

Contextual Variability of Team-Level High-Intensity Movement Profiles in the Turkish Super League: A 2024-2025 Season Analysis

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ABSTRACT

Purpose: High-intensity accelerations and decelerations are the external-load variables practitioners monitor most closely in elite football, yet the situational-variable literature rests almost entirely on speed-zone running, and no such data have been reported for the Turkish Super League. We examined how team-level change-of-speed load varies with match context, and how its variance is distributed between the match and the team.

Method: All 19 clubs were tracked with a semi-automated multi-camera optical system across the 2024–2025 season, for which eligible tracking data were available for 331 of the 342 scheduled fixtures (96.8%), yielding a near-complete season census. From these, 6,276 player-match observations from 427 outfield players completing at least 60 minutes were aggregated to 662 team-match observations across the 331 matches. Two per-minute outcomes were computed: high-intensity movement (HIM), the sum of acceleration ($>3 \text{ m}\cdot\text{s}^{-2}$) and deceleration ($<-3 \text{ m}\cdot\text{s}^{-2}$) distance, and the acceleration-to-deceleration ratio. Because each match contributes two observations, a crossed random-effects model with match and team was fitted, with variance components verified across five optimisers.

Results: Two-thirds of the variance in HIM was attributable to the match (66.3%) and only one-tenth to the team (10.1%). Neither match result ($p = 0.546$) nor match venue ($p = 0.649$) was associated with HIM, and equivalence testing bounded the venue and win–loss contrasts below 0.2 SD. Opponent quality was associated with both HIM, $\chi^2(3) = 19.09$, $p < 0.001$, and the ratio, $\chi^2(3) = 12.23$, $p = 0.007$, HIM being highest against second-quartile and lowest against third-quartile opponents ($d = 0.42$).

Conclusion: High-intensity load was therefore primarily a property of the contest; opponent standard shifts its expected value without determining it. These findings caution against treating team-level physical output as a stable club characteristic and imply that analyses pooling team–match observations must model match-level clustering.

Keywords: External Load, Acceleration, Deceleration, Opponent Quality, Variance Components

ÖZET

Türkiye Süper Ligi’nde Takım Düzeyinde Yüksek Şiddetli Hareket Profillerinin Bağlamsal Değişkenliği: 2024–2025 Sezon Analizi

Amaç: Yüksek şiddetli hızlanmalar ve yavaşlamalar, elit futbolda uygulayıcıların en yakından takip ettiği dış yük değişkenleridir; ancak durumsal değişken literatürü neredeyse tamamen hız bölgelerine dayalı koşullara dayanmaktadır ve Türkiye Süper Ligi için bu tür herhangi bir veri rapor edilmemiştir. Takım düzeyindeki hız değişimi yükünün maç bağlamına göre nasıl değiştiğini ve varyansının maç ile takım arasında nasıl dağıldığını inceledik.

Yöntem: Tüm 19 kulüp, 2024–2025 sezonu boyunca yarı otomatik çok kameralı optik sistem ile takip edildi. Planlanan 342 müsabakanın 331’ine (%96,8) ait uygun takip verisi mevcut olup bu, neredeyse tam bir sezon sayımı (near-complete season census) niteliğindedir. Bu verilerden, en az 60 dakika süre alan 427 dış saha oyuncusundan elde edilen 6,276 oyuncu-maç gözlemi, söz konusu 331 maç boyunca 662 takım-maç gözleminde birleştirildi. Dakika başına iki sonuç değişkeni hesaplandı: yüksek şiddetli hareket (HIM), hızlanma ($>3 \text{ m}\cdot\text{s}^{-2}$) ve yavaşlama ($<-3 \text{ m}\cdot\text{s}^{-2}$) mesafelerinin toplamı ve hızlanma-yavaşlama oranı. Her maç iki gözlem içerdiğinden, varyans bileşenleri beş farklı optimizasyon yöntemi üzerinden doğrulanarak, maç ve takımın yer aldığı çaprazlanmış rastgele etkiler modeli oluşturuldu.

Bulgular: HIM varyansının üçte ikisi maça (%66,3) ve yalnızca onda biri takıma (%10,1) atfedildi. Ne maç sonucu ($p = 0,546$) ne de maçın oynandığı saha ($p = 0,649$) HIM ile ilişkiliydi ve eşdeğerlik testi, saha ve galibiyet-mağlubiyet karşılaştırmalarını 0,2 SD’nin altında sınırlandırdı. Rakip kalitesi hem HIM, $\chi^2(3) = 19,09$, $p < 0,001$, hem de oran, $\chi^2(3) = 12,23$, $p = 0,007$ ile ilişkiliydi; HIM, ikinci çeyreklik

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dilimdeki rakiplere karşı en yüksek ve üçüncü çeyreklik dilimdeki rakiplere karşı en düşük düzeydeydi ($d = 0,42$).

