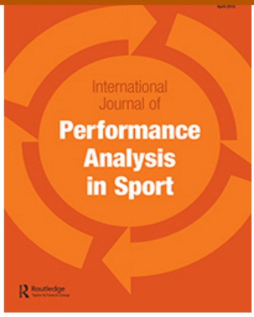

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External training loads and smartphone-derived heart rate variability indicate readiness to train in elite soccer

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ABSTRACT

Player readiness can affect the ability to perform and tolerate prescribed training load (TL); therefore, in a time-efficient and practice compatible manner, practitioners need objective evidence to inform readiness to train. Six male professional footballers (mean ± standard deviation [SD]; 26 ± 2 years, 79.0 ± 4.9 kg, 1.82 ± 0.05 m) participated. Heart rate variability (HRV) was recorded using a smartphone application prior to the daily training sessions (247 training sessions [41.17 ± 7.41 per player]). External TL was monitored during training using global positioning system devices. Linear mixed models were used to examine variations in HRV and TL across the study period and to determine relationships between HRV and TL. Differences in TL and HRV were expressed as standardised effect sizes (ES) ± 90% confidence limits. Changes in HRV (outcome) were expressed as the expected change for a 2-SD change in TL (predictor). Across the study period, all external TL measures varied substantially, demonstrating weekly fluctuations in load (ES range = 0.00–7.40). The relationship between morning HRV and external TL ranged from −0.10 for distance and 1.89 for equivalent distance index (EDI). Overall, EDI demonstrated the strongest relationship with morning HRV; therefore, EDI and smart-phone-derived HRV may provide an indicator of readiness to train within elite soccer.

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Fatigue; performance; autonomic nervous system; recovery; football

1. Introduction

Soccer is characterised by a variable and demanding fixture scheduling, whereby consecutive matches may be interspersed by only 2–3 days (Carling et al., 2015). Match-play and training can occur in environmental extremes of cold, hot and/or hypoxic climates (Aldous et al., 2015; Coull et al., 2015); with associated variable travel demands (Fullagar et al., 2015), these combine to increase the psychophysiological demands experienced by players across a season (i.e. "fatigue"). Poor management of

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fatigue may increase the risk of injury (Mohammadi & Roozdar, 2010), illness and non-functional overreaching (Borresen & Lambert, 2008). High-level football players believe that fatigue (38%) and environmental conditions (26%) are risk factors for injury (Zech & Wellmann, 2017). To mediate these risks in response to arduous match-play, training and travel schedules, and training load (TL) can be modified, ideally in an individualised rather than squad-wide generic manner (Nedelec et al., 2012).

Practitioners need to accurately and efficiently monitor an individual athlete's fatigue (readiness to train) to potentially make informed and immediate adjustments to their TL. Various objective and subjective measures have been utilised to inform practitioner decision-making (Saw, Main, & Gastin, 2015); however, a "gold-standard" single or battery of measures is not adopted within general practice (Halson, 2014) or soccer-specific practice (Akenhead & Nassis, 2016; Thorpe et al., 2015, 2016a, 2016b). Common methods employed are subjective questionnaires (Thorpe, Atkinson, Drust, & Gregson, 2017), visual analogue scales (Saw et al., 2015), blood and saliva indices (Ascensao et al., 2008; Morgans, Owen, Doran, Drust, & Morton, 2015; Thorpe & Sunderland, 2012), physical performance protocols and/or their physiological responses (Buchheit, 2014; Buchheit et al., 2013). Whilst potentially able to provide important information on fatigue and recovery, these measures possess several limitations (i.e. invasive, time consuming, high variability, cost etc.). A multi-method approach, including self-report measures (i.e. questionnaires), is frequently employed by soccer clubs (Akenhead & Nassis, 2016). However, this presents limitations in terms of time constraints in employing multiple measurements and over complications in dealing with different types of data. Subsequently, heart rate variability (HRV), although notwithstanding its own limitations, may be attractive due to its non-invasive nature, low cost, squad-wide simultaneous measurement capability and time efficiency (Buchheit, 2014). Moreover, technological advances of smart phone and tablet applications show good reproducibility and ecological validity (Flatt & Esco, 2013), relative to obtaining HRV indices from field-derived data. Indeed, the smartphone HRV application does not require electrocardiography equipment (which historically was required) to obtain HRV indices, which is evidently practically advantageous to the practitioner. It has been used in the Australian Football league (AFL) to predict AFL performance (correlation coefficient; $r \geq 0.70$) from HRV indices (Cornforth, Campbell, & Nesbitt, 2015), offering itself as a potential tool to provide evidence for practitioners to base player preparedness decisions (for training and competition) upon, in conjunction with TL. Female collegiate football players demonstrated a reduction in the coefficient of variation of resting HRV (i.e. less variability at rest), determined as a positive adaptation to training, during the initial 3 weeks of a 5-week training mesocycle (Flatt & Esco, 2016a) with use of the smartphone application. However, longitudinal data in elite soccer players are limited (Thorpe et al., 2017) despite the potential benefits this information may offer.

