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Original research

Wellbeing perception and the impact on external training output among elite soccer players

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ABSTRACT

Objectives: The objective of the investigation was to observe the impact of player wellbeing on the training output of elite soccer players.
Design: Prospective cohort design.
Methods: Forty-eight soccer players (age: 25.3 ± 3.1 years; height: 183 ± 7 cm; mass: 72 ± 7 kg) were involved in this single season observational study across two teams. Each morning, pre-training, players completed customised perceived wellbeing questionnaires. Global positioning technology devices were used to measure external load (total distance, total high-speed running distance, high speed running, player load, player load slow, maximal velocity, maximal velocity exposures). Players reported ratings of perceived exertion using the modified Borg CR-10 scale. Integrated training load ratios were also analysed for total distance:RPE, total high speed distance:RPE player load:RPE and player load slow:RPE respectively.
Results: Mixed-effect linear models revealed significant effects of wellbeing Z-score on external and integrated training load measures. A wellbeing Z-score of −1 corresponded to a −18 ± 2 m (−3.5 ± 1.1%), 4 ± 1 m (−4.9 ± 2.1%,) 0.9 ± 0.1 km h^{-1} (−3.1 ± 2.1%), 1 ± 1 (−4.6 ± 2.9%), 25 ± 3 AU (−4.9 ± 3.1%) and 11 ± 0.5 AU (−8.9 ± 2.9%) reduction in total high speed distance, high speed distance, maximal velocity, maximal velocity exposures, player load and player load slow respectively. A reduction in wellbeing impacted external:internal training load ratios and resulted in −0.49 ± 0.12 m min^{-1}, −1.20 ± 0.08 m min^{-1},−0.02 ± 0.01 AU min^{-1} in total distance:RPE, total high speed distance:RPE and player load slow:RPE respectively.
Conclusions: The results suggest that systematic monitoring of player wellbeing within soccer cohorts can provide coaches with information about the training output that can be expected from individual players during a training session.

1. Introduction

It is important for practitioners to fully appreciate the impact that player wellbeing can have on training output.[1] An imbalance between training/competition load and recovery over extended periods of time may contribute to long-term reductions in players training output and result in overtraining symptoms. This has resulted in attention increasingly being given to the evaluation of monitoring tools which may indicate the fatigue status of athletes. These indicators include heart-rate derived indices,[2] salivary hormones and neuromuscular indices.[3] In contrast to the above assessments, perceived wellbeing scales represent a valid, time-efficient and non-invasive method for practitioners to gain information related to a player's wellbeing status and overall readiness to train and compete.[1,4] Such characteristics are particularly important within soccer during the in-season competitive phase. During these periods players can compete in two or three matches over a 7-day period where time constraints may restrict the use of more invasive tests.[4] Therefore the use of maximal performance tests may further reduce the physical status of

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players and/or increase the risk of injury.[3] Therefore, practitioners have been encouraged to incorporate customised, shortened questionnaires[5,6] into their monitoring practices to assess the general fatigue and perceived wellbeing status of athletes.[6,7]

The research investigating the relationship between training and these customised questionnaires typically explores perceived wellbeing in response to training and/or match load.[8–10] In soccer cohorts Thorpe et al.[7] reported that wellbeing outcomes are reduced by 35–40% post-match day when contrast to pre-match day wellbeing measures ($p < 0.001$). These measures then improved by 17–26% between post-match day and 2 days post-match day. Wellbeing ratings were observed to remain stable between the second and fourth day post-match. Furthermore, smaller (7–14%) improvements occurred between the fourth day post-match and subsequent pre-match day ($p < 0.01$). Within rugby league cohorts, overall self-reported wellbeing was significantly reduced ($p < 0.01$, $d = -1.64$) 1 day post-match regardless of the length of the microcycle (5, 7 or 9 days between matches). At 2 days post-match wellbeing only remained reduced for the 7 day and 9 day cycles ($p < 0.05$, $d = -1.53$; $p < 0.05$, $d = -0.18$, respectively).[8]

Currently within soccer cohorts the effect of wellbeing on training output is not fully understood. Many investigations within soccer only report the relationship between wellbeing status across the training week after match play or the descriptive analysis of these measures across phases of the competitive cycle. With the prevailing popularity of customised, self-report questionnaires in team sport setting due to their practicality and ease of administration, the purpose of the current investigation was to examine the relationship between self-reported pre-training wellbeing scores and external training load outputs in training sessions across a competitive season. The impact of perceived wellbeing on a range of training load parameters such as total high speed running, player load, maximal velocity, RPE and integrated training load ratios in elite professional soccer players were explored.

