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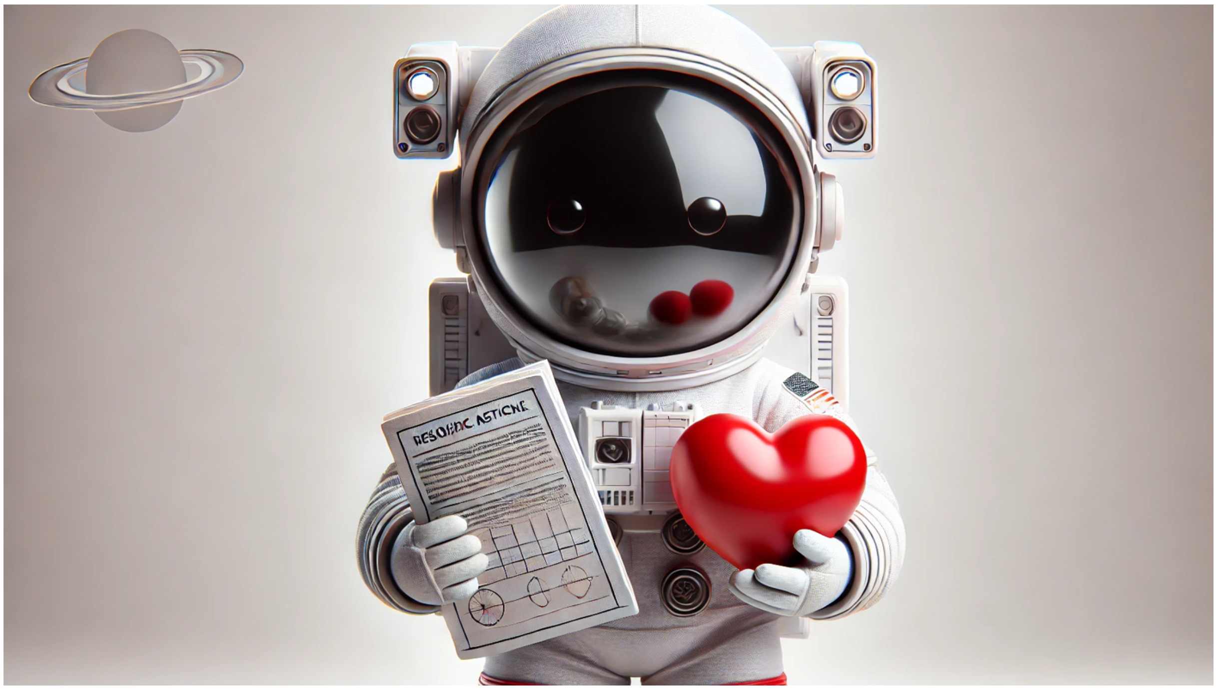

Time to drop running as a KPI in elite football: football fitness and freshness as match-day preconditions

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Match running activity | Fitness | Freshness | Readiness | Embedded monitoring | Machine learning | Professional football | Player status | Sport science 3.0

Headline

Predicting success in football is notoriously complex - even the most advanced machine learning models have yet to crack the code (Settembre, 2024). Perhaps that's part of why football remains the world's most beloved and unpredictable sport. When it comes to trying to identify important drivers for success, investigating the association between match outcomes and running activity is fundamentally flawed when viewed through the lens of football coaching. Success in football is built on creating scoring opportunities, defending effectively, and performing football actions—all of which naturally produce running as a byproduct of the game itself. Running itself should not be seen a strategic objective but rather a consequence of football actions (Buchheit 2024; Buchheit & Verheijen 2024; Verheijen 2025). Unfortunately, sports science has often prioritized what can be measured over what is truly impactful, leading to a misplaced focus on running as a key performance indicator (KPI). This reflects a broader issue in performance analysis, where simplistic metrics have been used to explain complex realities—a classic example of the misguided approach of "sports science 2.0" (Buchheit & Laursen, 2024).

Growing evidence suggests that running metrics have little to no direct association with match outcomes (Buchheit 2018; Hoppe, 2015; Oliva-Lozano, 2023; Teixeira, 2021). This is not surprising, given that match running performance is primarily influenced by tactical decisions, opposition behavior, and the evolving dynamics of the game itself (Bradley 2011; Carling, 2013; Ju, 2023; Mendez-Villanueva 2011b & Buchheit, 2011b; Paul, 2015). These context-dependent factors make running an unreliable and often misleading predictor of success. Yet the oversimplified belief persists—particularly among less-informed practitioners and the media—that greater physical capacities lead to more running, and that more running directly equates to better performance (Helgerud, 2001; Mohr, 2003).

