EUROPEAN JOURNAL OF SPORT SCIENCE
2022, VOL. 22, NO. 7, 1085–1093
https://doi.org/10.1080/17461391.2021.1936195

ORIGINAL INVESTIGATION

OPEN ACCESS

Does perceived wellness influence technical–tactical match performance? A study in youth international rugby using partial least squares correlation analysis

Carlos Ramírez-López [a,b,c], Kevin Till [a,d], Dan Weaving [a,d], Andy Boyd[e], Alexis Peeters[f], Grant Beasley[g], Sam Bradley[h,i], Pierosario Giuliano[j], Charlie Venables[a] and Ben Jones [a,c,d,k,l]

[a]Leeds Beckett University, Carnegie Applied Rugby Research (CARR) Centre, Carnegie School of Sport, Leeds, UK; [b]Yorkshire Carnegie Rugby Union Club, Leeds, UK; [c]England Performance Unit, The Rugby Football League, Leeds, UK; [d]Leeds Rhinos Rugby League Club, Leeds, UK; [e]Scottish Rugby Union, Murrayfield Stadium, Edinburgh, UK; [f]French Rugby Federation, Centre National de Rugby, Marcoussis, France; [g]Rugby Football Union, Twickenham Stadium, London, UK; [h]Welsh Rugby Union, Principality Stadium, Cardiff, UK; [i]English Institute of Sport, Manchester, UK; [j]Italian Rugby Federation, Stadio Olimpico, Rome, Italy; [k]School of Science and Technology, University of New England, Armidale, Australia; [l]Division of Exercise Science and Sports Medicine, Department of Human Biology, Faculty of Health Sciences, the University of Cape Town and the Sports Science Institute of South Africa, Cape Town, South Africa

ABSTRACT
The purpose of this study was to determine the relationship between matchday wellness status and a technical–tactical performance construct during rugby match-play. One hundred and thirty-three male rugby union players (73 forwards and 60 backs) from five under-18 national squads who participated in the under-18 Six Nations competition completed a subjective wellness questionnaire on each matchday morning. Players subjectively rated each item (sleep quality, fatigue, muscle soreness, stress and mood) on a five-point Likert scale to calculate their daily wellness status (i.e. difference between matchday and baseline perceived wellness). Technical–tactical performance during match-play was quantified by coding individual key performance indicators (e.g. number of carries, number of tackles). Partial least squares correlation analysis (PLSCA) was employed to compute the latent variables of perceived wellness status (*X* matrix) and technical–tactical performance (*Y* matrix) for each player observation ($n = 271$). The latent variables are a construct of each variable group, enabling higher dimensional data to be visualised more simply. Linear mixed-effect models were later conducted to assess the relationships between the latent variables. The effect of perceived wellness status on technical–tactical performance was statistically significant in forwards ($p = .042$), not statistically significant in backs ($p = .120$) and accounted for 4.9% and 1.9% variance in the technical–tactical performance construct, respectively. The findings of this study suggest that perceived wellness status can influence technical–tactical match performance, but the practical significance of these findings should be interpreted with caution given the amount of variance in technical–tactical performance accounted by the models.

KEYWORDS
Recovery; team sport; fatigue; performance

Introduction

Participation in rugby match-play leads to considerable neuromuscular, metabolic and psychological impairments that can last for several days after competition (Doeven, Brink, Kosse, & Lemmink, 2018). Accordingly, practitioners systematically monitor players' recovery status and aim to manage fatigue by making routine modifications in training loads as it is believed that incomplete recovery can negatively affect players' health and performance (Doeven et al., 2018). This becomes particularly important during periods of congested fixtures whereby the time to recover between matches may be insufficient (Johnston, Gabbett, & Jenkins, 2013). Research in post-match fatigue has highlighted that, on average, recovery is attained between short matchday cycles (Ramírez-López et al., 2020) (i.e. 96 h) and studies in different rugby cohorts agree that, on average, it takes up to 72 h to recover from a match (Ramírez-López et al., 2020 ; West et al., 2014). However, the time course of post-match recovery is highly variable between individual players, potentially leading to some being under-recovered on matchday (Ramírez-López et al., 2020 ; West et al., 2014). Therefore, daily individual monitoring of fatigue is often recommended to ensure athletes are prepared for competition.

CONTACT Carlos Ramírez-López c.ramirez@leedsbeckett.ac.uk Carnegie School of Sport, Leeds Beckett University, Room G08, Cavendish Hall, Headingley Campus, Leeds LS6 3QS, UK

Athlete-self report measures (ASRM) (Saw, Main, & Gastin, 2016) are the most widely used method for fatigue monitoring in high-performance sport (Taylor, Chapman, Cronin, Newton, & Gill, 2012). Typically, ASRM are non-invasive, easy to administer, sensitive to changes in load resulting from match-play and may have a greater sensitivity to changes in load than other commonly used objective measures (Saw et al., 2016). Empirical ASRM such as the Recovery-Stress Questionnaire for Athletes (REST-Q) (Kellmann & Kallus, 2001) and the Profile of Mood States (POMS) (Raglin & Morgan, 1994) provide valuable information about athletes' recovery status but can be time consuming and are not designed for daily use. Despite concerns about their reliability (Fitzpatrick, Akenhead, Russell, Hicks, & Hayes, 2019), self-reported wellness questionnaires are the most commonly used ASRM because they represent a time-efficient method for daily monitoring (Taylor et al., 2012). However, the real-world meaningfulness of their daily use has been questioned given the unclear associations with tangible outcomes of injury and technical–tactical performance (Carling et al., 2018).