2. Methods

The current investigation was a prospective cohort study of elite soccer players competing for two teams at the highest level of European competition (Liga NOS and Champions league). Data were collected for 48 players (Mean ± *SD*, age: 25.3 ± 3.1 years; height: 183 ± 7 cm; mass: 72 ± 7 kg) over one season. The study was approved by the local institute's research ethics committee and written informed consent was obtained from each participant. The study period involved all pitch based training sessions during the 2014/2015 season. In total 48 players participated in 460 training sessions resulting in the collection of data on 22,080 individual pitch based training sessions which were examined. Participants had been familiarized to all experimental protocols as these were part of day-to-day practice. Players were instructed to complete a customised perceived wellbeing questionnaire before any physical training, during the season, except on rest days. The questionnaire was designed to be short, specific and based on the components common in the shortened psychological tools used to assess training imbalances in the literature.[1,11] The questionnaire assessed the following elements of wellness: 1) muscular soreness, 2) sleep quality, 3) fatigue, 4) stress and 5) energy level, on a seven-point likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The five individual wellbeing responses for a given day were summed to provide a quantitative score of overall perceived wellness for each player with a maximal wellbeing score of 35 arbitrary units. Coefficients of variation for the five indices ranged from 9 to 14%. Only data from individual's whose wellbeing scores were deemed normally distributed were used.[12] Z-scores were calculated using the following formula: (individual players score − individual player's average)/individual player standard deviation, a Z-score is the number of standard deviations the response is above or below the mean of the distribution.

During the year all pitch based training sessions were monitored for external training load. Players wore a commercially available global positioning technology device, with tri-axial accelerometers (MinimaxX, Team 2.5, Catapult Innovations, Australia). The device was worn in a custom-made vest, fitting the unit tightly between the shoulder blades. Following each training GPS data were downloaded using proprietary software (Catapult Sprint 5.0.6 software), with the transition time in between training drills removed prior to analysis. This was completed in order to not underestimate the proportion of total distance covered in certain speed zones, or at maximal velocity during training drills.[13] Additionally, all data was reported relative to the time on the pitch during each training session to provide an understanding of session intensity ($\mathrm{m\,min^{-1}}$, $\mathrm{n\,min^{-1}}$, $\mathrm{AU\,min^{-1}}$). The data was then exported and placed into a customised spreadsheet (Microsoft Excel, Redmond, USA). The spreadsheet allowed analysis of distance covered (m) in the following categories; total distance (m); total high-speed distance ($\geq$19.8–25.2 $\mathrm{km\,h^{-1}}$) sprint distance ($\geq$25.2 $\mathrm{km\,h^{-1}}$),[14] maximal velocity ($\mathrm{km\,h^{-1}}$), maximal velocity distance (m), maximal velocity exposures (n), player load (AU) and player load slow (AU) were monitored for all players during training. Player load is a vector magnitude algorithm which combines the rate of change in acceleration from three planes of movement and is suggested to incorporate all forms of activity including skill- and contact-based activities. Recent research has suggested that player load provides different information to traditional speed-based time motion analysis. Initially players were tested for maximal velocity capacity. Maximal velocity was assessed via dual beam electronic timing gates that were placed at 0-, 10-, 20-, 30-and 40-m (Witty, Microgate, Bolzano, Italy). Speed was measured to the nearest 0.01 s with the fastest value obtained from 3 trials used as the maximal velocity score. The calculated velocity between the 20 and 40 m gates was used as a measure of maximal velocity.[15] The intra-class correlation coefficient for test-retest reliability and typical error of measurement for the 10, 20, 30 and 40 m sprint tests were 0.95, 0.97, 0.96 and 0.97 and 1.8, 1.3, 1.3 and 1.2%, respectively. Analysis of calculated speeds revealed a significant correlation ($r = 0.89$, $p = 0.02$) between GPS and timing gate measures, with no significant difference between measures of speeds measured by the timing gates (31.2 $\mathrm{km\,h^{-1}}$) and GPS measures (31.1 $\mathrm{km\,h^{-1}}$) ($p = 0.892$). If a player produced a maximum velocity in training that was greater than the test value this became the playersw' ne maximum velocity for the period.[16]