This flawed logic has also led to the widespread misuse of match running metrics as a proxy for players' maximal physical capacities, reinforcing outdated cause-and-effect assumptions. For example, it is commonly assumed that players who run more are fitter and therefore more effective, a notion that continues to distort performance analysis and player evaluation. However, research consistently shows that match running output is not directly determined by physical capacities. In fact, it often reflects situational demands. A classic example is when a team plays with one fewer player due to a red card, the remaining players often increase their running output (Carling & Bloomfield, 2010). They do so with the capacities they had at the start of the match; their fitness did not improve when the referee blew the whistle to send the player back on the bench. Furthermore, changes in physical capacities have not been shown to systematically predict changes in match running performance (Buchheit & Mendez-Villanueva, 2013; Mendez-Villanueva, 2011b; Byrkjedal, 2024), further undermining the validity of using running data to infer fitness.

To make matters clearer, we must revisit what we actually mean by "fitness" in football. In most sports science contexts, fitness is defined by physiological markers like maximal oxygen uptake (VO_2max), peak aerobic power, or other indicators of cardiovascular and metabolic capacity. While these 'generic' or 'basic' fitness measures have value in general athletic profiling, they fall short of capturing the sport-specific demands of elite football. These insights emphasize that the relationship between 'generic' physical capacities, running, and performance is far more complex than commonly assumed (Mendez-Villanueva & Buchheit, 2011b).

In the football context, fitness must be understood more holistically. As Verheijen (2025) puts it, football-specific fitness is "the ability to perform football actions as frequently as necessary to sustain a high tempo for 90+ minutes." This definition highlights the integrated nature of performance, and explains why even elite endurance athletes, such as marathon runners or triathletes, would likely struggle to meet the unique, intermittent, and decision-heavy demands of a football match—before we even consider their technical or tactical limitations. Therefore, when we speak of fitness in football, we are not referring to abstract physical capacity in isolation, but rather to a contextual readiness to meet the demands of the game (Verheijen 2025). In that sense, both freshness (players' neuromuscular status at the start of the match) and football fitness are better understood as preconditions for football performance—necessary to support football actions throughout the match, but not as key "performance" indicators themselves (Verheijen 2025). Despite being widely acknowledged in theory, their direct relationship with match success has rarely been tested using contextually valid, real-world data.

While previous approaches in sport science lacked the tools to evaluate this relationship effectively, the current era—termed Sport Science 3.0 (Buchheit & Laursen, 2024)—offers improved methods. One of the most impactful advancements is embedded monitoring, which allows for continuous, game-by-game tracking of players' estimated readiness throughout the season (Mandorino, 2024a; Mandorino 2023; Mandorino 2024b). Unlike older methods based on a few isolated tests each year (Buchheit & Mendez-Villanueva, 2013; Byrkjedal 2024; Mendez-Villanueva 2011b), this new approach reflects players' actual status for each match—a major step forward in applied sport science. In this study, players' readiness was estimated weekly via both physiological (fitness) and mechanical/neuromuscular (freshness) responses to standardized training drills using machine learning–based models, building on previous work (Mandorino 2024a; Mandorino 2023; Mandorino 2024b). This enables us to look beyond static assumptions and revisit long-standing beliefs with real, high-resolution data.

Aim

This study aimed to investigate, for the first time, how estimated players' readiness and running activity interact in relation to match outcomes. This was meant to offer a perspective that goes beyond the flawed emphasis on running volume as a KPI.

Methods

Subjects

This study was conducted over three consecutive football seasons (2022/2023, 2023/2024, and 2024/25) and involved a cohort of 25 elite male soccer players (age: 25.9 ± 3.1 years; body mass: 81.1 ± 6.2 kg; height: 184.9 ± 4.9 cm) from the first team of a professional Italian football club. The players participated in training sessions five times per week (training duration: 66.2 ± 14.5 minutes) and typically competed in one match per week, with an additional match in certain weeks for the Coppa Italia competition. A total of 73 matches were included in the current study, resulting in 32 wins, 19 draws, and 22 losses. All players were monitored daily during the season, and the data were collected as part of the club's routine monitoring processes. Therefore, formal ethical approval from an ethics committee was not required (Winter & Maughan, 2009). To ensure confidentiality of both the team and the players, all data were anonymized prior to analysis, and the study was conducted in accordance with the principles outlined in the Declaration of Helsinki.