Quantification of physical training demands or external TL using global positioning system (GPS) technology is a common practice in team sports (Cummins, Orr, O'Connor, & West, 2013). Using GPS devices, a wide range of movement indicators can be measured, such as total distance (TD) and high-speed distance (distance above a predefined speed threshold [HSD]). These variables however do not account for the energy expended (EE) during physical activity (Ardigo, Padulo, Zuliani, & Capelli, 2015). The equivalent distance (ED) and equivalent distance index (EDI) are power-based measures derived from TD. These variables account for the distance covered, as well as the “intensity” of which this distance was covered (Osgnach, Poser, Bernardini, Rinaldo, & di Prampero, 2010), and EDI is the ratio between ED and TD. Subsequently, two players may have the same TD, but their ED may differ. For example, player one may have performed the distances at a much higher intensity compared to player two, and therefore, the overall ED (and hence EE) for player one is much higher, and as a result, this player may experience a higher level of fatigue and decreased readiness to train. Therefore, the main aims of this study were to (1) identify any fluctuations in external TL which may cause physiological perturbations and (2) investigate the association between the smartphone application HRV and external TL in elite soccer players to establish if these measurements can be used as a marker of readiness to train.

2. Methods

2.1. Experimental approach to the problem

This experimental study recorded HRV prior to daily training sessions in elite soccer players across an 18-week period. Additionally, external TL was measured during training using GPS devices to quantify TD, HSD, high-metabolic load (HML), ED and EDI.

2.2. Subjects

Six elite male professional soccer players (mean ± standard deviation [SD]; 26 ± 2 years, 79.0 ± 4.9 kg, 1.82 ± 0.05 m) from an English Premier League squad (three defenders, three midfielders) agreed to participate in this study over a 4-month period (October–February). Data were collected for a total of 247 training sessions (mean ± SD; sessions per player = 41 ± 7). All participants were informed of the nature of the study and provided written consent to participate. Ethical approval was provided by The University of Bedfordshire Ethics Committee prior to commencement of the study, and all procedures were conducted in line with the Declaration of Helsinki.

2.3. Procedures

2.3.1. HRV

HRV data were measured using the ithlete application (HRV Fit Ltd., UK) on an Apple iPad 2 (Apple Inc., CA) and a Polar T31 heart rate transmitter (Polar Electro Ltd., Finland). HRV measures were collected for each participant prior to the daily training session. Participants were required to wear the heart rate transmitter whilst seated for 1 min, as per the protocol of the application, in a quiet room, free from distraction, holding the iPad in their lap. Recent research has demonstrated that this shortened more convenient HRV recording procedures can provide meaningful training status information (Flatt & Esco, 2016a). The room temperature was standardised and controlled at 18°C using a climate control system. On screen instructions were then followed to calculate daily HRV measures. The reading was taken within the same 15-min time slot each day (30–45 min before training), with the same clothing being worn, consisting of club issued training shorts and T-shirt. Players were instructed to follow their usual daily routine prior to taking the daily HRV test, HRV was averaged weekly, as this has been shown to provide a superior representation to training status.