The relationships between perceived wellness and physical performance during training and match-play have previously been investigated (Bellinger, Ferguson, Newans, & Minahan, 2020; Gallo, Cormack, Gabbett, & Lorenzen, 2016). However, the physical outputs that have been studied (e.g. distance covered at different velocity bands, accelerometer-derived metrics) are not directly associated with success (Dubois et al., 2020) and may even be greater in losing teams (Kempton & Coutts, 2016). Assessments of technical and tactical match actions through key performance indicators (KPI) (Colomer, Pyne, Mooney, McKune, & Serpell, 2020) may be more appropriate to quantify player performance because of their associations with success measures (Bennett, Bezodis, Shearer, Locke, & Kilduff, 2019). As a result, researchers and practitioners have shown interest in investigating the player characteristics that underpin technical–tactical performance on match day. For instance, Cunningham et al. (2018) identified positive relationships between physical qualities (e.g. strength and fitness) and KPIs (e.g. number of carries, number of tackles) during rugby union match-play via correlation analyses. Also, Hunkin et al. (2014) reported negative associations between plasmatic concentrations of creatine kinase ([CK]; an objective biomarker of muscle damage) with player performance coach ranking scores in Australian rules football. Furthermore, Fox, Santon, Scanlan, Masaru, and Sargent (2020) used univariate linear regression to identify positive associations ($p < .05$) between perceived sleep quality and technical–tactical performance in basketball players. However, to date, no published research has examined the relationships between perceived wellness and technical–tactical performance in rugby union. This is important to consider conceptually because of recent questions related to the content validity of self-reported wellness questionnaires within high-performance environments (Jeffries et al., 2020).

Analysing relationships between predictor variables such as "physical qualities", "sleep" or "wellness" with performance data as a response can be a challenging task, especially when sample sizes are small and the data are highly correlated (Weaving et al., 2019). Whereas multiple performance indicators are routinely collected, there is a requirement to group these variables to represent an overall technical–tactical construct. However, problems arise when attempting to understand relationships between distinct and multidimensional constructs (e.g. fatigue, performance) through univariate analysis. This is because univariate analysis assumes that the studied variables within a construct are independent of each other and therefore does not account for the unique and shared variance captured between them. To address this issue, Weaving et al. (2019) recently demonstrated how partial least squares correlation analysis (PLSCA) can be used as a multivariate analysis method for analysing performance data in sport. Different from the commonly used univariate analysis methods, PLSCA considers the correlation between two matrices rather than between two variables and analyses their covariance to understand the information shared between sets of data (Abdi & Williams, 2013), making it more appropriate to analyse relationships between multiple variables within sport. Therefore, the purpose of this study was to investigate the relationship between matchday wellness status and a technical–tactical performance construct during youth international rugby match-play by using PLSCA. It is expected that by doing so, some light can be shed on the real-world meaningfulness of the information gathered through self-reported wellness questionnaires.

Methodology

Participants

One hundred and thirty-three international-level male Under (U)18 rugby union players (age 17.7 ± 0.3 years; stature 186.9 ± 7.4 cm; body mass 92.5 ± 13.3 kg) from five European national squads participated in this study. Participants were divided into positional groups as forwards ($n = 73$) and backs ($n = 60$). Participants were selected to represent their country during the 2018 edition of the U18 Six Nations competition. The competition was held in Wales, and no participant travelled more than a single time zone to the tournament site. Before data collection, participants received verbal and written explanations of the aims of the study in their home language and signed informed consent to provide daily wellness information and to use their technical–tactical KPIs from tournament match-play. A total of 271 player observations derived from 15 team matches were included in this study. Ethics approval was obtained by the university's Local Research Ethics Committee.

Study design

A prospective observational design was used to investigate the relationships between player's wellness status on matchday morning and match performance assessed by individual technical–tactical KPIs. Each national squad played three matches against three different opposing teams over a nine-day period. Matches were separated by an average of 94.5 ± 2.6 h, and the starting time varied between 12:00 and 15:00.

Perceived wellness

Participants were instructed to complete an electronic questionnaire built-in Google Forms (Google, CA, USA) every morning during the length of the competition. The questionnaire was based on previous literature (McLean, Coutts, Kelly, McGuigan, & Cormack, 2010) and asked participants to rank their perceptions of sleep quality, fatigue, muscle soreness, stress and mood by using a five-point Likert scale. A total wellness score was obtained by summing the scores of the mentioned subscales. All participants completed the questionnaire within the same two-hour window (7:30–9:30 AM) from their own mobile device and on their own to prevent any influence from diurnal variations and from their peers. Participants were allowed a 7-day familiarisation period with the questionnaire before the start of the competition. The highest total wellness score recorded on the three days leading into the first match by each individual was considered baseline along with its corresponding subscales. The differences between both individual total wellness score with its subscales on matchday morning and baseline individual total wellness score with its subscales were used to build the perceived wellness status constructs.