The intensity of all training and match play sessions (including rehabilitation sessions) were estimated using the modified Borg CR-10 rate of perceived exertion (RPE) scale, with ratings obtained from each individual player within 30 min each training session. Players were educated in the RPE scale, with players encouraged to give a global rating of the entire session using any intensity cues they deemed relevant. Referencing the anchors, a rating of 0 was deemed as rest and 10 as the hardest exercise exertion ever performed; players were prompted for their RPE individually using a touch sensitive customised spreadsheet (Microsoft Excel, Redmond, USA) on a portable tablet (iPad, Apple Inc., California, USA). Each player selected his RPE rating by touching the respective score on the tablet, which was then automatically saved under the player's profile. This method helped minimize factors that may influence a player's RPE rating, such as peer pressure and replicating other players' ratings.[17] Each individual RPE value was multiplied by the session duration to generate an RPE-load value.[18] This allowed for the creation of integrated training load ratios with external load placed into perspective relative to internal load.[1,19]

Initial exploratory analysis revealed that the data from both teams were sufficiently similar to be pooled for the primary analysis. In order to examine the effect of wellbeing Z-score on the external load parameters and RPE, generalised mixed-linear models were performed using the statistical software JMP (Version 10.0.2; SAS Institute, USA). Mixed linear modelling can be applied to repeated-measures data from unbalanced designs, which was the case in the current study[20] since players differed in terms of the number of training sessions they participated in due to differing periodization strategies employed by teams. In the current study, player position and player Z-Scores were treated as fixed effects. Random effects were associated with the individual players training session outputs. Models were constructed using an iterative approach beginning with simple models and building incrementally to a full model. Player training performance as represented by the GPS load variables was the main outcome variable. Player training load were log-transformed in order to report the change in GPS performance as a percentage change per 1-Z-score wellbeing change. Schwarz criterions between candidate models were compared with the coefficient of wellbeing Z-score ± 90% confidence limits (±90% CL) was then taken as the value of the effect of wellbeing on player training load variables within a session. The magnitudes of the effects were reported as Cohen's effect sizes (|*d*|) with |d| ± 90% CL described as <0.2 trivial, 0.2–0.6 small, 0.6–1.2 moderate, 1.2–2.0 large, 2.0–4.0 very large.[21] The qualitative interpretation that the true value of the effect represented an important change was determined with magnitude-based inferences as <75% *trivial*, ≥75% *likely*, >95% *very likely*, >99.5% *almost certainly* that the effect size exceeded 0.20.[22] An effect where there was >5% chance of the change being positive or negative was deemed as unclear.