Training External and Internal Load collection

Players' external load during training sessions was assessed using the WIMU Pro system (RealTrack Systems, Almería, Spain), whose validity and reliability have been previously established (Gomez-Carmona 2019, 2020). Internal load data, represented by heart rate (HR), were collected at a sampling frequency of 4 Hz using a Garmin HR band (Garmin Ltd.), synchronized via the WIMU PRO telemetry system (Gomez-Carmona 2020). The physiological intensity of the training sessions was expressed as a percentage of each player's individual maximum HR (HRmax), which was determined at the beginning of the season using an incremental treadmill protocol. The protocol began at 8 km/h, increasing by 2 km/h every 3 minutes until exhaustion (Buchheit 2020).

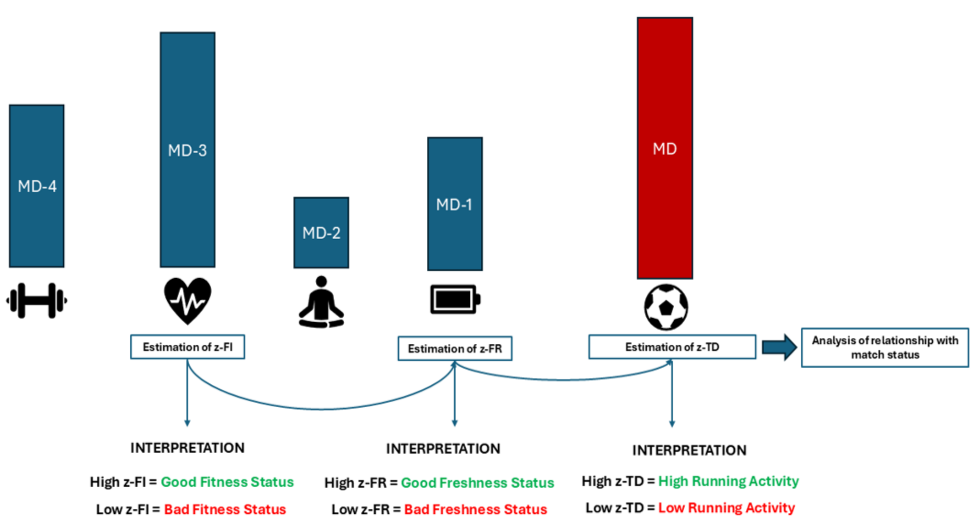

Fig. 1. Flow chart of the data collection.

Data analysis

Players' readiness: football fitness and freshness

As stated in the introduction, football fitness and freshness are preconditions for performance in football, but cannot be directly measured. To approximate these states, we used *key precondition indicators* generated using machine learning models, as described in previous work (Mandorino, 2023; 2024a; 2024b). More precisely, we looked at physiological and mechanical responses during training that reflect underlying fitness and freshness status, respectively.

The 'fitness index" (FI) served as a physiological key precondition indicator. It was calculated by comparing the actual heart rate (HR) response during training (e.g., small-sided games) to predicted HR values from a Random Forest Regression model (Mandorino, 2024a). A positive FI (FI $>$ 0) indicated lower-than-expected HR during exertion, suggesting reduced physiological strain and a favorable fitness condition. The validity of this index has been supported by a strong correlation ($r = 0.7$) with submaximal fitness tests (Mandorino, 2024a).

The 'freshness index" (FR) represented a mechanical/neuromuscular key precondition indicator. It was derived by comparing predicted PlayerLoad (PL) from a Random Forest model to actual PL recorded during training (Mandorino, 2023). A positive FR ($FR > 0$) implied lower mechanical strain than expected for a given external load, indicating locomotor efficiency and low neuromuscular fatigue (Barrett 2016). A negative FR suggested the opposite. This index has shown sensitivity to load variation across weekly cycles and season phases (Mandorino, 2023; 2024b).

Both FI and FR indices were further standardized relative to each player's baseline and normal variation across the seasons (z-score transformation: z-FI, z-FR). The z-FI was assessed on match day minus 3 (MD-3), typically designated for metabolic training with small-sided games, making it ideal for evaluating players' fitness. The z-FR was assessed on MD-1, after a recovery day (MD-2), to evaluate player readiness before the match. The external load metrics used to predict HR and PL values were presented in Table 1.