Technical–tactical performance

Actions on and around the ball performed by each individual player from the 15 analysed matches were coded from video footage by two experienced performance analysts working with professional rugby (>8 years combined experience). Coder 1 analysed eight randomly assigned matches (intra-coder ICC > 0.96), whilst coder 2 analysed the remaining seven matches (intra-coder ICC > 0.94). Inter-coder reliability is presented in Table 1 alongside the definitions of the match actions used for the analyses. These actions were selected as they were deemed individual KPIs that are considered important for match success in rugby union (Cunningham et al., 2018; James, Mellalieu, & Jones, 2005).

Statistical analyses

Partial least squares correlation analysis (PLSCA) (Abdi & Williams, 2013; Weaving et al., 2019) was used to

Table 1. Definitions of technical–tactical key performance indicators (KPI) coded for constructing the technical–tactical performance construct.

Action	Description	Inter-coder ICC
Possession	Count of times the player had possession of the ball	0.98
Carry	Count of times the player carried the ball into contact while making an obvious attempt to go forward with the ball in hand	0.96
Positive gain line	Count of times the player in possession of the ball crossed the gain line	0.90
Dominant carry	Count of times the player carried the ball into contact resulting in the defender's hips touching the ground after the collision	0.93
Pass	Count of times the player passed the ball with purpose to a teammate	0.99
Handling error	Count of handling errors incurred by the player – includes knock-ons, forwards passes and balls dropped behind which did not result in a penalty	0.92
First three in attack	Count of times the player was in the first three support players to the ruck while their team was attacking	0.96
Attacking actions	Sum of attacking actions excluding handling errors	0.96
Tackle	Count of times the player attempted to halt the progression or dispossess an opponent in possession of the ball	0.97
Missed tackle	Count of times the player failed to affect a tackle on an opposition player when they were in a reasonable position to make the tackle	0.94
Dominant tackle	Count of tackles made by the player resulting in the attacker's hips touching the ground after the collision	0.98
First three in defence	Count of times the player was in the first three support players to the ruck while their team was defending	0.96
Defensive actions	Sum of defensive actions excluding missed tackles	0.95

Note: ICC: intra-class correlation coefficient.

investigate the composite relationship between perceived wellness status and technical–tactical performance for both the forwards and backs positional groups as per previous methods (Emmonds et al., 2020). Similar to simple ($X_1 \rightarrow Y_1$) or multiple ($X_1, \ldots, X_n \rightarrow Y_1$) linear regression models, PLSCA aims to understand the relationships between predictor and response variables. However, when the analysis involves a large number of predictor and response variables, linear regression requires the construction of multiple models as only one response variable can be evaluated each time (i.e. Y_1). These models are also sensitive to multicollinearity between predictors (Weaving et al., 2019). Partial least squares correlation analysis allows consideration of matrices of both predictor and response variables ($X_1, \ldots, X_n \rightarrow Y_1, \ldots Y_n$) allowing the covariance between both multiple predictor and response variables to be evaluated concurrently whilst facilitating a reduced number of models compared to linear regression (Abdi & Williams, 2013; Weaving et al., 2019).

To conduct PLSCA, the forwards and backs datasets were first mean centred and standardised to unit variance. The PLSCA model included a $[n \times 6]$ matrix, X, for each positional group containing the six variables that represent perceived wellness for each player observation ($n = 154$ in forwards; $n = 117$ in backs) and a $[n \times 13]$ matrix, Y, for each positional group containing the 13 technical–tactical performance variables for each player observation. A PLSCA model was conducted for each positional group. Partial least squares correlation analysis involves storing the X and Y matrices in a covariance matrix, R (Y^TX) and performing singular value decomposition on this covariance matrix (Abdi & Williams, 2013; Weaving et al., 2019). Through this, PLSCA creates orthogonal (uncorrelated) dimensions – the number of dimensions constructed is equal to the number of inputted variables within the X matrix (i.e. 6 perceived wellness variables). For each dimension of the PLSCA model: (1) the saliences (weights) of X for each dimension (perceived wellness status), (2) the saliences (weights) of Y for each dimension (technical–tactical performance) and (3) the singular values are computed.

The saliences (weights) are the linear weighted contribution of the original variables for X (e.g. soreness) and Y (e.g. possessions) to each dimension of the PLSCA model. By multiplying the saliences with the original mean centred and standardised data for each original variable – a latent variable score can be created for each observation. Therefore, the latent variables are a composite score of perceived wellness status and technical–tactical performance derived from the PLSCA model, enabling higher dimensional data to be visualised more simply.

The sum of the singular values provides the inertia of the PLSCA model with higher inertia values signifying stronger relationships between X and Y (Weaving et al., 2019). The amount of variance captured by each dimension can be calculated from the singular values (square of the singular values for that dimension divided by total singular values of the model). To establish the significance of the observed singular value inertia (i.e. the shared information between X and Y), a permutation test involving 10,000 permutations of the Y matrix was conducted. For the permutation test, odds of less than 500/10,000 ($p < .05$) were deemed to be significant relationships.