The ithlete application has shown good intraclass correlation with a gold standard measure, with an *R*-value of 0.80 (Sandercock, Bromley, & Brodie, 2005). Furthermore, reliability was deemed acceptable in a short pilot study conducted prior to commencing data collection. The HRV score generated by the application refers to 20× Ln root mean square of the successive differences. This time-domain measure has been shown to be reliable in test–retest situations (Guijt, Sluiter, & Frings-Dresen, 2007). Furthermore, the application utilises a paced breathing protocol of 7.5 breaths/min, also shown to improve reliability when measuring HRV (Pinna et al., 2007).

2.3.2. External TL

Participants were engaged in their usual training schedule and were required to wear a 10 Hz STATsports Viper GPS unit (STATsports Ltd., Republic of Ireland) that has an embedded accelerometer. The following variables were obtained from the devices: TD covered, HSD covered, (≥5.5 m/s), HML distance (combination of HSD and distance covered while accelerating or decelerating >2 m/s^2), ED which is the distance the player would have covered with the same EE running at a constant speed and EDI described as the ratio between ED and TD (Osgnach et al., 2010).

The GPS units were turned on 30 min prior to each session to allow appropriate satellite signals to be obtained and each participant wore the same unit each day to minimise any inter-unit variability (Jennings, Cormack, Coutts, Boyd, & Aughey, 2010). Different playing positions place different physical demands upon players (Carling, 2010; Gaudino et al., 2013); therefore, only possession-based training drills were analysed. Possession-specific drills do not specify playing positions for individuals, serving to reduce influence of player’s position on results. Furthermore, they were typically employed in the first portion of training sessions, thus reducing the influence of acute fatigue.

2.4. Statistical analysis

Prior to any inferential statistical analyses, descriptive statistics were checked for normality using quantile–quantile plots. Linear mixed models were used to establish if there were any differences in external TL and HRV across each week of the study period. In the model design, study week was included as a fixed effect, and athlete identification as a random effect, used to separate between-subject variability. Differences were assessed using standardised effect sizes (ES) and 90% confidence limits (CL), categorised using the thresholds of <0.2 trivial, 0.21–0.60 small, 0.61–1.20 moderate, 1.21–2.0 large and >2.0 very large (Hopkins, Marshall, Batterham, & Hanin, 2009). Further, differences were considered real if there was a >75% likelihood of the observed effect exceeding the smallest worthwhile difference (0.20) and are described as *likely* (>75%), *very likely* (>95%) and *most likely* (>99.5%) substantial difference (Hopkins et al., 2009). To determine the relationship between HRV and EDI, again linear mixed models were used. In these models, HRV was entered as the dependent variable, each TL variable was entered as a fixed effect and athlete identification as a random effect using a random intercept and slope design. TL variables were log transformed to align with the other metrics to assist in fitting the model. Relationships between daily HRV and EDI were standardised by multiplying the final model slope by 2× the between-subject SD (Hopkins et al., 2009) obtained using a mixed model reliability analysis. Two SD represents the expected change in HRV given a 2 SD change in EDI, or otherwise the change from a typically low (−1 SD) to a typically high value (+1 SD). This change was then converted to an ES using the between-subject SD, categorised using the scale of magnitudes above, and further effects were considered if the likelihood of the observed effect being greater than 0.20 exceeded 75%. All statistical analyses were performed using R Studio (v 3.1.38). All data are reported as mean ± 90% CI, unless otherwise stated.

3. Results

3.1. HRV

Individual HRV responses (A) and squad mean ± SD (B) across the study are depicted in Figure 1.

3.2. External TLs

External TLs across the study period are depicted in Figure 2.

3.3. Relationship between external TL and HRV

Figure 3 depicts the relationships between each TL measure and HRV, expressed as ES ± 90% CL.