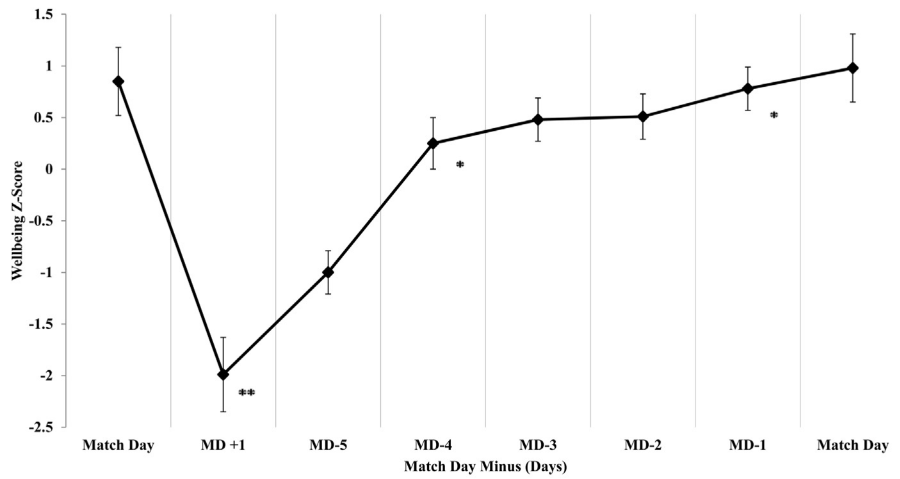
3. Results

The mean ± SD training time during the season was 68 ± 25 min with an average irate of perceived exertion of 476 ± 95 AU. The average external load during each training session 6182 ± 698-m total distance, 515 ± 213-m total high speed distance, 85 ± 15-m high speed distance, 523 ± 88 AU player load, 129 ± 20 AU player load slow, 31.2 ± 3.3 km h^{-1} maximal velocity, 8 ± 5 maximal velocity exposures. This equates to a relative internal load of 7.2 ± 3.8 AU min^{-1} and a relative external load of 90.91 ± 27.92 m min^{-1}, 7.57 ± 4.52 m min^{-1}, 1.30 ± 0.60 m min^{-1}, 7.69 ± 3.52 m min^{-1} for total distance, total high speed distance, total sprint distance and player load respectively. Fig. 1 presents the match day minus change in wellbeing Z-score. Significant differences were observed between match day wellbeing Z-score (Z-score ± 90% CL: 0.85 ± 0.24) and all other days during the week with MD + 1 (Z-score ± 90% CL: −1.99 ± 0.38) representing the lowest wellbeing Z-score across the week. Table 1 shows the mixed effect linear models reporting the impact a reduction in wellbeing Z score of −1 had on training output variables. The table shows that a reduction in wellbeing resulted in a negative impact on total high speed distance, sprint distance, maximal velocity, maximal velocity exposures, player load and player load slow for player during training. Specifically a wellbeing Z-score of −1 corresponded to a −18 ± 2 m (−3.5 ± 1.1%), 4 ± 1 m (−4.9 ± 2.1%,) 0.9 ± 0.1 km h^{-1} (−3.1 ± 2.1%), 1 ± 1 (−4.6 ± 2.9%), 25 ± 3 AU (−4.9 ± 3.1%) and 11 ± 0.5 AU (−8.9 ± 2.9%) reduction in total high speed distance, high speed distance, maximal velocity, maximal velocity exposures, player load and player load slow respectively, compared to those without reduced wellness. Additionally a wellbeing Z-score of −1 impacted external:internal training load ratios and resulted in −0.49 ± 0.12 m min^{-1}, −1.20 ± 0.08 m min^{-1},−0.02 ± 0.01 AU min^{-1} in total distance:RPE, total high speed distance:RPE and player load slow:RPE respectively. Table 2 and Fig. S1 present the effect size and the likelihood that the effect represents an important change for selected training output variables.

4. Discussion

The aim of the current study was to observe the relationship between perceived wellbeing and training outputs within elite professional soccer players. The main findings of the current investigation were that significant differences exist between match day wellbeing Z-score (Z-score ± 90% CL: 0.85 ± 0.24) and all other days during the week with MD + 1 (Z-score ± 90% CL: −1.99 ± 0.38) representing the lowest wellbeing Z-score across the week. A wellbeing Z-score of −1 was shown to have a significant impact on running performance during the subsequent training session. Specifically a wellbeing Z-score of −1 corresponded to a − 18 ± 2 m (−3.5 ± 1.1%), 4 ± 1 m (−4.9 ± 2.1%), 0.9 ± 0.1 km h^{-1} (−3.1 ± 2.1%), 1 ± 1 (−4.6 ± 2.9%), 25 ± 3 AU (−4.9 ± 3.1%) and 11 ± 0.5 AU (−8.9 ± 2.9%) reduction in total high speed distance, high speed distance, maximal velocity, maximal velocity exposures, player load and player load slow respectively, compared to those without reduced wellness. Furthermore, a wellbeing Z-score of −1 impacted the external:internal training load ratio and resulted in −0.49 ± 0.12 m min^{-1}, −1.20 ± 0.08 m min^{-1},−0.02 ± 0.01 AU min^{-1} in total distance:RPE, total high speed distance:RPE and player load slow:RPE respectively. Through the utilisation of magnitude-based analysis our study allowed for the practical interpretation of the size of the effects and qualitative inference about their true values. Furthermore the utilisation of the Z-score allowed for the interpretation of the effect a standard reduction in wellbeing would have on training performance for players. A reduction in wellness had a *likely negative to very likely negative* impact on a number of absolute and relative running performance variables (Table 2). Therefore the data suggests that wellbeing can have an impact on the training output of elite soccer players.

