Quantifying Athlete Wellness: Investigating the Predictive Potential of Subjective Wellness Reports Through a Player Monitoring System

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Abstract

This study investigated the potential of self-reported wellness data from a player monitoring system and its predictive power of individual match performance among a female professional football player cohort. Using longitudinal data collected from the Pm Reporter Pro mobile application and corresponding individual performance scores (InStat Index), the study investigated if pre-match perceived wellness could predict individual match performance. The results show no significant evidence for a correlation between the two. This result may suggest that other factors might have a larger impact on performance, that the data quality captured by the current version of the player monitoring system is not sufficient, or that the impact of personally perceived wellness on performance is minimal. The limitations of bias in self-reported data and relatively small sample size might have affected the results. Despite these findings, the study provides valuable insights into the use of data-driven analytics with a concrete and widely used player monitoring system and suggests recommendations for future research.

Keywords: Elite athletes, Football performance, Player monitoring system, Subjective Wellness, Sport analytics, InStat, Sport technology, Soccer, Toppfotball Kvinner, Hooper Index, Soccer, PMSYS

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1. Introduction

In the multibillion industry of professional football, top clubs are chasing new ways to develop and realize improved performance from their athletes. To this end, technology has become a vital tool in optimizing performance. Some of the most prevalent examples are the use of player monitoring systems, which utilize a range of Internet of Things devices to gather data on various aspects of an athlete's physical activity, sleep patterns, and overall wellness [1,2]. Furthermore, such data can be used in complex statistical methods such as machine learning to gain valuable insights or even future predictions [3,4]. As data-driven research in sports technology and elite athlete performance becomes more prevalent, the need for advanced software for large-scale data collection is increasing, as machine learning algorithms typically require large datasets for training purposes.

In response to this growing demand, we developed PMSys over a decade ago in close collaboration with coaches and players at the highest national level [5,6]. Since then, we have collaborated with athletes and coaches to develop a scalable digital system, with an app for wellness reporting, PM Reporter Pro [2,7]. The app has been available free of charge to teams in the top division of female football in Norway for the past three years and has hundreds of daily users. The system includes an online portal for tracking team and individual statistics and has been customized to meet the specific needs and preferences of coaches and players.

Recent research has shown promising results in using machine learning to predict the wellness of professional football athletes, both on an individual and team level [3]. While machine learning has great potential for future predictions of wellness and indirectly predicting injuries or performance, the accuracy of these predictions is limited by the quality of the data used. As the use of player monitoring systems becomes more widespread and the reliance on data-driven analysis increases, it becomes even more important to ensure that these systems are providing accurate and high-quality data. The current version of PM Reporter Pro, for example, is designed for practical use by coaches and players, prioritizing ease of use and speed over precision requirements commonly found in sports science. This design was specifically requested by sports scientists working in the field, where daily invasive reporting might receive diminished emphasis. Simultaneously, while developing this app in its current version, user perspectives have been considered to some degree by reducing some of the science-inspired reporting demands. Consequently, with the recent surge in machine learning and the use of player monitoring systems, it is essential to re-evaluate the granularity and accuracy of the data collected by these systems to ensure it is suitable for this new approach to data-driven sports analysis.

Despite the widespread use of player monitoring systems, and the promising prospects of using machine learning to predict player wellness, there is currently a gap in research linking perceived wellness factors to individual player performance. Although research has explored the associations between wellness factors and various measures, such as injuries, training load, and rate of perceived exertion [8–10], there is limited evidence demonstrating a causal relationship between wellness and individual player performance in elite football. Within sports literature, there is a consensus that maintaining balance in wellness and psychological well-being can improve elite athlete performance [11,12]. Recent reviews have investigated the effects of wellness and sleep on exercise and sport performance, suggesting that these effects vary based on the demands of the sport [13]. Nevertheless, most research on wellness and athletic performance is based on inference, with the underlying assumption that wellness is critical for cognitive function, and cognitive function is essential for performing at the highest level in elite sports [13]. Therefore, more research is needed to evaluate any causal relationship between perceived wellness and objective match performance at the individual level.