Definition of match running activity

Since high-speed running (HSR) and total distance (TD) displayed the same behavior via preliminary analyses and were very highly correlated, we only used TD for simplicity. Additionally, TD is reported in all UEFA reports for years, making it a more familiar and interpretable metric for practitioners. Adding a fourth variable might overcomplicate the analysis, especially since it would require a four-way interaction, which could make data interpretation more challenging. We agree that this could be the focus of further analyses. Match running activity was quantified using total distance covered (TD) during matches. To account for individual variability, TD was standardized relative to each player's baseline and typical variation across matches using a z-score transformation (z-TD). The z-TD calculation included only players who participated in at least one half of a match ($\geq$60 minutes) to exclude those with limited playing time as substitutes, as their running activity could be influenced by pacing strategies (Mandorino & Lacome, 2024). A schematic overview of the data collection process and interpretation of the variables was presented in Figure 1.

Table 1. External load metrics employed for the prediction of HR and PL

Target Variable	Features Selected for the prediction	ML model adopted	Index Developed
HR	Average speed (km/h), minutes since the start of training session (min), work:rest ratio (AU), distance above 7.2 km/h (m), max speed (km/h), PlayerLoad (AU), number of decelerations < -3 m/s^2 (cnt)	Random Forest Regression model	z-FI
PL	Total distance (m), distance above 7.2 km/h (m), number of decelerations < -2.5 m/s^2 (cnt), number of accelerations > 2.5 m/s^2 (cnt), max speed (km/h), max deceleration (m/s2), max acceleration (m/s^2)	Random Forest Regression model	z-FR

Statistical analysis

A generalized Mixed model with a multinomial logistic structure was employed to examine the effects of readiness (z-FR), fitness (z-FI), and running activity (z-TD) on match outcomes. The dependent variable represented three possible outcomes: win, draw, and loss. The MLM accounted for random effects: the model included group-level variability (i.e., player id) to account for clustering effects, and fixed effects: the model incorporated main effects for z-FR, z-FI, z-TD. In addition, the full model included two-way interactions between the independent variables, as well as a three-way interaction term to capture complex dependencies among freshness, fitness, and running activity. The analysis estimated separated model for Win vs. Draw, Loss vs. Draw, Win vs. Loss, allowing for a detailed understanding of how these factors influenced match outcomes across different comparisons. The regression models were estimated using Maximum Likelihood Estimation and odds ratios (ORs) were calculated to facilitate the interpretation of the models and provide a measure of how each prediction influenced the probability of a given match outcome. A stratified chart was employed to visualize the interaction terms, specifically showing how the combined effects of freshness, fitness, and running load influenced match outcomes. To enhance interpretability, each continuous predictor (z-FR, z-FI, z-TD) was binarized into two categories: "Low" and "High" based on the median split of its distribution. The transformed variables were then combined to assess their impact on match status, which was treated in this case as a binary variable (Loss/Draw = 0, Win = 1) to identify the optimal predictor combination for increasing winning probability. Odds ratios (ORs), confidence intervals (CIs), and p-values were calculated and are presented in Table 3. In addition, a repeated measures correlation (rrm) was employed to evaluate the linear associations between z-FR and z-FI with z-TD. The analysis was conducted using Python 3.9, with the statsmodels library employed for multinomial regression modeling. Data preprocessing was performed using pandas and numpy, while matplotlib and seaborn were used to visualize the interaction effects. Statistical significance was evaluated using the conventional threshold of $p < 0.05$.

Results

Match outcomes were associated with freshness (z-FR), fitness (z-FI), and running activity (z-TD) (Table 2, Figure 3). In the Draw vs. Loss comparison, z-TD was the only significant predictor, with higher running activity being associated with greater odds of drawing rather than losing (OR = 1.99, p < 0.001). No significant interactions were found in this condition.

For the Win vs. Loss comparison, a significant three-way interaction was observed (OR = 0.52, p < 0.01), indicating that the combined effects of freshness, fitness, and running activity on winning differed from their individual associations. A similar pattern was found in the Win vs. Draw comparison (OR = 0.54, p < 0.05). Additionally, higher running activity was associated with a lower likelihood of winning compared to drawing (OR = 0.47, p < 0.001). The highest probability of winning was observed when high freshness and high fitness were combined with low running activity.