Perceived ratings of wellbeing represent an increasingly popular method to assess athlete fatigue. Within our study there was an observed daily fluctuation in Z-score wellbeing for players. This is in line with previous work in both elite soccer[4,7] and Australian Rules football[23] players demonstrated that such ratings are sensitive to daily fluctuations in training load. Further information concerning the validity of potential markers of fatigue needs to be derived by examining their sensitivity to prescribed changes in training load over extended periods of time. The current study observed for the first time in elite soccer cohorts that external load variables as represented by training output measures that high speed and maximal velocity running performance was significantly affected by wellness Z-score measures. The data agrees with previous literature showing that total distance (m) can be maintained despite a reduction in wellbeing measures. This relationship between wellbeing and training output has been explored in elite Australian rules football players. Gallo et al.[1] reported that a Z-score reduction of −1 resulted in a −4.9 ± 3.1 and −8.6 ± 3.9% reduction player load and player load for these players. Interestingly wellbeing had a non significant impact on total distance (m min^{-1}) and high speed running distance (m min^{-1}) for players. Cormack et al.[24] demonstrated that Australian rules football players in fatigued states were able to maintain total running and high speed running distance (m) during competitive match-play. However, in contrast to the same investigation, results from this current study demonstrate that players with a Z-score of −1 reduced both high-speed and maximal running during training. It is feasible that players with low perceived wellness, and therefore incorporated an altered movement strategy within training sessions with an element of self-pacing



* Significantly different from match day +1 wellbeing Z-Score (p < 0.05)
** Significantly different from match day wellbeing Z-Score (p < 0.01)

Fig. 1. Weekly Z-score wellbeing of soccer players.

Table 1
Parameter estimates for the linear mixed models ($n = 22{,}080$).

Training output variables	R^2	SBIC	Coefficient ± 90% CL	p Value
Total distance (m)	0.35	4.115	0.02 ± 0.03	0.089
Total high speed distance (m)	0.65	−18.115	0.08 ± 0.03	0.021**
High speed distance (m)	0.69	−39.510	0.09 ± 0.03	0.001**
Maximal velocity (km h^{-1})	0.59	−54.514	0.15 ± 0.09	0.045**
Maximal velocity exposures (n)	0.66	−87.100	0.28 ± 0.08	0.012**
Player load (AU)	0.45	−77.500	0.25 ± 0.04	0.015**
$PlayerLoad_{slow}$ (AU)	0.54	−65.600	0.26 ± 0.09	0.021**
RPE (AU)	0.59	5.547	−0.04 ± 0.02	0.680
Total distance (m min^{-1})	0.21	6.954	0.04 ± 0.02	0.542
Total high speed distance (m min^{-1})	0.56	−19.541	0.21 ± 0.05	0.038**
High speed distance (m min^{-1})	0.69	−115.150	0.26 ± 0.03	0.005**
Maximal velocity exposures (n min^{-1})	0.66	−65.400	0.18 ± 0.08	0.033**
Player load (AU min^{-1})	0.57	−77.551	0.28 ± 0.06	0.048**
$PlayerLoad_{slow}$ (AU min^{-1})	0.38	−101.110	0.26 ± 0.09	0.041**
RPE (AU min^{-1})	0.69	1.250	−0.15 ± 0.02	0.870
Total distance:RPE (m min^{-1})	0.28	4.110	−0.13 ± 0.03	0.025**
Total high speed distance:RPE (m min^{-1})	0.48	−10.110	−0.08 ± 0.06	0.015**
Player load:RPE (AU min^{-1})	0.41	−15.550	0.15 ± 0.03	0.515
$PlayerLoad_{slow}$:RPE (AU min^{-1})	0.26	−43.220	0.05 ± 0.01	0.001**

** Significant effect during fixed effect testing ($p < 0.05$).

Table 2
The size (d) magnitude descriptor and qualitative inference for Z-score of −1 on the external training load output and RPE.

