers using a modified version of the training impulse method, European Journal of Sport Science, 15:2, 85-93,
19. Mitchell LJ et al. European Journal of Sport Science, 2020 Vol. 20, No. 10, 1329–1338,
20. Akubat I et al. **The Validity of External:Internal Training Load Ratios in Rested and Fatigued Soccer Players** *Sports* **2018**, *6*, 44
21. BUSSO, T., R. CANDAU, and J. R. LACOUR. Fatigue and fitness modelled from the effects of training on performance. *Eur. J. Appl. Physiol. Occup. Physiol.* 69:50–54, 1994.
22. FITZ-CLARKE, J. R., R. H. MORTON, and E. W. BANISTER. Optimiz- ing athletic performance by influence curves. *J. Appl. Physiol.* 71:1151–1158, 1991.
23. MORTON, R. H. The quantitative periodization of athletic training: a model study. *Sports Med. Training Rehabil.* 3:19–28, 1991.
24. MORTON, R. H. Modeling training and overtraining. *J. Sports Sci.* 15:335–340, 1997.
25. MUJIKA, I., T. BUSSO, L. LACOSTE, F. BARALE, A. GEYSSANT, and J. C. CHATARD. Modeled responses to training and taper in com- petitive swimmers. *Med. Sci. Sports Exerc.* 28:251–258, 1996.
26. BUSSO, T.. Variable Dose-Response Relationship between Exercise Training and Performance. *Medicine & Science in Sports & Exercise, 35* (7), 1188-1195.
27. Philippe Hellard, Marta Avalos, Lucien Lacoste, Frederic Barale, Jean-Claude Chatard & Gregoire P. Millet(2006) Assessing the limitations of the Banister model in monitoring training, Journal of Sports Sciences,24:5, 509-520.
28. Billman GE, Huikuri HV, Sacha J, Trimmel K. An introduction to heart rate variability: methodological considerations

and clinical applications. Front Physiol (2015) 6:55.
29. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. *Front Public Health*. 2017;5:258
30. *Ernst G (2017) Heart-Rate Variability—More than Heart Beats? Front. Public Health 5:240.*
31. Aubert AE, Seps B, Beckers F. Heart rate variability in athletes. Sports Med 2003;33: 889-
919.
32. Bernardi L, Piepoli ME. Autonomic nervous system adaption during physical exercise. Ital Heart J 2001;2: 831-839.
33. Hottenrott K, Hoos O, Esperer HD. Heart rate variability and physical exercise. Current status. Herz 2006 31 (6): 544-552.
34. Routledge FS, Campbell TS, McFetridge-Durdle JA, Bacon SL. Improvements in heart rate variability with exercise therapy. Can J Cardiol 2010; 26 (6): 303-312.
35. Sandercock GRH, Bromley PD, Brodie DA. Effects of exercise on heart rate variability:
inferences from meta-analysis. Med Sci Sports Exerc 2005; 37 (3): 433-439
36. De Meersman RE. Heart rate variability and aerobic fitness. Am Heart J (1993) 125:726–31.
37. Aubert AE, Seps B, Beckers F. Heart rate variability in athletes. Sports Med (2003) 33:889–919.
38. Wu S, Deng F, Liu Y, Shima M, Niu J, Huang Q, Guo X. Temperature, traffic related air pollution, and heart rate variability in a panel of healthy adults. Environ Res 2013; 120: 82-89.
39. Bucheit M. Monitoring training status with HR measures: do all roads lead to Rome? Front Physiol 2014: 5: 1-19.
40. Bigger JT, Fleiss JL, Steinman RC, Rolnitzky LM, Schneider WJ, Stein PK. RR variability in healthy, middle-aged persons compared with patients with chronic coronary heart disease or recent acute myocardial infarction. Circulation (1995) 91:1936–43.
41. Agelink M, Boz C, Ullrich H, Andrich J. Relationship between major depression and heart rate variability. Clinical consequences and implications for antidepressive treatment. Psychiatry Res (2002) 113:139–49
42. Jeyhani V, Mahdiani S, Peltokangas M, Vehkaoja A. Comparison of HRV parameters derived from photoplethysmography and electrocardiography signals. *Conf Proc IEEE Eng Med Biol Soc* 2015;**2015**:5952–5.
43. Penttilä J, Helminen A, Jartti T, et al. Time domain, geometrical and frequency domain analysis of cardiac vagal outflow: effects of various respiratory patterns. *Clin Physiol* 2001;**21**:365–76.
44. Shcherbina A, Mattsson C, Waggott D, et al. Accuracy in wrist-worn, sensor-based measurements of heart rate and energy expenditure in a diverse cohort. *J Pers Med* 2017;**7**:3.
45. Fraley MA, Birchem JA, Senkottaiyan N, Alpert MA. Obesity and the electrocardiogram. Obes Rev 2005; 6 (4): 275-81
46. Kuusela T. Methodological aspects of heart rate variability analysis. In: Kamath MV, Watanabe MA, Upton ARM, editors. *Heart Rate Variability (HRV) Signal Analysis*. Boca Raton, FL: CRC Press (2013). p. 9–42.
47. Kleiger RE, Stein PK, Bigger JT Jr. Heart rate variability: measurement and clinical utility. *Ann Noninvasive Electrocardiol* (2005) 10:88–101.
48. Hamilton JL, Alloy LB. Atypical reactivity of heart rate variability to stress and depression across development:

Systematic review of the literature and directions for future research. *Clin Psychol Rev*. 2016;50:67-79.

49. Agorastos A, Kellner M, Stiedl O, Muhtz C, Wiedemann K, Demiralay C. Blunted autonomic reactivity to pharmacological panic challenge under long-term escitalopram treatment in healthy men. *Int J Neuropsychopharmacol*. 2014;18(5):pyu053.
50. Hursch S et al. https://ibrinc.org/wp-content/uploads/2016/06/sae-hursh-04dhm-14.pdf

51. Achermann, P. and A. Borbely, (1991). Combining different models of sleep regulation. Journal of Sleep Research, 1, 144-147.

52. Borbely, A. and P. Achermann, (1992). Concepts and models of sleep regulation: an overview, Journal of SleepResearch, 1, 63-79.