Due to the non-independence arising from the repeated measurements of perceived wellness status and technical–tactical performance alongside the random effect of time on the pitch we conducted a linear mixed-effects model using the *lme4* package (Bates, Mächler, Bolker, & Walker, 2015) in R Studio (Version 1.2.1335). The 1st dimension Y latent variable (technical–tactical performance) was identified as the dependent variable, the 1st dimension X latent variable (perceived wellness status) as the fixed effect with the duration on the pitch and Player ID selected as random effects. To estimate the amount of variance explained by the X latent variable (perceived wellness status) and the random effects, a coefficient of determination (Nagelkerke, 1991) (pseudo-R^2) was calculated using the "MuMIn" R package (Barton, 2016).

All PLSCA analysis was undertaken in R Studio (version 3.3.2: utilising the packages: "*psych*"; "*car*"; and "*pracma*") (open source software). For all analyses, p values <.05 were deemed to be significant.

Results

Table 2 shows descriptive statistics for the observed wellness scores and its subscales, its difference from baseline and the KPIs included in the X and Y matrices.

Table 3 details the saliences of the first and second dimensions of the PLSCA model for each the forwards and the backs model along with the percentage variance captured by each dimension. As such, the weighted contributions of each of the variables to its respective construct are presented. The 1st dimension of the X and Y matrices from the refined PLSCA captured 74.13% of the variance in the dataset for the forwards model and 53.95% for the backs model. To create the latent variables (composite variable) for each player observation, the saliences of the 1st dimension (Table 3) were

Table 2. Descriptive statistics for perceived wellness and technical–tactical variables included in the *X* and *Y* matrices.

Descriptive statistics	Forwards (*n* = 154)	Backs (*n* = 117)
Perceived Wellness Status		
Fatigue	3.6 ± 0.7	3.6 ± 0.7
Sleep quality	3.8 ± 0.8	3.9 ± 0.6
Soreness	3.6 ± 0.7	3.5 ± 0.8
Stress	3.5 ± 0.7	3.5 ± 0.7
Mood	4.0 ± 0.6	3.9 ± 0.5
Total wellness score	18.8 ± 2.5	18.4 ± 2.4
Total wellness score from baseline	−1.2 ± 2.1	−1.9 ± 1.6
Technical–Tactical Performance		
Possession	6.2 ± 4.4	15.7 ± 17.5
Carry	4.5 ± 3.3	4.1 ± 2.8
Positive gain line	1.6 ± 1.8	1.6 ± 1.6
Dominant carry	0.8 ± 1.2	0.4 ± 0.7
Pass	2.1 ± 1.5	9.8 ± 16.5
Handling error	0.6 ± 0.8	0.7 ± 1.1
First three in attack	9.3 ± 6.4	4.0 ± 4.0
Attacking actions	24.8 ± 14.9	38.1 ± 33.8
Tackle	7.4 ± 4.8	4.6 ± 3.7
Missed tackle	0.6 ± 0.9	1.2 ± 1.3
Dominant tackle	0.4 ± 0.7	0.1 ± 0.5
First three in defence	2.1 ± 2.5	0.9 ± 1.4
Defensive actions	10.8 ± 7.0	7.4 ± 5.3

Note: Data are presented as mean ± SD for n = player observations.

Table 3. The saliences for the 1st and 2nd dimensions of the forwards and backs PLSCA models including the percentage variance explained by each dimension.

	Forwards		Backs	
Percentage of variance explained	1st dimension 74.13%	2nd dimension 14.34%	1st Dimension 53.95%	2nd Dimension 20.85%
Perceived Wellness Status (X matrix)				
Fatigue	0.58	0.05	0.29	−0.15
Sleep quality	0.31	0.75	0.65	−0.15
Soreness	0.32	−0.26	0.30	0.59
Stress	0.40	−0.58	0.42	−0.07
Mood	0.22	0.16	−0.04	−0.78
Total wellness score	0.53	0.04	0.48	−0.08
Technical–Tactical Performance (Y matrix)				
Possession	0.47	−0.22	0.14	0.06
Carry	0.37	−0.30	0.02	0.24
Positive gain line	0.20	−0.02	0.27	0.56
Dominant carry	0.13	−0.10	0.05	−0.52
Pass	0.50	0.17	0.10	0.08
Handling error	−0.12	−0.09	0.5	−0.21
First three in attack	0.10	0.19	0.25	0.19
Attacking actions	0.37	−0.07	0.20	0.13
Tackle	0.13	0.50	0.01	0.02
Missed tackle	0.21	0.46	0.27	0.05
Dominant tackle	−0.30	0.30	0.55	0.09
First three in defence	0.08	0.08	0.31	−0.48
Defensive actions	0.13	0.46	0.27	−0.11

multiplied by the original standardised and mean centred data for the *X* and *Y* matrices for both the forwards and backs models (Figure 1). The observed singular value inertia was significant ($p = .0034$) for the forwards model but not significant for the backs model ($p = .9912$).

For forwards, both fatigue (0.58) and total wellness score (0.53) provided a similar weighted contribution to the construction of the latent *X* variable (i.e. perceived wellness status) whilst passes (0.50) and possessions (0.47) provided greater weighted contributions to the construction of the latent *Y* variable (i.e. technical–tactical performance) than the remaining coded match actions (Table 3).

For backs, sleep quality (0.65) and total wellness score (0.48) provided the highest contribution to the construction of the latent *X* variable (i.e. perceived wellness status) whilst dominant tackles (0.55) and handling errors (0.50) provided greater weighted contributions to the construction of the latent *Y* variable (i.e. technical–tactical performance) than the remaining coded match actions (Table 3).