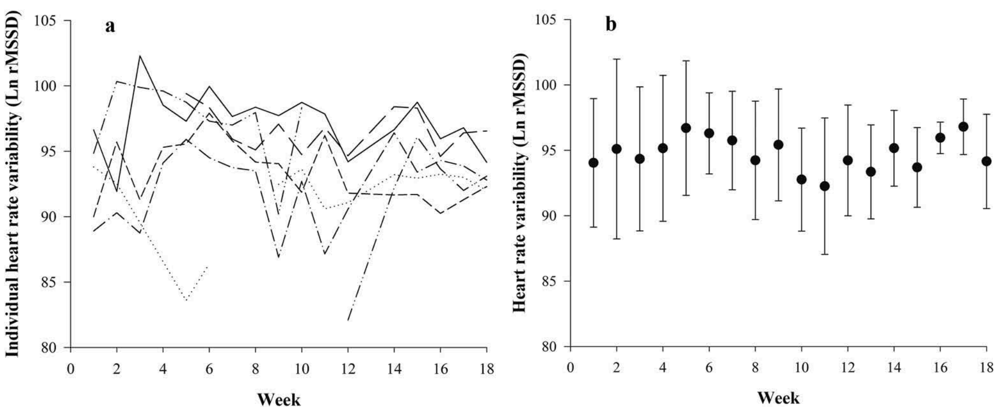

Figure 1. Individual mean weekly (A) and group mean and standard deviation (B) HRV responses across the 18-week study period.

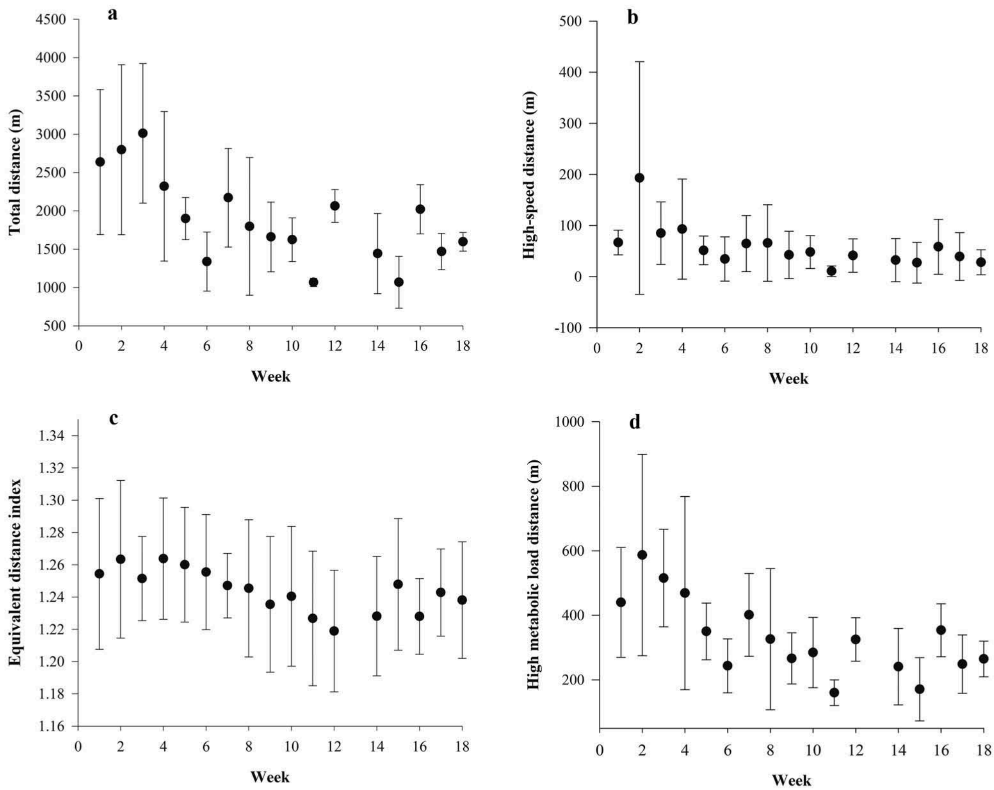

Figure 2. Group mean and standard deviation for external load variables across the 18-week study period. Part (A) Depicts total distance, (B) illustrates high-speed distance, (C) is equivalent distance index and (D) represents high-metabolic load distance.