The main objective of this study was to determine whether pre-match self-reported wellness factors can predict individual match performance in professional female football players. In addition, we explored the quality of self-reported wellness data collected using a player monitoring system, and the potential to use these types of data for individual match performance predictions.

2. Method

2.1 Participants

The sample consisted of 65 elite female football players (age 15 - 32, M = 21.18), all playing in Toppserien, the national top female football league in Norway, during the 2021 season. The four clubs were already selected for a larger project in sports science and performance development, in corporation with Top Football Women (Toppfotball Kvinner), the organization for the clubs at the two highest levels in Norway. All players gave their written informed consent to participate.

2.2 Instruments

Subjective wellness was measured using a smartphone application, PM Reporter Pro. The application is a part of the PMSys online sports logging system where athletes can track subjective wellness, training load, sickness, and injuries [7]. The subjective wellness scale is an adjusted version of the Hooper Index [14]. The scale has been adapted to meet the needs of coaches and players developed over a decade together with elite athletes to consider user buy-in and ease of use. Wellness factors measured were comprised of Mood, Stress, Sleep quality, Sleep duration, Fatigue, Readiness to train, and Soreness. Items were rated on a Likert scale from 1-5, except readiness (from 1- 10) and sleep length (reported in hours). The application can schedule for push messages to remind participants to report data daily, preferable every morning, but the application allowed players to specify temporal parameters (e.g., the player could report data in the evening should they forget it in the morning and specify that the reported wellness is from earlier in the day).

Objective match performance was measured using InStat, a service provided by a performance analysis company that provides position-specific index scores as a measure of football performance. The InStat Index is based on manual video analysis and event tagging after each match, calculated by multiplying action coefficients (such as passes, dribbles, and shots) by a weighted match level coefficient. The weighted match level coefficient is automatically determined based on the quality of a player's actions, the quality of their teammates' actions, and the level of their opponent. The number of key parameters used to assess action performance can vary depending on a player's position and style of play, with a total of 12-14 typically used. To be eligible for an InStat Index score, players must spend a certain amount of time on the field and perform a minimum number of actions. InStat Index scores have been used in previous research as a measure of match performance and are considered to have a high inter-operator reliability [11,12,14]. In the 2021 season of the women's top league, most matches had InStat Index data recorded, but some players were not given a score due to factors such as non-participation in the match, inadequate playtime, inadequate actions, or unavailability of video systems at the stadium.

2.3 Statistical Methods

Data filtering and analysis were done in the programming languages R and Python 3.8, using the packages Tidyverse, lme4 and Pandas [15–19].

To calculate an approximate R-squared for the selected models, we calculated the proportion of the variance in models' residuals to the variance in the model's response variable using the following formula: $\mathrm{R}^2 = 1 - \frac{Variance\ (Residual)}{Variance\ (Response\ )}$. To calculate the intraclass correlation, which measures the proportion of total variance in the dependent variable that is due to differences between groups, as opposed to within-group variability, the following formula was used: $\mathrm{ICC} = \frac{Variance\ (Group)}{Variance\ (Group\ ) + Variance\ (Residual)}$. To examine the relationship between pre-match wellness factors and individual football performance, we utilized wellness data from three sources: (1) the day of the match (matchday wellness), (2) the day before the match (matchday-1 wellness), and (3) a combination of both. We included these data sources for several reasons. First, we wanted to determine whether wellness recorded before the football match had any predictive value on individual performance and, therefore, could be useful for the coaching team in selecting the starting lineup. Second, due to a large amount of missing wellness data reported on *matchday*, including an average of *matchday-1* and *matchday* significantly increased the amount of *wellness – InStat Index data* pairs. Third, the current version of the PM Reporter Pro application did not export the exact timestamp of the logged session, only the date. The lack of exact logging time means that there is no absolute guarantee that matchday reports were submitted before the match, despite players being encouraged and notified (via push notifications) to report their wellness in the morning. Some matchday reports could have been retrospectively added after the match, which could compromise the assumption that all matchday reports are "pre-match" reports.