For the forwards model, the results of the linear mixed-effects models suggest that the fixed effect of the latent *X* variable (perceived wellness status) on the *Y* variable (technical–tactical performance) was significant ($p = .042$). The coefficient of determination (pseudo-R^2) for the fixed effect was 0.049 (i.e. explaining 4.9% of the variance).

For the backs model, the results of the linear mixed-effects model suggest that the fixed effect of the latent *X* variable (perceived wellness status) on the *Y* variable (technical–tactical performance) was not significant ($p = .120$). The coefficient of determination (pseudo-R^2) for the fixed effect was 0.019 (i.e. explaining 1.9% of the variance).

Discussion

The purpose of this study was to investigate the relationships between perceived wellness status and a construct of technical–tactical performance during youth international rugby match play. Using PLSCA and linear mixed effects models, this study identified a significant and greater relationship (singular value inertia and pseudo-R^2) between wellness and technical–tactical performance for the forwards than backs. However, despite significance, the low coefficients of determination for these relationships (pseudo-R^2 = 0.019–0.049) must be considered when interpreting if these are of practical significance.

The present study provides evidence of a statistically significant association between perceived wellness status and a construct of technical–tactical performance in the forwards position. To date, no published research had examined these relationships in rugby or any other team sport. In the only study to evaluate the relationships between a self-reported measure and a technical–tactical performance construct, the authors

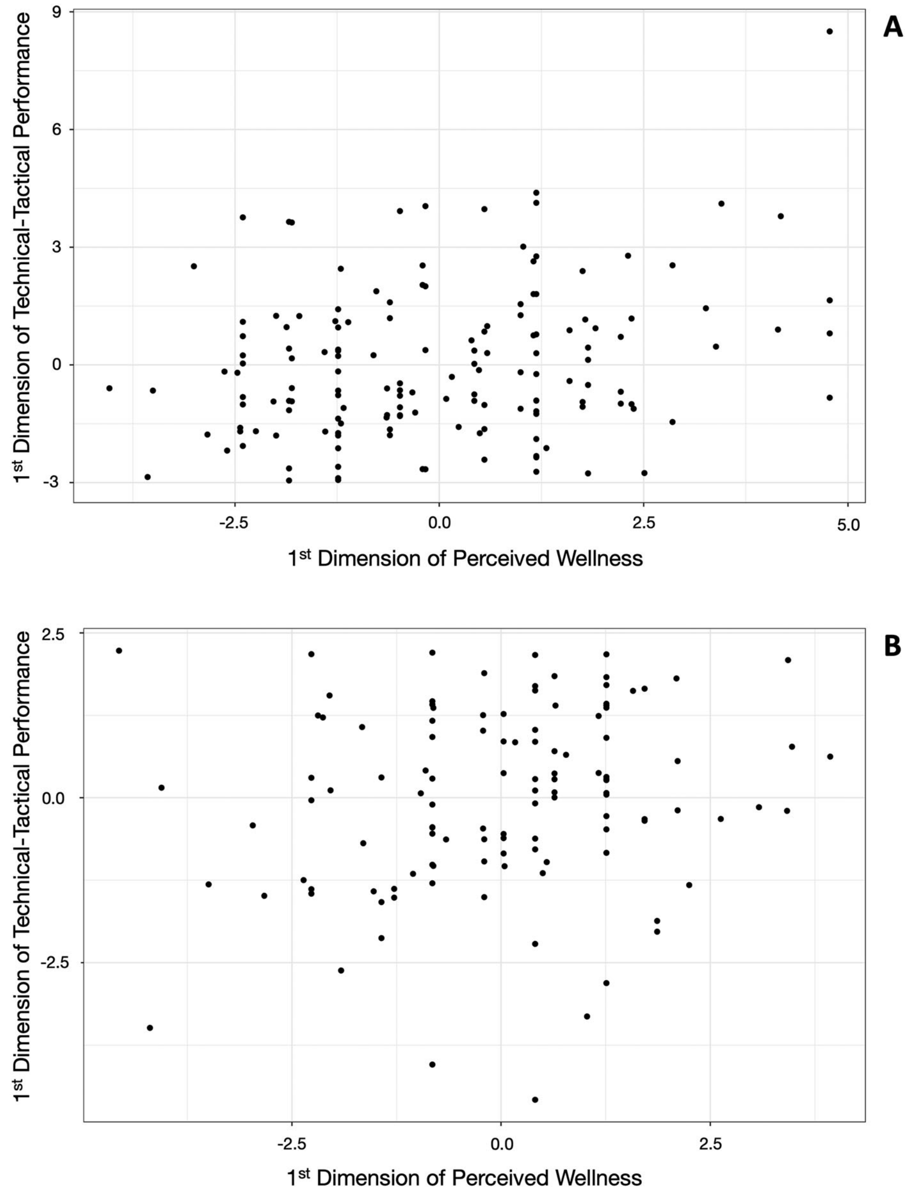

Figure 1. Scatterplot of the latent variables of perceived wellness status (*X* matrix dimension 1) and technical–tactical performance (*Y* matrix dimension 1) for the 1st dimension for the forwards (a) and backs (b) models.