4. Discussion

The major experimental finding was that increased HRV was substantially associated with increased EDI (Figure 3). The other external TL measures showed trivial-to-small associations with HRV (ES range = −0.10–0.34). The association between EDI and HRV suggests that when players were more "recovered" (as demonstrated by a higher HRV), they were able to express higher EDI. Smartphone-derived HRV may therefore be an appropriate practical tool to aid decision-making relative to readiness to train in elite soccer players if EDI is considered. The EDI values reported (Figure 2) are similar to those described for soccer players (1.20 ± 0.03) (Osgnach et al., 2010) and higher than those for referees (1.05 ± 0.05) (Ardigo et al., 2015). Previous research has suggested that players who covered less ground (EDI of ≤1.15) were considered "lazy" (Osgnach et al., 2010).

HRV (Figure 1), EDI and the other external TL measures (Figure 2) varied substantially across the study period, with major individual differences, as demonstrated by the large 90% CL. If an athlete's HRV is reduced (i.e. worse) compared to their "normal" baseline measure, this may be an indication that the athlete is not "fully" recovered, and the coach and/or practitioner may need to modify the training session (i.e. modify TL to reduce the expected overall ED and EDI) to reduce the risk of non-

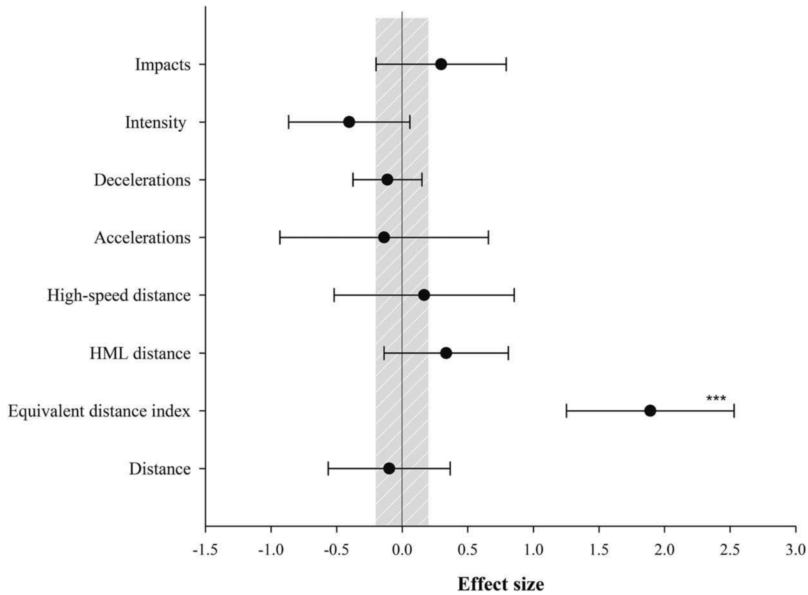

Figure 3. The association between each training load variable and daily heart rate variability. The grey shaded area represents the smallest worthwhile effect (0.2). *** = effect *most likely* >0.2. HML: High-metabolic load.