The distribution of running activity across match outcomes (Win, Draw, Loss) is shown in Figure 1, while Figure 2 illustrates the three-way interaction using a stratified chart. Table 3 presents the impact of different predictor combinations, highlighting that the combination of high z-FR, high z-FI, and low z-TD was the only significant factor linked to an increased probability of winning.

The repeated measures correlation revealed a small significant association between z-FR and z-TD (rrm = 0.16 [0.04, 0.27], p < 0.01) but not between z-FI and z-TD (rrm = -0.06 [-0.18, 0.05], p = 0.024). The results of the repeated measures correlation were presented in Figure 4.

Table 2. Multinomial regression analysis.

Draw vs. Loss					
Predictor	Coefficient	Std. Error	p-value	95% CI	Odds Ratio
Intercept	-0.124	0.147	0.398	-0.413, 0.164	0.88
z-FR	-0.018	0.153	0.902	-0.319, 0.281	0.98
z-FI	-0.113	0.152	0.454	-0.411, 0.184	0.89
z-FR * z-FI	0.008	0.182	0.964	-0.348, 0.365	1.00
z-TD	0.688	0.188	**0.001**	0.319, 1.058	1.99
z-FR * z-TD	-0.269	0.205	0.190	-0.672, 0.133	0.76
z-FI * z-TD	-0.297	0.209	0.155	-0.707, 0.112	0.74
z-FR * z-FI * z-TD	-0.043	0.241	0.585	-0.515, 0.429	0.95
Win vs. Loss					
Intercept	0.358	0.131	0.007	0.097, 0.609	1.42
z-FR	-0.013	0.137	0.923	-0.281, 0.255	0.98
z-FI	-0.107	0.137	0.434	-0.375, 0.161	0.89
z-FR * z-FI	0.146	0.175	0.403	-0.197, 0.489	1.15
z-TD	-0.047	0.157	0.762	-0.354, 0.259	0.95
z-FR * z-TD	-0.212	0.183	0.246	-0.571, 0.146	0.80
z-FI * z-TD	-0.154	0.181	0.394	-0.510, 0.201	0.85
z-FR * z-FI * z-TD	-0.651	0.237	0.006	-1.116, -0.187	0.52
Win vs. Draw					
Intercept	0.477	0.136	0.001	0.210, 0.744	1.61
z-FR	0.005	0.142	0.968	-0.273, 0.284	1.00
z-FI	0.006	0.142	0.964	-0.273, 0.286	1.00
z-FR * z-FI	0.137	0.183	0.451	-0.221, 0.497	1.14
z-TD	-0.735	0.179	0.001	-1.086, -0.386	0.47
z-FR * z-TD	0.057	0.197	0.772	-0.329, 0.444	1.05
z-FI * z-TD	0.142	0.194	0.463	-0.238, 0.522	1.15
z-FR * z-FI * z-TD	-0.608	0.235	0.010	-1.068, -0.148	0.54

Table 3. Impact of predictors combination (z-FR, z-FI, z-TD) on probability of winning.

z-FR	z-FI	z-TD	OR	95% CI p-value	
High	High	Low 2.60	1.04, 6.51	0.04	
High	Low	High	0.78	0.31, 1.94	0.59
High	Low	Low 1.17	0.43, 3.19	0.74	
Low	High	High	1.37	0.51, 3.64	0.52
Low	High	Low	1.00	0.40, 2.47	0.99
Low	Low	High	0.85	0.32, 2.20	0.74
Low	Low	Low	1.76	0.69, 4.48	0.22