To analyze the data, we used a linear mixed effects regression model as the data contained repeated measurements from individuals and to account for potential differences between teams (see Figure 3). To account for these dependencies in the data, we nested the players within teams. However, due to the relatively small sample size of four teams, we compared various clustering options including using teams as a fixed factor as well as different combinations of random slopes and intercepts. We compared these clustering options using simple analysis of variance tests with Log Likelihood ratio, Akaike information criterion (AIC), and Bayesian information criterion (BIC) as benchmarks to determine the best model fit. Our analysis showed that a model with random intercepts for players and teams, with players nested within teams, provided the best fit. For further analysis, we used this hierarchical structure and included InStat Index as the dependent variable and the fixed effect predictors of Mood, Stress, Fatigue, Readiness, Soreness, Sleep quality, and Sleep duration as independent variables.

3. Results

3.1 Descriptive Statistics

The dataset from the 2021 season had minimal variance in the predictor variables as shown in Table 1 and Figure 1. The correlation among wellness variables was moderate to high, whereas their correlation with the performance variable, InStat Index, was low as shown in Figure 2.

Table 1.

Variable descriptive statistics for perceived wellness reported on matchday

Variable name	Mean	*SE* of mean	*SD*	Min	Max
InStat Index	156.98	0.95	21.87	114	215
Mood	3.54	0.03	0.62	2	5
Stress	3.32	0.03	0.62	2	5
Fatigue	3.41	0.03	0.62	1	5
Readiness	7.78	0.06	1.39	3	10
Soreness	3.26	0.04	0.80	1	5
Sleep quality	3.34	0.03	0.77	2	5
Sleep duration	8.47	0.04	0.89	3	12

Note. Descriptive statistics of all the variables on matchday with corresponding InStat Index scores (N = 530).

Figure 1. *Response ratio on Likert scales for Mood and Stress on matchday*

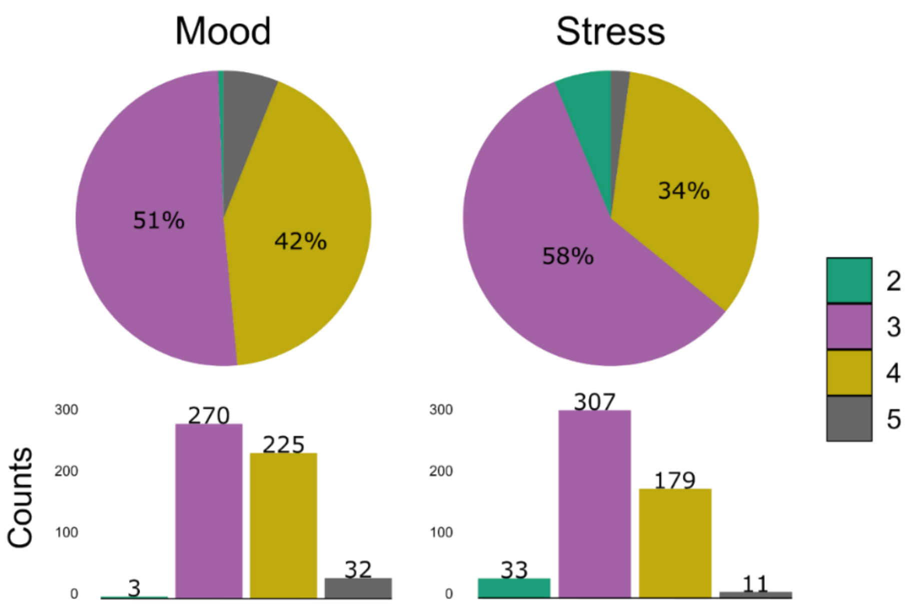


Figure 2.