functional overreaching, illness and/or injury. Conversely, an increase in the individual athlete's HRV (i.e. better) may indicate that the player is fully recovered and, therefore, could cope with an increase in the overall TL (i.e. expected ED and EDI for that session). Therefore, it would be inappropriate to alter TL across the whole squad (albeit convenient) based on an overall mean shift in HRV and/or EDI (or the relationships shown elsewhere between mean squad HRV values and movement categories/performance tests [Flatt & Esco, 2013; Oliveira, Leicht, Bishop, Barbero-Alvarez, & Nakamura, 2013]). If TL was altered according to the squad mean, "fatigued" athletes may be exposed to inappropriately high TL, risking non-functional overreaching, injury and/or illness. Conversely, at a time when HRV is increased, an individual athlete could be exposed to a greater TL, in order to increase adaptation and performance. Evidently, if such deviations from "optimal" practice are seen across a macrocycle (i.e. whole season), athletes may either experience increased injury and/or illness, or detraining, and subsequent reduced performance. It is important to note that HRV is affected not only by physical stress but also psychological stress (Kumar, Agarwal, & Gautam, 2013), and therefore, the change in HRV in the present study may also provide information not only on whether the athlete is physically able to train but their mental readiness to train (i.e. holistic psychophysiological athlete preparedness). Moreover, there is a distinct lack of standardisation of HRV measures within the literature, which could lead to misinterpretation of findings. For example, the supine position may be more sensitive to TL variation compared to the upright position (Flatt & Esco, 2016b). Nevertheless, in some athletes, HRV data collection in the upright position does not always eliminate parasympathetic saturation (Kiviniemi, Hautala, Kinnunen, & Tulppo, 2007), and upright positions (supine and standing) can decrease athlete compliance when it comes to HRV testing (Plews, Laursen, & Buchheit, 2016). Additionally, a minimum number of three tests per week is likely necessary to ascertain credible inferences (Plews et al., 2014). Other factors that could contribute to the variability in HRV response include the magnitude of change in TL and individual differences. For example, low-to-moderate changes in TL may have been too small to meaningfully affect cardiac autonomic function (Nakamura et al., 2016). Furthermore, large individual differences in autonomic changes may exist, suggesting that heterogeneity of athletes may be an important consideration when utilising HRV measures. Subsequently, HRV should be interpreted carefully alongside other measures, but most importantly at the level of the individual and compared to their own robust baseline (likely obtained on multiple occasions to establish their "normal" measure variation).

5. Conclusion

The smartphone HRV application, in combination with EDI, may provide a practical, highly accessible and ecologically valid tool for practitioners to monitor readiness to train in players at the level of the individual. The use of a simple and highly accessible HRV monitoring tool (tablet application) means practitioners can adopt the methods used within the study at minimal expense and without extensive training. The use of metabolic power-based measures (i.e. EDI) may provide a greater insight into the physical training performance (i.e. TL) compared to traditional distance and time variables.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Akenhead, R., & Nassis, G. P. (2016). Training load and player monitoring in high-level football: Current practice and perceptions. *International Journal of Sports Physiology and Perform*, *11* (5), 587–593.

Aldous, J. W., Chrismas, B. C., Akubat, I., Dascombe, B., Abt, G., & Taylor, L. (2015). Hot and hypoxic environments inhibit simulated soccer performance and exacerbate performance decrements when combined. *Frontiers in Physiology*, *6*, 421.

Ardigo, L. P., Padulo, J., Zuliani, A., & Capelli, C. (2015). A low-cost method for estimating energy expenditure during soccer refereeing. *Journal of Sports Science*, *33*(17), 1853–1858.

Ascensao, A., Rebelo, A., Oliveira, E., Marques, F., Pereira, L., & Magalhaes, J. (2008). Biochemical impact of a soccer match - analysis of oxidative stress and muscle damage markers throughout recovery. *Clinical Biochemistry*, *41*(10–11), 841–851.

Borresen, J., & Lambert, M. I. (2008). Autonomic control of heart rate during and after exercise - Measurements and implications for monitoring training status. *Sports Medicine*, *38*(8), 633–646.

Buchheit, M. (2014). Monitoring training status with HR measures: Do all roads lead to Rome? *Frontiers in Physiology*, *5*, 73.

Buchheit, M., Racinais, S., Bilsborough, J. C., Bourdon, P. C., Voss, S. C., Hocking, J., … Coutts, A. J. (2013). Monitoring fitness, fatigue and running performance during a pre-season training camp in elite football players. *Journal of Science Medicine in Sport*, *16*(6), 550–555.