Sonuç: Yüksek şiddetli yük bu nedenle öncelikle mücadelenin bir özelliği; rakip standardı beklenen değeri değiştirirken bunu belirlememektedir. Bu bulgular, takım düzeyindeki fiziksel çıktının istikrarlı bir kulüp özelliği olarak ele alınmasına karşı dikkatli olunması gerektiğini ortaya koymakta ve takım-maç gözlemlerini bir araya getiren analizlerin maç düzeyindeki kümelenmeyi modellemesi gerektiğini göstermektedir.

Anahtar Kelimeler: Dış Yük, Hızlanma, Yavaşlama, Rakip Kalitesi, Varyans Bileşenleri

INTRODUCTION

Accelerating and decelerating at high intensity is among the most mechanically demanding actions a footballer performs, and practitioners have recognised this in their monitoring choices. In a survey of 41 elite clubs, acceleration-based variables were ranked as the most important external-load metric monitored, ahead of total distance covered (Akenhead & Nassis, 2016). The empirical basis is well established: a systematic review and meta-analysis of elite team-sport match play showed that high-intensity accelerations and decelerations constitute a distinct locomotor demand not captured by speed-zone running, and that football exhibits the largest imbalance of any sport reviewed, with substantially more high-intensity decelerations than accelerations (Harper et al., 2019). Decelerations are of particular interest because braking imposes high eccentric loads on the lower limb, with consequences for neuromuscular fatigue and tissue damage that differ mechanistically from those of acceleration (Harper et al., 2022). Methodological conventions in this literature nevertheless remain inconsistent, with variation in thresholds, minimum effort durations and reporting units (Silva et al., 2022).

A parallel line of enquiry holds that physical output in football cannot be interpreted in isolation from the circumstances in which it is produced (Paul et al., 2015). A systematic review of situational and environmental influences on match running concluded that contextual effects are genuine but typically small and inconsistent across studies (Trewin et al., 2017), and it has been argued that physical metrics reported without tactical context are of limited practical value (Bradley & Ade, 2018). Three situational variables have dominated this literature since they were formalised in analyses of possession strategy: match venue, quality of opposition and match status (Lago, 2009), and their influence on distance covered at different speeds was subsequently demonstrated directly (Lago et al., 2010).

Evidence for each is uneven. For match outcome, a full-season Bundesliga analysis found running performance related to possession time but insufficient to determine victory (Hoppe et al., 2015), and a Turkish first-division study using analysis of covariance and logistic regression

likewise reported that running performance was not a strong determinant of winning (Plakias et al., 2025). Other work points the opposite way, associating sprinting activity with match outcome in the German first division (Andrzejewski et al., 2018) and reporting that a professional English club recorded its highest frequencies of high-intensity accelerations and decelerations in matches that were won (Rhodes et al., 2021); a further league-level analysis found the running–success relationship weak and context-dependent (Andrzejewski et al., 2022). For match venue, home advantage is firmly documented as a points and scoring phenomenon (Pollard & Gomez, 2014), but its expression in physical output is less certain: a single-club Turkish Super League study reported venue-related differences in high-speed running by position (Coskun & Torun, 2025), whereas league-level analyses have found location effects that are small or absent (Plakias et al., 2025). For opponent quality the evidence is more consistent. Less successful Serie A teams covered greater total distance but less high-intensity distance with the ball (Rampinini et al., 2009); opponent ranking systematically modulated running output across five seasons of English professional football (Morgans et al., 2025); and in the Turkish first division opponent quality affected medium- and high-intensity running with small effect sizes (Plakias & Michailidis, 2024). Complementing these findings, tier-specific analysis of the English Premier League showed that higher-ranked teams were distinguished not by gross output but by contextualised on-ball high-intensity running (Ju et al., 2023).

Three gaps follow. First, the situational-variable literature is overwhelmingly built on speed-zone running; the few studies examining accelerations and decelerations in context have done so at player level within a single club (Rhodes et al., 2021), leaving open whether contextual effects on change-of-speed load exist at team level across an entire league. Second, no acceleration or deceleration data have been reported for the Turkish Super League, whose existing analyses use speed-zone metrics at league level (Plakias et al., 2025; Plakias & Michailidis, 2024) or acceleration-based metrics within one club (Coskun & Torun, 2025). Third, accelerations and decelerations are almost always analysed as separate outcomes despite being strongly collinear; the imbalance between them has been quantified as a between-sport standardised difference but has not been operationalised as a within-match, team-level descriptor (Harper et al., 2019).