identified positive associations ($p < .05$) between subjective sleep quality with free-throw accuracy, rebounds, assists, steals and offensive ratings in basketball players (Fox et al., 2020). However, coefficients of determination, and as such, the amount of variance in performance explained by their models were not reported, making it difficult to interpret the practical significance of their findings. Also, the data were analysed using univariate linear regression, therefore not accounting for any covariance between the technical–tactical actions which can be overcome using more appropriate statistical analysis techniques. Hunkin, Fahrner, and Gastin (2014) examined the relationships between pre-match [CK] and a technical–tactical player performance score in a sample of Australian rules football athletes. Similar to this study, and despite reporting a significant small relationship ($r = 0.149$, $p = .035$), the authors expressed concerns about the practical ability of pre-match [CK] for predicting performance based on player performance scores. However, the magnitude of pre-match [CK] was significantly associated with performance based on coaches' ratings ($p = .002$). It may be that the use of coaches' ratings as a performance metric captures some information missed by adopting solely quantitative analysis of performance indicators. There are arguments in favour of using coaches' ratings as the gold standard measure of performance due to coaches' experience and expertise acquired through years of playing and coaching their sport (Hunkin et al. 2014).

In this study, the results of the forwards' models showed a statistically significant relationship ($p = .042$) which explained 4.9% of the variation of the performance construct (pseudo $R^2 = 0.049$). The practical significance of this finding should be interpreted with caution for a number of reasons. Limited attention has been given to the concept and interpretation of match-to-match variation of technical–tactical performance in team sports. Due to the highly complex and dynamic nature of rugby match-play, technical–tactical performance is influenced by situational factors (Colomer et al., 2020) (e.g. quality of opposition, partial score, location on the pitch where a given action takes part) potentially leading to high variability of the measures. Indeed, an investigation in Australian rules football reported a high between-match variability of technical measures (CV = 31.5%; smallest worthwhile change = 9.1%) (Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015). A high degree of variability in technical–tactical performance may be fundamental to team sports, resulting from fine adjustments to situational factors. Therefore, researchers and practitioners should consider the inherently high match-to-match variability within models alongside empirical measures such as the smallest worthwhile change for making informed conclusions related to technical–tactical performance. To date, no efforts have been made to describe the match-to-match variation of technical–tactical performance in rugby codes.

The results of the backs models were not significant ($p = .12$) and explained only 1.9% of the variance (pseudo-$R^2 = 0.012$). Differences in the fit of models may be due to the different demands of the sport and the subsequent different fatigue responses between positional groups. A recent investigation (Ramírez-López et al., 2020) reported that the perceived wellness response to match-play differs between youth international forwards and backs. Forwards are typically exposed to a greater number of collisions while backs are typically exposed to higher locomotor demands, potentially explaining the differences in wellness responses (Ramírez-López et al., 2020). It is possible that wellness questionnaires are capturing different aspects of player recovery in different positional groups.

Perceived wellness questionnaires are the most commonly used tool for monitoring recovery status in high-performance sport because of their relative ease of use and their responsiveness to acute load variations. However, these questionnaires have not proven to be reliable (Fitzpatrick et al., 2019), have not undergone a rigorous validation process and may lack the sensitivity and specificity to capture a true representation of an individual's status (Jeffries et al., 2020). This has led to researchers questioning the benefit of their daily use in practice (Carling et al., 2018; Jeffries et al., 2020; Saw, Kellmann, Main, & Gastin, 2017). Fatigue is a multifactorial process, and it may be that to register subtle performance-related-changes monitoring should be conducted on a multidimensional level (i.e. psychological, physiological and neuromuscular) (Heidari et al., 2019). It is possible that the performance of a model in explaining the amount of variance in technical–tactical performance can be maximised if valid measures from different fatigue dimensions are included.

Player performance can be understood as a complex dynamical system and is likely affected by contextual factors, resulting in fine-tuned adjustments in decision making and player behaviour (Colomer et al., 2020). Moreover, it is likely that multiple performance solutions exist for any given game situation, allowing players to choose from an array of "correct" solutions to a singular problem. Therefore, it is also possible that player performance is only directly affected by recovery status if a state of non-functional overreaching is reached, (Heidari et al., 2019) which may not have been the case with the participants in this study. Furthermore, the notion of a direct influence of a factor (e.g. fatigue) on performance may be reductionist, implying that causality is mono-directional (i.e. for every cause there is a preceding effect) and may not apply to a complex system such as rugby union competition (Dalton-Barron et al., 2020).

The present study used PLSCA to address issues of multicollinearity that can be found in sports performance data, allowing to investigate relationships between constructs rather than between isolated variables representing each construct. As such, PLSCA appears to be a useful analytical tool and should be considered in future research designs. The number of participants included, which allowed to assess the players by positional group (i.e. forwards and backs) is also a strength of this investigation. However, despite the number of participants, the total number of games analysed ($n = 15$) must be acknowledged as a limitation. Also, additional monitoring tools that may be used in practice (Gathercole, Sporer, Stellingwerff, & Sleivert, 2015) (e.g. performance tests) and capture different dimensions of players' recovery status were not considered for building a wider fatigue construct. Similarly, player performance ratings based on coaches' opinions may capture valuable information related to technical–tactical performance but were not included within the performance construct. Further research should investigate the relationships between different commonly used player monitoring tools and tangible outcomes (e.g. technical–tactical performance, injury) within a longitudinal design.