Heatmap correlation matrix of matchday wellness reports

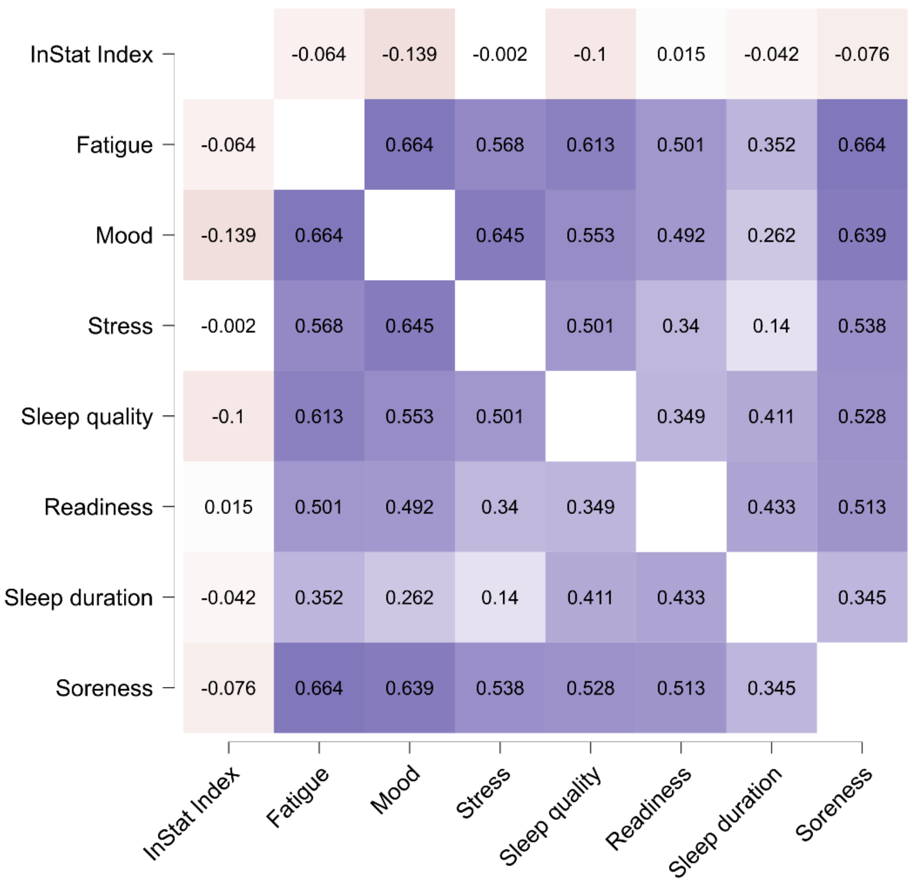
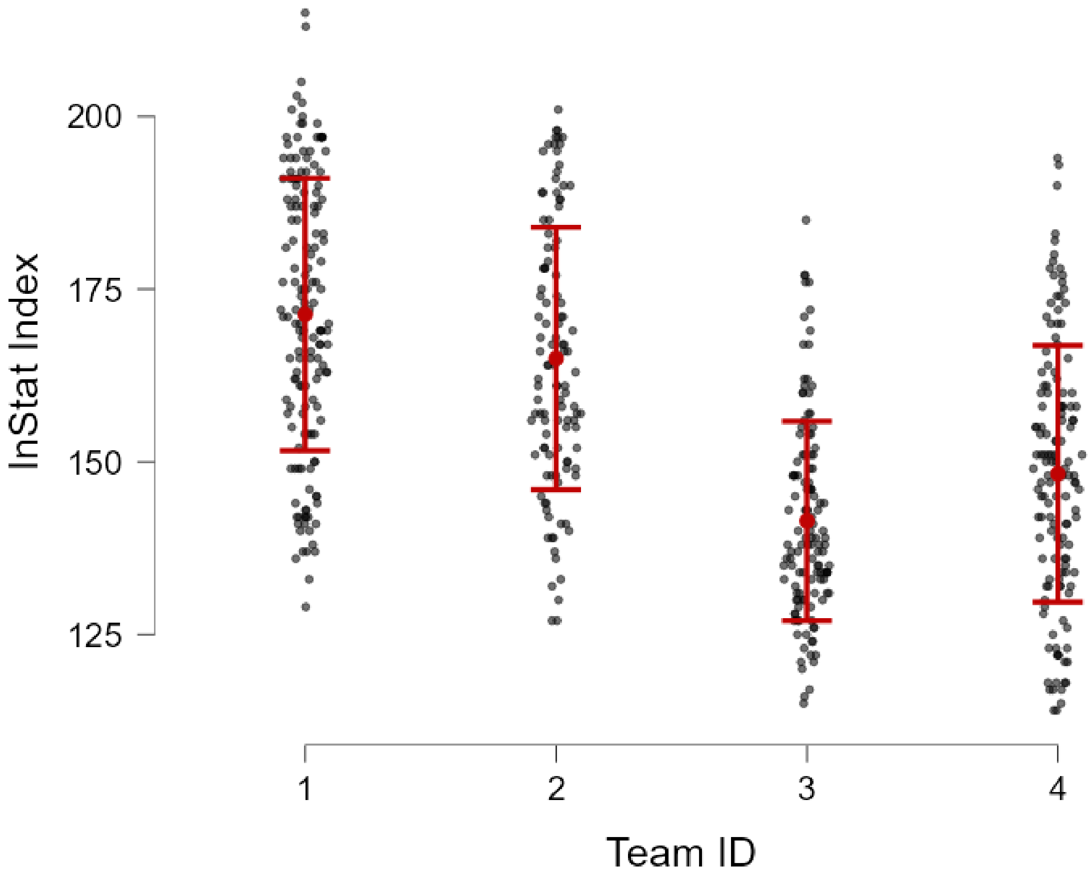