A fourth and more basic question has been neglected altogether. Studies of this kind implicitly treat physical output as a property of the team and interpret differences between teams or between contexts accordingly. Whether that premise holds is an empirical matter: in any

competitive fixture, two opposing teams share the same pitch, referee, tempo and tactical exchange, so their loads may co-vary strongly. If the greater share of variance in change-of-speed load resides at the level of the contest rather than the team, then both the interpretation of team profiles and the statistical treatment of such data require revision. To our knowledge this variance structure has not previously been quantified for acceleration and deceleration metrics in football.

These questions matter practically. Coaching staff plan the training week against a named forthcoming opponent, and the variable they most often monitor is acceleration load (Akenhead & Nassis, 2016). If change-of-speed demands are governed principally by the identity of the opposition, load planning should be anchored to opponent characteristics; if they are governed largely by the contest itself, the predictability of such planning is correspondingly limited. Because the deceleration component carries the greater eccentric cost (Harper et al., 2019), establishing which factor moves this load bears directly on the scheduling of braking-intensive work.

The aim of this study was therefore twofold: to quantify how the variance in team-level high-intensity change-of-speed load is distributed between match, team and residual levels; and to determine whether that load, and the balance between its accelerative and decelerative components, varies with match result, match venue and opponent quality across a complete season of the Turkish Super League. Based on the more consistent evidence for opposition effects (Rampinini et al., 2009; Plakias & Michailidis, 2024; Morgans et al., 2025) we hypothesised that both outcomes would differ according to opponent quality (H1). Because the evidence concerning match outcome (Hoppe et al., 2015; Plakias et al., 2025; Andrzejewski et al., 2018; Rhodes et al., 2021; Andrzejewski et al., 2022) and match venue (Pollard & Gomez, 2014; Plakias et al., 2025; Coskun & Torun, 2025) is genuinely mixed, the corresponding hypotheses were tested in a state of equipoise, with no directional prediction specified for match result (H2) or match venue (H3). The variance-structure question was addressed descriptively, without a directional hypothesis.

METHODS

Research Design

This was a retrospective, cross-sectional observational study using a near-complete season census of competitive match data. The 2024–2025 season was contested by 19 clubs in a double round-robin of 342 scheduled fixtures. Eligible tracking data were available for 331

of these fixtures (662 team-match observations); the 11 fixtures not represented are itemised under Unit of analysis and aggregation. Because the analysis enumerates almost the entire population of the season's fixtures rather than a probability sample drawn from it, no sampling was performed and no a priori sample-size calculation was applicable; the basis on which inferential statistics are nonetheless reported is set out under Statistical analysis. Reporting follows the STROBE recommendations for cross-sectional studies (von Elm et al., 2007). The aggregation rule, inclusion threshold, outcome definitions and robustness analyses were specified before hypothesis testing.

Setting and data source

Data were obtained from the official league-wide match-tracking provision supplied to all clubs by the Turkish Football Federation for the 2024-2025 season and comprised every competing club. Player positional data were captured by a single, standardised semi-automated multi-camera optical tracking system (Sportsbase), in which fixed camera arrays installed within each stadium detect and track players by computer vision, and every trajectory was subjected to human video-verification by trained operators. Because the same accredited system, operating under a single processing version, generated the data for every match and every club, measurement was uniform across the entire dataset. Derived locomotor variables, including distance accumulated above defined acceleration and deceleration thresholds, were exported by the provider at player-match level.

This official, standardised provenance ensures uniform, league-wide data capture, but it does not substitute for independent measurement validation: no peer-reviewed validation study of this specific system has been published, which is acknowledged as a limitation. The closest published evidence concerns technologically equivalent systems. Football-specific validation of multi-camera optical tracking against a criterion motion-capture system has established acceptable agreement for position, speed and acceleration, while showing that error for acceleration exceeds that for distance (Linke et al., 2020). More directly relevant, a recent validation of a coupled multi-camera optical platform reported high agreement for the total number of accelerations and decelerations (coefficients of determination of 0.954 and 0.950, respectively), but also showed that the optical platform systematically underestimated both accelerations and decelerations relative to a GPS-IMU criterion, with markedly weaker agreement at higher intensity thresholds ($R^2 = 0.338$ for accelerations above $4 \text{ m} \cdot \text{s}^{-2}$) (Gonzalez-Rodenas et al., 2025). Broader field validation of electronic performance and tracking systems (Linke et al., 2018) and of a comparable semi-automated video system in a major European

league (Felipe et al., 2019) supports the use of such systems for match physical demands. Because all observations derive from a single system operating under a single processing version within one season, any systematic error that is common to all teams, matches and contextual conditions cannot generate spurious differences between contextual groups. This argument protects the contextual contrasts of result, venue and opponent quality, but it does not protect the variance decomposition itself: factors fixed to the venue, including the geometry and calibration of a stadium's camera installation, could in principle inflate the match-level variance component. This possibility is examined directly in a stadium-augmented sensitivity analysis (see Model structure and variance components) and discussed below.