Carling, C. (2010). Analysis of physical activity profiles when running with the ball in a professional soccer team. *Journal of Sports Sciences*, *28*(3), 319–326.

Carling, C., Gregson, W., McCall, A., Moreira, A., Wong Del, P., & Bradley, P. S. (2015). Match running performance during fixture congestion in elite soccer: Research issues and future directions. *Sports Medcine*, *45*(5), 605–613.

Cornforth, D., Campbell, P., & Nesbitt, K. (2015). Prediction of game performance in Australian football using heart rate variability measures. *International Journal of Signal and Imaging Systems Engineering*, *8*(1/2).

Coull, N. A., Watkins, S. L., Aldous, J. W., Warren, L. K., Chrismas, B. C., Dascombe, B., Taylor, L. (2015). Effect of tyrosine ingestion on cognitive and physical performance utilising an intermittent soccer performance test (iSPT) in a warm environment. *European Journal of Applied Physiology*, *115*(2), 373–386.

Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: A systematic review. *Sports Medicine*, *43*(10), 1025–1042.

Flatt, A. A., & Esco, M. R. (2013). Validity of the ithlete smart phone application for determining ultra-short-term heart rate variability. *Journal of Human Kinetics*, *39*, 85–92.

Flatt, A. A., & Esco, M. R. (2016a). Evaluating individual training adaptation with smartphone-derived heart rate variability in a collegiate female soccer team. *Journal of Strength and Conditioning Research*, *30*(2), 378–385.

Flatt, A. A., & Esco, M. R. (2016b). Heart rate variability stabilization in athletes: Towards more convenient data acquisition. *Clinical Physiology and Functional Imaging*, *36*(5), 331–336.

Fullagar, H. H., Duffield, R., Skorski, S., Coutts, A. J., Julian, R., & Meyer, T. (2015). Sleep and recovery in team sport: Current sleep-related issues facing professional team-sport athletes. *International Journal of Sports Physiology Perform*, *10*(8), 950–957.

Gaudino, P., Iaia, F. M., Alberti, G., Strudwick, A. J., Atkinson, G., & Gregson, W. (2013). Monitoring training in elite soccer players: Systematic bias between running speed and metabolic power data. *International Journal of Sports Medicine*, *34*(11), 963–968.

Guijt, A. M., Sluiter, J. K., & Frings-Dresen, M. H. (2007). Test-retest reliability of heart rate variability and respiration rate at rest and during light physical activity in normal subjects. *Archives of Medical Research*, *38*(1), 113–120.

Halson, S. (2014). Monitoring training load to understand fatigue in athletes. *Sports Medicine*, *44* (Suppl 2), S139–S147.

Hopkins, W., Marshall, S., Batterham, A., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise*, *41*(1), 3–13.

Jennings, D., Cormack, S., Coutts, A., Boyd, L., & Aughey, R. (2010). Variability of GPS units for measuring distance in team sport movements. *International Journal of Sports Physiology Perform*, *5*(4), 565–569.

Kiviniemi, A. M., Hautala, A. J., Kinnunen, H., & Tulppo, M. P. (2007). Endurance training guided individually by daily heart rate variability measurements. *European Journal of Applied Physiology*, *101*(6), 743–751.

Kumar, Y., Agarwal, V., & Gautam, S. (2013). Heart rate variability during examination stress in medical students. *International Journal of Physics*, *1*(1), 83–86.