Figure 3.

Differences in InStat Index scores between the four teams



Note: The error bars indicate one standard deviation.

3.2 Matchday Wellness Factors on Individual Performance

To study the relationship between individual performance in football matches and self-reported wellness factors, we used a linear mixed effects regression model. The InStat Index score was utilized as the performance-reflecting dependent variable, while the independent variables included fixed effects for Mood, Sleep duration, Sleep quality, Fatigue, Readiness, Soreness, and Stress. As specified in the methodology section, User ID was nested within Team ID as random effects. Overall, the model indicated a reasonable fit with most of the variance explained by the User ID and Team ID (ICC = 0.48, R^2 = 0.50). To select which predictors should be included in our model, we used backward elimination to remove predictors that were not significant based on their *t*-values. This process resulted in the null model, which indicates that none of the predictors were able to significantly predict individual player performance reflected in the InStat Index score. We also compared the full model to the null model using simple analysis of variance (ANOVA), and the results showed that the predictor variables included in the full model (Mood, Stress, Fatigue, Readiness, Soreness, Sleep quality, Sleep duration) did not provide significant additional predictive power (see Tables 2 & 3). Note that *p*-values are reported in Tables 2 and 4, however, *p*-values from mixed effects models assume knowledge of denominator degrees of freedom in the *F* statistic and should therefore be interpreted carefully.

Table 2.

Full model for predicting performance using data from matchday

Fixed effects	Coefficient	*SE*	*t*	*p*
Intercept	156.77	12.47	12.58	
Mood	-2.40	2.18	-1.10	0.27
Stress	1.27	1.93	0.66	0.51
Fatigue	1.70	1.99	0.86	0.39
Readiness	0.43	0.97	0.44	0.66
Soreness	-1.52	1.66	-0.92	0.36
Sleep quality	1.45	1.40	1.04	0.30
Sleep duration	−0.75	1.11	-0.67	0.25
Random effects	Variance	*SD*		
Residual	263.34	16.22		
Players	73.01	8.54		
Teams	173.76	13.19		

Note: N = 530, 65 players, four teams.

3.3 Matchday-1 Wellness

To test whether wellness could predict individual football performance the following day, another linear mixed model was run, starting with the full model using backward elimination to select the final model. This process resulted in keeping stress as the only significant predictor (Table 4), being significantly better than a null model (Table 5).

Table 3.

ANOVA of the null versus the full model for matchday data

Model	Parameters	Log Likelihood	*AIC*	*BIC*	*p*
Null model	4	-2269	4563.1	4563.1	
Full model	11	-2266.9	4555.9	4602.9	0.77

Note: p-value derived from a Chi-square test. Comparison between the two models, indicating that adding the wellness predictors Mood, Stress, Fatigue, Readiness, Soreness, Sleep quality and Sleep duration does not make the model significantly better.

Table 4.

Final model for predicting match performance using data from matchday-1

Fixed effects	Coefficient	*SE*	*t*	*p*
Intercept	144.14	9.14	15.76	
Stress	3.52	1.75	2.02	.045
Random effects	Variance	*SD*		
Residual	286.88	16.94		
Players	58.31	7.64		
Teams	192.82	13.89		

Note. N = 601, 65 players, four teams.