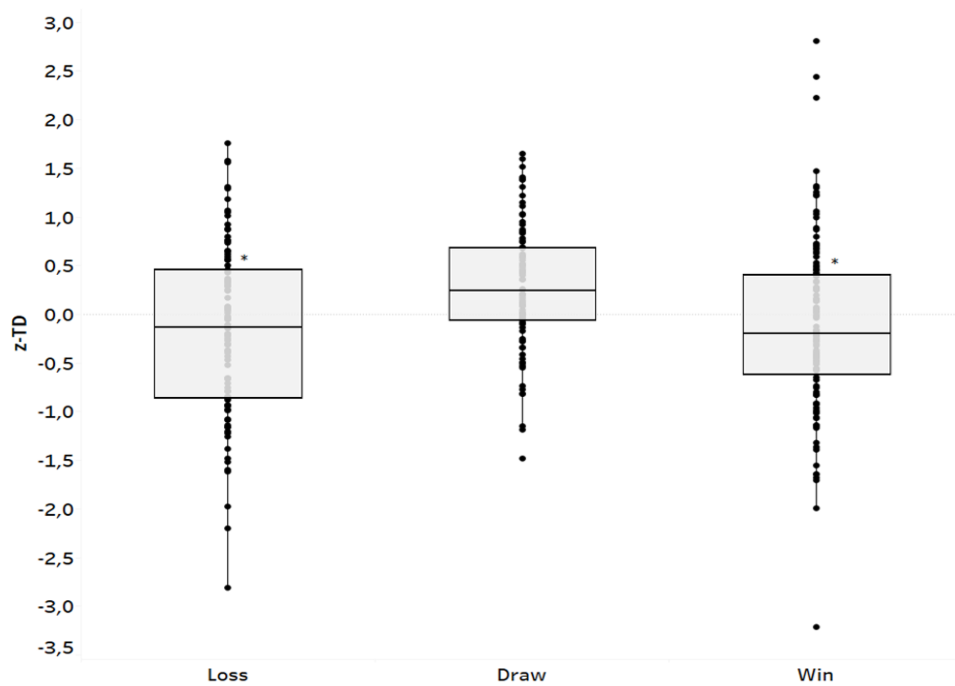

Fig. 2. **Box-plot of running activity (z-TD) based on match status (Loss, Draw, Win). * denotes a significant difference vs. Draw ($p < 0.001$)**

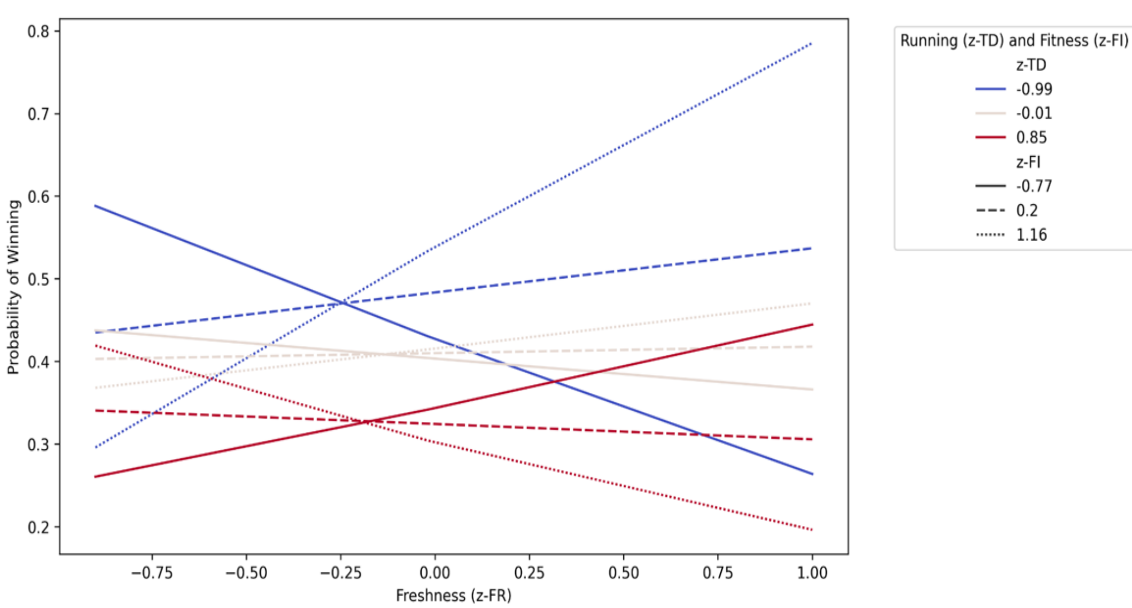

Fig. 3. **Effect of Triple Interaction (Freshness x Fitness x Running Activity) on Win Probability**
X-Axis = z-FR (Freshness)
Y-Axis = probability of winning
Color Coding = represents different levels of z-TD: blue (low running activity), grey (medium running activity), red (high running activity)
Line Style = represents different levels of z-FI: solid line (low fitness), dashed line (medium fitness), dotted line (high fitness).