Mohammadi, F., & Roozdar, A. (2010). Effects of fatigue due to contraction of evertor muscles on the ankle joint position sense in male soccer players. *American Journal of Sports Medicine*, *38*(4), 824–828.
Morgans, R., Owen, A., Doran, D., Drust, B., & Morton, J. P. (2015). Prematch salivary secretory immunoglobulin a in soccer players from the 2014 World Cup qualifying campaign. *International Journal of Sports Physiology Perform*, *10*(3), 401–403.
Nakamura, F. Y., Pereira, L. A., Rabelo, F. N., Flatt, A. A., Esco, M. R., Bertollo, M., & Loturco, I. (2016). Monitoring weekly heart rate variability in futsal players during the preseason: The importance of maintaining high vagal activity. *International Journal of Sports Science*, *34*(24), 2262–2268.
Nedelec, M., McCall, A., Carling, C., Legall, F., Berthoin, S., & Dupont, G. (2012). Recovery in soccer part i - post-match fatigue and time course of recovery. *Sports Medicine*, *42*(12), 997–1015.
Oliveira, R. S., Leicht, A. S., Bishop, D., Barbero-Alvarez, J. C., & Nakamura, F. Y. (2013). Seasonal changes in physical performance and heart rate variability in high level futsal players. *International Journal of Sports Medicine*, *34*(5), 424–430.
Osgnach, C., Poser, S., Bernardini, R., Rinaldo, R., & di Prampero, P. E. (2010). Energy cost and metabolic power in elite soccer: A new match analysis approach. *Medicine and Science in Sports and Exercise*, *42*(1), 170–178.
Pinna, G., Maestri, R., Torunski, A., Danilowicz-Szymanowicz, L., Szwoch, M., La Rovere, M., & Raczak, G. (2007). Heart rate variability measures: A fresh look at reliability. *Clinical Science*, *113*, 131–140.
Plews, D. J., Laursen, P. B., & Buchheit, M. (2016). Day-to-day Heart Rate Variability (HRV) recordings in world champion rowers: Appreciating unique athlete characteristics. *International Journal of Sports Physiology Perform*, 1–19. doi:10.1123/ijspp.2016-0343
Plews, D. J., Laursen, P. B., Le Meur, Y., Hausswirth, C., Kilding, A. E., & Buchheit, M. (2014). Monitoring training with heart rate-variability: How much compliance is needed for valid assessment? *International Journal of Sports Physiology Perform*, *9*(5), 783–790.
Sandercock, G. R. H., Bromley, P. D., & Brodie, D. A. (2005). Effects of exercise on heart rate variability: Inferences from meta-analysis. *Medicine and Science in Sports and Exercise*, *37*(3), 433–439.
Saw, A. E., Main, L. C., & Gastin, P. B. (2015). Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. *British Journal of Sports Medicine*. doi:10.1136/bjsports-2015-094758
Thorpe, R., & Sunderland, C. (2012). Muscle damage, endocrine, and immune marker response to a soccer match. *Journal of Strength and Conditioning Research*, *26*(10), 2783–2790.
Thorpe, R. T., Atkinson, G., Drust, B., & Gregson, W. (2017). Monitoring fatigue status in elite team sport athletes: Implications for practice. *International Journal of Sports Physiology Perform*, 1–25. doi:10.1123/ijspp.2016-0434
Thorpe, R. T., Strudwick, A. J., Buchheit, M., Atkinson, G., Drust, B., & Gregson, W. (2015). Monitoring fatigue during the in-season competitive phase in elite soccer players. *International Journal of Sports Physiology Perform*, *10*(8), 958–964.
Thorpe, R. T., Strudwick, A. J., Buchheit, M., Atkinson, G., Drust, B., & Gregson, W. (2016a). The influence of changes in acute training load on daily sensitivity of morning-measured fatigue variables in elite soccer players. *International Journal of Sports Physiology Perform*, 1–23. doi:10.1123/ijspp.2016-0433
Thorpe, R. T., Strudwick, A. J., Buchheit, M., Atkinson, G., Drust, B., & Gregson, W. (2016b). Tracking morning fatigue status across in-season training weeks in elite soccer players. *International Journal of Sports Physiology Perform*, *11*(7), 947–952.
Zech, A., & Wellmann, K. (2017). Perceptions of football players regarding injury risk factors and prevention strategies. *PLoS One*, *12*(5), e0176829.