Training output variables	d ± 90% CL	Descriptor	Qualitative inference (negative/trivial/positive)
Total distance (m)	0.33 ± 0.29	Small	*Trivial (0/85/15)*
Total high speed distance (m)	−0.69 ± 0.19	Moderate	*Likely negative (76/14/0)*
High speed distance (m)	−0.69 ± 0.19	Moderate	*Likely negative (84/16/10)*
Maximal velocity (km h^{-1})	−1.11 ± 0.33	Moderate	*Likely negative (80/20/0)*
Maximal velocity exposures (n)	−1.25 ± 0.11	Large	*Very likely negative (95/5/0)*
Player load (AU)	−0.33 ± 0.29	Small	*Trivial (10/75/15)*
$PlayerLoad_{slow}$ (AU)	−0.12 ± 0.09	Small	*Trivial (0/85/15)*
RPE (AU)	0.06 ± 0.28	Trivial	*Trivial (0/91/9)*
Total distance (m min^{-1})	0.33 ± 0.29	Small	*Trivial (5/95/0)*
Total high speed distance (m min^{-1})	0.03 ± 0.29	Trivial	*Trivial (0/90/10)*
High speed distance (m min^{-1})	−0.39 ± 0.09	Small	*Likely negative (75/10/15)*
Maximal velocity exposures (n min^{-1})	−0.38 ± 0.19	Small	*Likely negative (84/6/10)*
Player load (AU min^{-1})	−1.21 ± 0.33	Moderate	*Likely negative (78/12/10)*
$PlayerLoad_{slow}$ (AU min^{-1})	−1.45 ± 0.11	Large	*Very likely negative (95/2/3)*
RPE (AU min^{-1})	−0.22 ± 0.29	Small	*Trivial (30/65/5)*
Total distance:RPE (m min^{-1})	0.33 ± 0.29	Small	*Trivial (0/85/15)*
Total high speed distance:RPE (m min^{-1})	0.03 ± 0.29	Trivial	*Likely negative (72/12/16)*
Player load:RPE (AU min^{-1})	−0.29 ± 0.19	Small	*Trivial (0/72/28)*
$PlayerLoad_{slow}$:RPE (AU min^{-1})	−0.49 ± 0.33	Small	*Trivial (0/82/18)*

that resulted in reduced high speed and maximal velocity running performance but allowed for the maintenance of total global running measures. This has important consequences for management and coaches within team sports as reduced wellbeing may inhibit the ability of players to attain maximal velocity and elements of high-speed running that result in the under-preparation of players that may increase player's susceptibility to injury in subsequent match play or training environments.[16,25] This is supported by previous observations which found that players who covered more distance at very-high speed thresholds suffered less time loss from injury when compared to those who covered less distance at similar thresholds.[25] Furthermore, we observed that when players had a Z-score of -1 maximal velocity capabilities and players maximal velocity exposures were reduced by 0.9 ± 0.1 km h^{-1} ($-3.1 \pm 2.1\%$), 1 ± 1 ($-4.6 \pm 2.9\%$) respectively. Previously, Malone et al.[16] reported that players who attained 6–11 maximal velocity exposures per week and higher relative maximal velocities within training and match-play were less likely to sustain a subsequent injury. This highlights that wellbeing has an important role in the ability of players to produce their maximal velocity capabilities, which may increase a player's susceptibility to injury risk.

Our data showed that post-session RPE (AU) remained unaltered despite Z-score reductions in the overall wellbeing. This is despite reductions reported for high-speed and maximal velocity activities during training sessions. Therefore, these players completed less external work than their counterparts within specific training sessions. The *trivial* effect for wellbeing reduction on RPE agrees with previously reported literature that showed perceived wellness did not impact RPE in sub-maximal aerobic exercise.[26] The externally paced nature of the protocol used by Haddad et al.[26] presented no opportunity for self-pacing whereas training sessions are non-controlled environments and therefore allowed players to self-regulate their exercise intensity within training environments.[27] Given that RPE (AU) remained unaltered despite a reduction in high-speed training output this may question the use of the CR-10 RPE scale alone to assess fatigue and/or reduced wellness within players. The above findings may support the concept of the integration of the external and internal load variables to provide a ratio that helps coaches understand the cost of the external load completed. Previously these ratios have been related to soccer player's aerobic fitness.[19] The current investigation observed that a wellbeing Z-score impacted the external:internal training load ratios. A wellbeing Z-score of -1 resulted in *likely negative* -1.20 ± 0.08 m min^{-1} in total high speed distance:RPE. These findings suggest that a reduction in wellbeing can impact players training output resulting in a reduction in training output per unit of RPE. This suggests that although a player's internal load remains similar there is a reduced level of output, suggesting that players with reduced wellbeing may alter their high speed movement patterns within training. These findings are in contrast to Gallo et al.[1] would found a small *trivial* effect for wellbeing on high speed running:RPE (m min^{-1}).