Table 5.

ANOVA of the null versus full model for matchday-1

Model	Parameters	Log Likelihood	*AIC*	*BIC*	*p*
Null model	4	-2593.5	5195.1	5212.7	
Final	5	-2591.5	5193.0	5215	0.045

Note. P-value: Chi-square test. Comparison between the two models indicating that adding the predictor Stress significantly improves the model.

3.4 Matchday-1 and Matchday Averaged

Finally, we ran the model again using the average scores from the last two reports before the match (matchday and matchday-1) as a compromise between validity and power. This compromise resulted in 648 observations, compared to the 530 observations obtained using only matchday reports, and 601 reports using matchday-1 data only. Using backward elimination starting with the full model, the final model selected for this sample was again the null model.

4. Discussion

The purpose of this study was to determine the potential of using a player monitoring system to predict individual match performance among female professional football players. We used longitudinal self-reported data from the PM Reporter Pro app and individual performance scores from InStat to investigate this association. We observed no connection between any of the wellness variables we collected (including Mood, Stress, Fatigue, Readiness, Soreness, Sleep quality, and Sleep duration). These results indicate that other factors such as tactical skill, physical fitness, and technical ability may be more important, or that the quality and quantity of self-reported data are not sufficient for these types of predictions.

Our results suggest that using player monitoring systems in their current design, built for minimal invasiveness and for capturing larger deviations from personalized normalization, are not suitable for performance prediction or match lineup selection. While we observed a significant effect of stress reported on the day before the match on player performance, this effect was not present for matchday reports, or when data from both days were combined. Additionally, the effect was quite small and was discovered through exploratory data analysis rather than pre-specified hypotheses. Therefore, more research is needed, ideally in the form of high-powered registered reports, to determine whether pre-match stress has a real and significant impact on match performance.

4.1 System Design and Intended Use

Player monitoring systems have traditionally been used to provide physical coaches with training load data to prevent injuries and reduce pre-match overload [8–10]. However, with the slowly increasing focus on psychological factors and the use of mental coaches by professional teams, it is important that player monitoring systems are validated, and their measurements are tested before any practical implications can be drawn [11]. While the current state of player monitoring systems may not allow for a causal link between perceived wellness and performance to be established, information about mentality factors such as stress or sleep at the team level still has significant practical value for coaching staff. By identifying potential issues related to team wellness, coaching staff can intervene to ensure player well-being. For example, if the monitoring system captures that a team is experiencing high levels of stress, the coaching staff may need to implement strategies to reduce stress or adjust the team's training schedule. Similarly, if the monitoring system indicates that a team has poor sleep patterns, the coaching staff may need to adjust the team's schedule or provide guidance on sleep hygiene.

4.2 Performance Measure

In this study, we used an established performance indicator, the InStat Index score to measure individual football performance, along with corresponding longitudinal matching wellness scores for each player over the course of a season. This approach represents a deviation from previous studies that have typically relied on match outcome or player goals/assist as a mediator of football performance [20]. To account for both individual and team differences, we utilized linear mixed effects regression modeling in our analysis. This approach allowed us to assess the potential relationship more accurately between performance and perceived wellness in football.

While the InStat Index is a state-of-the-art personalized scoring system that measures individual football match performance, there are certain factors that it cannot capture. For example, the InStat Index does not account for positioning skills without the ball, which is an important factor in match performance. Additionally, InStat Index does not disclose its full algorithm due to commercial reasons, so there is some uncertainty regarding its validity and reliability.

4.3 Self-Reported Data and Data Quality

When using subjective self-reported data, user buy-in must be considered. Previous research has highlighted potential issues with subjective self-reporting and the accuracy of such data [21]. In addition, studies have shown that user buy-in and precision in reporting through player monitoring systems gradually decreases over longer periods, which can compromise the validity of the reports [22]. As Figure 1 shows, the range of scales used to report is often very low, which could be interpreted as low effort or false reporting. It is possible that players did not report accurate data to avoid being deemed unfit to play or to avoid conflict with the coaching staff. This type of bias in reporting could lead to players reporting middle-of-the-pack results even if they are feeling fatigued or not ready to play. The players and the coaching staff might have different goals in mind, whereas a player might favor their own career advancement over their team (wanting to play regardless of wellness), the head coach is primarily responsible for the team (and in turn their own success). Ultimately, this conflict between the goals of the players and the coaching staff could affect the validity of the self-reported data.