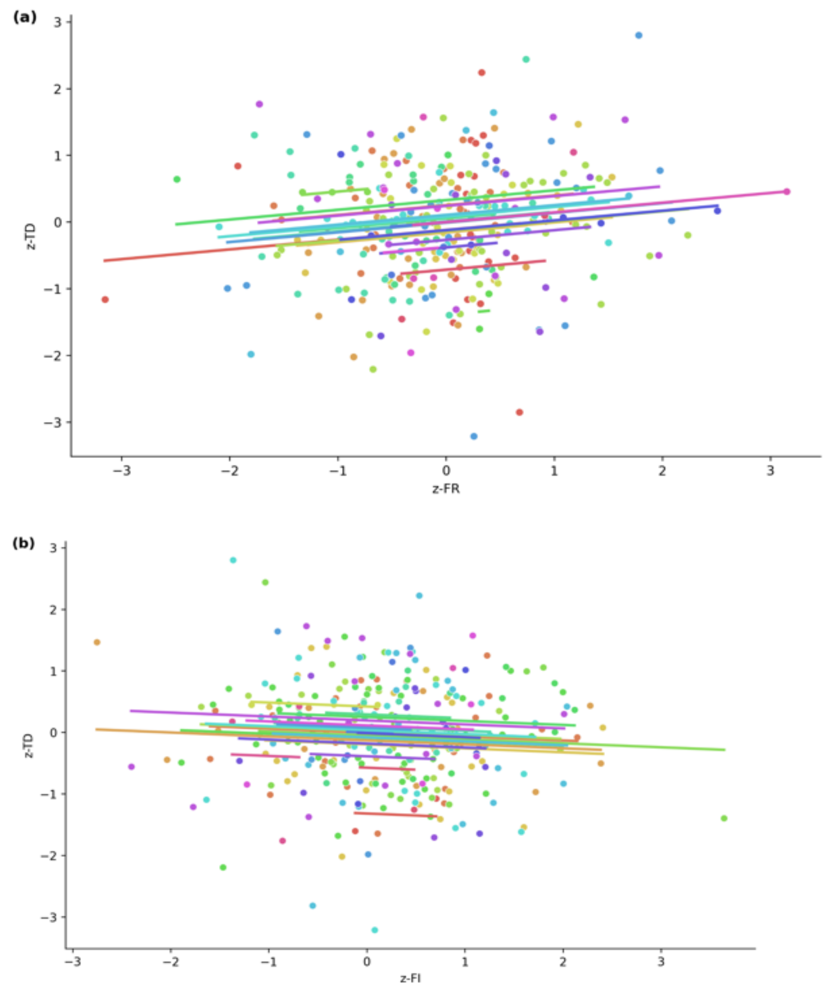

Fig. 4. Relationship between z-FR and z-TD (a) and between z-FI and z-TD (b)

Discussion & Conclusion

This study is the first to examine the interplay between players' readiness and match running activity in relation to game outcomes using a Sport Science 3.0 approach (Buchheit & Laursen 2024). By leveraging embedded monitoring and machine learning–based models (Mandorino 2023; 2024a; 2024b), we captured weekly, match-specific variations in players' *key precondition indicators* (i.e., physiological and mechanical responses during standardized training drill that reflect underlying fitness (FI) and freshness (FR) levels, respectively) - marking a significant methodological advance over previous studies that relied on a few isolated physical capapacity tests per season (Buchheit & Mendez-Villanueva, 2013; Byrkjedal 2024; Mendez-Villanueva 2013).

The highest probability of winning was observed when players combined high FI and high FR with lower running activity (OR = 2.6, Table 3). Conversely, the least favorable scenario was when teams ran more despite low FI (OR = 0.78–0.85, Table 3). These findings support the view that match success depends on the quality of football actions and the player's ability to sustain them throughout the game. Relying on running volume as a key performance indicator is not only misleading—it is outdated and should be dropped entirely (Buchheit & Verheijen, 2024; Verheijen, 2025). Also, while these results provide compelling insights, it is important to stress that they reflect associations—not causal relationships.

Higher running activity was most evident when teams were drawing (Figure 2), likely because both sides were actively pushing to break the deadlock—an observation consistent with findings from Buchheit's 2018 study on the 2011 Asian Cup in Qatar (Buchheit 2018). This reinforces the idea that running is not an independent performance driver but a consequence of tactical decisions and match context. Running more does not inherently lead to better performance; rather, it reflects the demands imposed by a team's playing style and match circumstances.