The application of wellbeing questionnaires is now common place within team sport environments. Previously a survey of Australian and New-Zealand high performance sport on current trends of wellbeing monitoring revealed that 84% of responders used wellbeing questionnaires with 80% of these bespoke designs.[28] However, the process of how best intervene when a player or large proportions of the team have reduced wellbeing Z-scores within team sport settings to enhance a training programme design will most likely be influenced by other factors such as match-to-match micro-cycles and coaching philosophy.[1] One of the more commonly proposed applications is to use wellbeing scores as an indicator of fatigue and to adjust subsequent training in response.[5–7] The results of the current investigation show that perceived wellbeing does indeed impact external training output within elite soccer cohorts in particular the high speed and maximal velocity elements of running performance especially when there is a large reduction in wellbeing Z-score.

The following must be considered with a number of limitations. The current investigation was only conducted across a single season therefore the models are only explanatory in nature and require cross-validation with additional data from additional seasons of data or a similar comparable data set. Therefore we advocate additional longitudinal investigations within soccer cohorts to add credence to the hypothesis that wellbeing impacts the training output of elite soccer players. These results are potentially impacted by issues surrounding the reliability and validity of GPS parameters[29] and accurate and honest self-reporting by players for wellness measures.[10,11] It is also acknowledged that the relationship between load and wellness may be non-linear and therefore, linear modelling techniques may be limited in their ability to reflect such relationships.[1] Furthermore, while the variability between players speeds at which they begin to run at high-speed is a further limitation of the current investigation. The utilisation of individual wellbeing indices as an overall measure of perceived wellness may restrict the ability to identify specific relationships between individual wellbeing components and different external load variables and may be a valuable direction for future research.[4,7]

5. Conclusions

The current study has highlighted the utility of simple non-invasive measures of wellbeing and their potential to reduce player's training output within elite soccer players. A reduction in Z-scores corresponded to a significant reduction in training performance for players within the current investigation. Specifically a wellbeing Z-score of -1 corresponded to a $-$ 18 ± 2 m ($-3.5 \pm 1.1\%$), 4 ± 1 m ($-4.9 \pm 2.1\%$,) 0.9 ± 0.1 km h^{-1} ($-3.1 \pm 2.1\%$), 1 ± 1 ($-4.6 \pm 2.9\%$), 25 ± 3 AU ($-4.9 \pm 3.1\%$) and 11 ± 0.5 AU ($-8.9 \pm 2.9\%$) reduction in total high-speed distance, high-speed distance, maximal velocity, maximal velocity exposures, player load and player load slow. Furthermore, a wellbeing Z-score of -1 impacted the external:internal training load ratio and resulted in -0.49 ± 0.12 m min^{-1}, -1.20 ± 0.08 m min^{-1}, -0.02 ± 0.01 AU min^{-1} in total distance:RPE, total high-speed distance:RPE and player load slow:RPE respectively showing that wellbeing can result in players covering lower external distances per a similar unit of RPE. Overall, the current study provides support for the utility of wellbeing measures and the relationship between wellbeing measures and the reduction in training output measures within elite soccer cohorts.

Practical implications

- The non-invasive and simple measurement of wellbeing is for the first time is shown to have relationships with external and integrated training load measures in elite soccer settings.
- Substantial associations between a reduction in overall Z-score for wellbeing and reductions in high-speed, player load, integrated ratios and maximal velocity outputs have been observed within elite soccer players.
- The current data supports the process of incorporating of a self-report wellbeing tool into monitoring practices by elite soccer teams to allow for the identification of players with reduced wellbeing Z-Scores as this impacts players training output.
- The reduction in player's wellbeing Z-Score was shown to have a *likely negative to very likely negative* impact on player's ability to complete high speed distance and maximal velocity distance within training.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jsams.2017.03.019.

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