An alternative explanation is that elite football players form a uniform group with consistent and stable wellness attributes. The findings indicate minimal variation in the assessed wellness factors among these athletes, which could be a common trait of professional football players. To excel in elite football, players may either have innate stable wellness traits or develop the ability to manage these traits. Additionally, they may be proficient in controlling psychological factors before and during matches, minimizing their potential impact on performance. Furthermore, the current use of wellness data, using data from players who have participated in a match, those who are not feeling well or who are injured and not playing are excluded as they do not have recorded match scores. This limitation may introduce bias towards players who are feeling well and ready to play.

4.4 Sample Size and Missing Data

The relatively small sample size of this study, consisting of 65 players from four teams and a total of 530, 601, and 648 matches respectively in the three datasets, may not allow for the detection of smaller effects of wellness factors on football performance. The results indicated that over 40% of the variations in the response variable could be attributed to differences between teams. It is recommended that future studies include more teams and encourage more user involvement to prevent missing data. Another approach to increasing the sample size, should there be significant amounts of missing data, could be to combine match day reports with reports from previous days leading up to the match (assuming they are far enough away from a previous match). However, this approach also assumes that wellness factors reported a few days before the match have the same predictive power as those reported on the day of the match. One way to address this issue could be to weigh the day of the report differently depending on how close it is to match day, with the assumption that wellness closer to the match is a stronger predictor of matchday performance.

4.5 Future Directions

Additional research is needed to determine whether wellness data collected through a player monitoring system can predict individual match performance in female football players. This study offers new exploratory insights and proposes a concrete approach for future investigations. To improve the sensitivity of future studies, it will be important to ensure the validity and granularity of self-reported wellness measurements. Improving the sensitivity can be achieved by educating players and staff on how to properly report data, or by modifying the scales to capture nuances in wellness factors, ideally using a combination of both approaches. Additionally, future studies should aim to include more football teams and players in the analysis. The framework employed in this study (using longitudinal wellness data paired with individual match performance), can also be expanded upon and used to investigate how match outcome affects post-match wellness factors, such as mood and fatigue. Including individual performances, in addition to match results, could provide valuable insight into player mentality and coping skills. It could also be interesting to investigate how individual player performance affects perceived wellness during a long competitive season. In a full season with at least one game per week, longitudinal wellness deviations might not be picked up when only using pre-match reports. It is possible that players are becoming over-loaded in a macro cycle, which might only be perceived by the athletes themselves during post-match recovery and thus not captured in pre-match wellness reports.

5. Conclusion

In conclusion, using longitudinal data collection through player monitoring systems together with corresponding match performance scores, could provide valuable insights into the relationship between wellness and performance in professional female football players.

However, the current granularity and data quality of these systems need to be evaluated and potentially modified to support a more data-driven analytical approach. Although the current versions of PM Reporter Pro and PMSys are useful for identifying potential outliers and providing coaches and players with general wellness information, future developments of these systems should focus on re-evaluating measurement scales and improving data reporting. However, the subjective nature of self-reported wellness factors makes it difficult to capture the nuances of wellness accurately without compromising other aspects of data collection, such as time or invasiveness. Moreover, in situations where there is a conflict of interest between players and coaches, such as when players may feel pressure to downplay their symptoms, the accuracy of self-reported wellness measures may be further compromised. Overall, this study did not find a clear connection between the current state of self-reported wellness factors and individual performance. Further research is needed to confirm or refute this association. Additionally, it is important to note that football performance is a complex construct and other factors such as technical skills, teamwork, and tactical assessment may have a larger impact on performance than individual perceived wellness.

Declaration of Interest: *The authors report no conflict of interest.*

Data Availability: The data that support the findings of this study are available on request from the corresponding author, AA. The data are not publicly available due to the privacy of research participants.

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