A key takeaway from these results is that a lower relative internal load—achieved through high FI and FR with reduced running activity—may contribute to better decision-making and overall gameplay quality (Mendez-Villanueva 2013; Rampinini 2008). While not statistically significant, trends indicated that excessive running alone was unfavorable, but greater FI helped mitigate some of its potential downsides (OR changed from 0.8 to 1.37, Table 3). Similarly, when players showed lower FI and FR (likely indicative of being neither fresh nor fit), limiting running appeared to be a viable strategy for managing internal load and relative intensity (OR changed from 0.85 to 1.76, Table 3). Importantly, however, any recommendations arising from these findings—such as reducing unnecessary displacements or optimizing physical exertion—should be considered in the context of the football actions that generate running, rather than focusing on running as an isolated variable (Buchheit & Verheijen 2024; Verheijen 2025).

Contrary to the common belief that fitter or "fresher" players automatically run more during matches, our data show that estimated readiness metrics had a limited influence on match-running activity. The repeated measures correlation revealed only a small positive association between estimated readiness (z-FR) and total distance (z-TD), with $r = 0.16$ [0.04, 0.27], $p < 0.01$. In contrast, no significant association was found between estimated fitness (z-FI) and z-TD ($r = -0.06$ [–0.18, 0.05], $p = 0.24$). Present results confirm that absolute match running performance is not simply a reflection of physical capacity (Buchheit & Mendez-Villanueva, 2013; Byrkjedal 2024; Mendez-Villanueva & Buchheit, 2011a, Mendez-Villanueva 2011b), and caution against assuming a direct causal relationship (Figure 4). As stated before, an increased level of physical capacity may be associated with a decreased internal relative load, which in turn could enhance decision-making procedures (Rampinini 2008; Mendez-Villanueva 2013). We recognize the importance of football fitness, however, we posit that the utilization of absolute running metrics as a substitute for either football or 'generic' fitness is irrelevant (Buchheit & Verheijen 2024; Verheijen 2025).

Finally, these findings must be interpreted with some limitations in mind. First, the results are based on data from a single professional club over three seasons, which may restrict their generalizability to other teams, leagues, or playing styles. Expanding the analysis across multiple teams and competitions would help validate these observations in different contexts. Second, while this study specifically aimed to estimate *key precondition indicators* (i.e., physiological and mechanical responses during training that reflect underlying fitness and freshness, respectively) against running—often wrongly assumed to reflect either football or 'generic' fitness—it does not account for many other factors influencing match success. Variables such as team strength (e.g., ELO ranking), fixture congestion, squad rotation (Settembre 2024), and tactical strategies were not included in the model. Future research should incorporate a broader range of performance determinants to better capture the complexity of match outcomes.

Take-home messages

- **Running volume should be dropped as a key performance indicator** - Match success is linked to the quality and sustainability of football actions, not the total distance covered.
- **Running is a consequence, not a cause, of match outcomes** - it reflects tactical choices, game context, and team strategies rather than driving success on its own.
- **Readiness (as a combination of football fitness and freshness) is a precondition for performance** - winning was associated with high values of *key precondition indicators* (i.e., physiological and mechanical responses during training that reflect high fitness and freshness, respectively) combined with lower running activity.
- **Readiness showed limited association with match running activity** - while it may impact relative (internal) load, estimated physical readiness is unlikely to strongly influence absolute match running activity.
- **More running does not necessarily mean better performance** - excessive running was not linked to winning, and trends suggested that high estimated fitness helped mitigate some of its potential downsides.
- **Drawing matches was linked to higher running activity** -likely because both teams were still pushing to make a difference, reinforcing the idea that running is dictated by game demands rather than fitness levels.
- **When players are neither fresh nor fit, limiting running may be a viable strategy** - managing energy expenditure could be crucial for maintaining effectiveness in matches.
- **Lower internal load may enhance decision - making and game quality**—players with high readiness, while maintaining controlled running, may be better equipped to execute tactical and technical actions.
- **These results describe associations, not causal effects** - while certain patterns emerged, running alone should not be assumed to influence match success directly.
- **Many other factors influence match outcomes** - team strength, fixture congestion, squad rotation, and tactical strategies all play critical roles and should be considered in future research.

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