Conclusion

The findings of this study show a statistically significant effect of perceived wellness status on a technical–tactical performance construct in youth international rugby union forwards but not in backs. The different results of the models may be explained by the monitoring tool capturing different aspects of player recovery between positions, or different requirements within a match. The practical relevance of these results should be interpreted carefully given the low pseudo-R^2 obtained by the models while considering the potentially inherently high match-to-match variation in technical–tactical performance.

Practical applications

Although the practical significance of the association found between perceived wellness status and a technical–tactical performance construct on this study was unclear, the value of player monitoring should not be disregarded. Monitoring of perceived wellness is a popular and cost-effective strategy that is often used to inform decisions related to player selection and training scheduling in practice. Therefore, it is crucial for practitioners to critically evaluate how confident they can be on the information that is acquired through subjective wellness questionnaires. Practitioners should consider choosing existing empirical measures for player monitoring (e.g. REST-Q, (Kellmann & Kallus, 2001) POMS (Raglin & Morgan, 1994)) as an alternative to perceived wellness in light of their feasibility within their particular context. Further research should aim to develop monitoring tools that are valid, reliable, non-invasive, quick to administer and demonstrate clear associations with player performance.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Carlos Ramírez-López http://orcid.org/0000-0003-1605-3484
Kevin Till http://orcid.org/0000-0002-9686-0536
Dan Weaving http://orcid.org/0000-0002-4348-9681
Ben Jones http://orcid.org/0000-0002-4274-6236

References

Abdi, H., & Williams, L. J. (2013). Partial least squares methods: Partial least squares correlation and partial least square regression. *Alternatives to Laboratory Animals : ATLA*, *27*, 549–579.

Barton, K. (2016). MuMIn: multi-model inference. R Package Version 1.15.6. https://cran.r-project.org/package=MuMIn.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), doi:10.18637/jss.v067.i01

Bellinger, P. M., Ferguson, C., Newans, T., & Minahan, C. L. (2020). No influence of prematch subjective wellness ratings on external load during elite Australian Football match play. *International Journal of Sports Physiology and Performance*, 15, 6, 801–807.

Bennett, M., Bezodis, N., Shearer, D. A., Locke, D., & Kilduff, L. P. (2019). Descriptive conversion of performance indicators in rugby union. *Journal of Science and Medicine in Sport*, *22* (3), 330–334. doi:10.1016/j.jsams.2018.08.008

Carling, C., Lacome, M., McCall, A., Dupont, G., Le Gall, F., Simpson, B., & Buchheit, M. (2018). Monitoring of post-match fatigue in professional soccer: Welcome to the real world. *Sports Medicine*, *48*(12), 2695–2702. doi:10.1007/s40279-018-0935-z

Colomer, C. M. E., Pyne, D. B., Mooney, M., McKune, A., & Serpell, B. G. (2020). Performance analysis in rugby union: A critical systematic review. *Sports Medicine - Open*, *6*(1). doi:10.1186/s40798-019-0232-x

Cunningham, D. J., Shearer, D. A., Drawer, S., Pollard, B., Cook, C. J., Bennett, M., … Rogan, S. (2018). Relationships between physical qualities and key performance indicators during match-play in senior international rugby union players. *PLoS One*, *13*(9), e0202811. doi:10.1371/journal.pone.0202811

Dalton-Barron, N., Whitehead, S., Roe, G., Cummins, C., Beggs, C., & Jones, B. (2020). Time to embrace the complexity when analysing GPS data? A systematic review of contextual factors on match running in rugby league. *Journal of Sports Sciences*, *38*(10), 1161–1180. doi:10.1080/02640414.2020.1745446

Doeven, S. H., Brink, M. S., Kosse, S. J., & Lemmink, K. A. P. M. (2018). Postmatch recovery of physical performance and biochemical markers in team ball sports: A systematic review. *BMJ Open Sport & Exercise Medicine*, *4*(1), e000264. doi:10.1136/bmjsem-2017-000264

Dubois, R., Bru, N., Paillard, T., Le Cunuder, A., Lyons, M., Maurelli, O., … Cortis, C. (2020). Rugby game performances and weekly workload: Using of data mining process to enter in the complexity. *PLoS One*, *15*(1), e0228107–21. doi:10.1371/journal.pone.0228107

Emmonds, S., Weaving, D., Dalton-Barron, N., Rennie, G., Hunwicks, R., Tee, J., … Jones, B. (2020). Locomotor characteristics of the women's inaugural super league competition and the rugby league world cup. *Journal of Sports Sciences*, *38*(21), 2454–2461. doi:10.1080/02640414.2020.1790815

Fitzpatrick, J. F., Akenhead, R., Russell, M., Hicks, K. M., & Hayes, P. R. (2019). Sensitivity and reproducibility of a fatigue response in elite youth football players. *Science and Medicine in Football*, *3*(3), 214–220. doi:10.1080/24733938.2019.1571685

Fox, J., Santon, R., Scanlan, A., Masaru, T., & Sargent, C. (2020). The association between sleep and in-game performance in basketball players. *International Journal of Sports Physiology and Performance*, *16*(3), 333–341. doi:10.1123/ijspp.2020-0025

Gallo, T. F., Cormack, S. J., Gabbett, T. J., & Lorenzen, C. H. (2016). Pre-training perceived wellness impacts training output in Australian football players. *Journal of Sports Sciences*, *34*(15), 1445–1451. doi:10.1080/02640414.2015.1119295

Gathercole, R. J., Sporer, B. C., Stellingwerff, T., & Sleivert, G. G. (2015). Comparison of the capacity of different jump and sprint field tests to detect neuromuscular fatigue. *Journal of Strength and Conditioning Research*, *29*(9), 2522–2531. doi:10.1519/JSC.0000000000000912

Heidari, J., Beckmann, J., Bertollo, M., Brink, M., Kallus, K. W., Robazza, C., & Kellmann, M. (2019). Multidimensional monitoring of recovery status and implications for performance. *International Journal of Sports Physiology and Performance*, *14*(1), 2–8. doi:10.1123/ijspp.2017-0669

Hunkin, S. L., Fahrner, B., & Gastin, P. B. (2014). Creatine kinase and its relationship with match performance in elite Australian rules football. *Journal of Science and Medicine in Sport*, *17*(3), 332–336. doi:10.1016/j.jsams.2013.05.005

James, N., Mellalieu, S. D., & Jones, N. M. P. (2005). The development of position-specific performance indicators in professional rugby union. *Journal of Sports Sciences*, *23*(1), 63–72. doi:10.1080/02640410410001730106

Jeffries, A. C., Wallace, L., Coutts, A. J., McLaren, S. J., McCall, A., & Impellizzeri, F. M. (2020). Athlete-Reported outcome measures for monitoring training responses: A systematic review of risk of bias and measurement property quality according to the COSMIN guidelines. *International Journal of Sports Physiology and Performance*, *15*(9), 1203–1215. doi:10.1123/ijspp.2020-0386

Johnston, R. D., Gabbett, T. J., & Jenkins, D. G. (2013). Influence of an intensified competition on fatigue and match performance in junior rugby league players. *Journal of Science and Medicine in Sport*, *16*(5), 460–465. doi:10.1016/j.jsams.2012.10.009

Kellmann, M., & Kallus, K. W. (2001). *Recovery-stress questionnaire for athletes: User manual*. Champaign, IL: Human Kinetics. https://books.google.es/books/about/Recovery_stress_Questionnaire_for_Athlet.html?id=tyYBWi0pc68C&redir_esc=y.

Kempton, T., & Coutts, A. J. (2016). Factors affecting exercise intensity in professional rugby league match-play. *Journal of Science and Medicine in Sport*, *19*(6), 504–508. doi:10.1016/j.jsams.2015.06.008

Kempton, T., Sullivan, C., Bilsborough, J. C., Cordy, J., & Coutts, A. J. (2015). Match-to-match variation in physical activity and technical skill measures in professional Australian football. *Journal of Science and Medicine in Sport*, *18*(1), 109–113. doi:10.1016/j.jsams.2013.12.006

McLean, B. D., Coutts, A. J., Kelly, V., McGuigan, M. R., & Cormack, S. J. (2010). Neuromuscular, endocrine, and perceptual fatigue responses during different length between-match microcycles in professional rugby league players. *International Journal of Sports Physiology and Performance*, *5*(3), 367–383. doi:10.1123/ijspp.5.3.367

Nagelkerke, N. J. D. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, *78*(3), 691. doi:10.1093/biomet/78.3.691

Raglin, J., & Morgan, W. (1994). Development of a scale for use in monitoring training-induced distress in athletes. *International Journal of Sports Medicine*, *15*(02), 84–88. doi:10.1055/s-2007-1021025

Ramírez-López, C., Till, K., Sawczuk, T., Giuliano, P., Peeters, A., Beasley, G., … Jones, B. (2020). A multi-nation examination of the fatigue and recovery time course during the inaugural under-18 six nations rugby union competition. *Journal of Sports Sciences*, *38*(6), 644–651. doi:10.1080/02640414.2020.1722589

Saw, A. E., Kellmann, M., Main, L. C., & Gastin, P. B. (2017). Athlete self-report measures in research and practice: Considerations for the discerning reader and fastidious practitioner. *International Journal of Sports Physiology and Performance*, *12*(Suppl 2), S2-127–S2-135. doi:10.1123/ijspp.2016-0395

Saw, A. E., Main, L. C., & Gastin, P. B. (2016). Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. *British Journal of Sports Medicine*, *50*(5), 281–291. doi:10.1136/bjsports-2015-094758

Taylor, K., Chapman, D., Cronin, J., Newton, M., & Gill, N. (2012). Fatigue monitoring in high performance sport: A survey of current trends. *The Journal of Australian Strength and Conditioning*, *20*(1), 12–23.

Weaving, D., Jones, B., Ireton, M., Whitehead, S., Till, K., Beggs, C. B., & Connaboy, C. (2019). Overcoming the problem of multicollinearity in sports performance data: A novel application of partial least squares correlation analysis. *PLoS One*, *14*(2), e0211776–16. doi:10.1371/journal.pone.0211776

West, D. J., Finn, C. V., Cunningham, D. J., Shearer, D. A., Jones, M. R., Harrington, B. J., … Kilduff, L. P. (2014). Neuromuscular function, hormonal, and mood responses to a professional rugby union match. *Journal of Strength and Conditioning Research*, *28*(1), 194–200. doi:10.1519/JSC.0b013e318291b726