Eligibility criteria and data flow

The raw export contained 11,351 records. Provider-generated per-team seasonal totals and per-team seasonal averages were removed. Goalkeepers were excluded because their locomotor profile is not comparable with that of outfield players. Outfield records were restricted to players completing at least 60 minutes. This threshold, approximately two-thirds of regulation time, was applied because per-minute normalisation becomes unstable over short exposures, in which a single high-intensity effort can distort the rate estimate; it also excludes late substitutes. A single-position criterion was additionally specified; among outfield records meeting the minutes criterion, no observation carried a multi-position code, so this criterion excluded no further records. The analytical file contained 6,276 player-match observations from 427 unique outfield players, who played a mean of 91.7 (SD 12.3) minutes. The full flow is presented in Table 1.

Unit of analysis and aggregation

Because the research question concerns team behaviour rather than individual player behaviour, the unit of analysis was the team-match. For each team in each match, the per-minute values of all eligible outfield players were averaged, yielding one acceleration and one deceleration value per team per match. This produced 662 team-match observations from 331 unique matches and 19 teams, with a mean of 9.5 (SD 0.8; range 6 to 10) eligible players per value. These 331 matches represent 331 of the 342 scheduled fixtures. The 11 fixtures not represented were absent from the tracking data as supplied by the provider, for reasons not documented in the source; the data were received by the authors in this form. The pattern of this shortfall was nonetheless diffuse and unrelated to the study factors: it involved 18 of the 19 clubs, with no club losing more than two fixtures (per-club coverage 34 to 36 fixtures, mean 34.8); the missing team-slots were evenly distributed across opponent-quality quartiles (6, 5, 5

and 6 for the first to fourth quartiles, against 5.8, 5.8, 5.8 and 4.6 expected under a random loss); and, because whole fixtures were absent, both competing teams were removed together, leaving venue representation exactly balanced (331 home and 331 away). The missingness is therefore consistent with a loss that is ignorable with respect to venue, club and opponent quality, and the dataset is best characterised as a near-complete season census rather than a complete enumeration. Aggregating to the team mean removes within-squad dispersion, an ecological consequence addressed in the limitations.

Outcome variables

Two per-minute outcomes were derived, so that they represent intensity rather than accumulated volume. High-intensity movement (HIM) was defined as the sum of high-intensity acceleration distance ($>3 \text{ m}\cdot\text{s}^{-2}$) and high-intensity deceleration distance ($<-3 \text{ m}\cdot\text{s}^{-2}$) in meters per minute, representing the total magnitude of high-intensity change-of-speed load. The acceleration-to-deceleration ratio (AD ratio) was defined as high-intensity acceleration distance divided by high-intensity deceleration distance, representing the balance of that load between its components.

The decision to combine the two raw variables in this way was empirically motivated and the supporting correlations are reported in Results (Table 2): the two raw variables proved strongly collinear, so analysing them as separate outcomes would have tested largely the same information twice and inflated the number of comparisons, whereas expressing the same information as a magnitude term and a balance term yielded two only moderately correlated outcomes. The threshold of $3 \text{ m}\cdot\text{s}^{-2}$ lies within the conventional range for high-intensity accelerations and decelerations in elite football (Harper et al., 2019; Silva et al., 2022). Absolute rather than individualised thresholds were applied because individual physical-capacity data were unavailable; the absence of consensus on absolute versus individualised thresholds is recognised (Gualtieri et al., 2023) and revisited in the limitations.

Contextual variables

Match venue was determined from the match record, in which the home team is named first, and coded as home or away. Match result was derived from the final score from the perspective of the team contributing the observation, and coded as win, draw or loss. Opponent quality was operationalised as the quartile of the opponent's final league position: first quartile (positions 1 to 5), second (6 to 10), third (11 to 15) and fourth (16 to 19). Because the league comprised 19 teams, the fourth quartile contained four rather than five clubs, accounting for the smaller number of observations in that stratum. End-of-season position is a stable, objective

index of opponent standard but is retrospective and does not reflect form at the time of a given fixture; this is addressed in the limitations.

Statistical analysis

Analyses were conducted in Python 3.12 using pandas and statsmodels, with the significance level set at 0.05. Because the dataset approaches the complete population of the season rather than a probability sample, the reported p-values, confidence intervals and equivalence bounds are not interpreted as generalisations from a sample to a finite population. They instead characterise the parameters of the stochastic match-generating process of this league, the observed season being treated as one realisation of that process; the contextual effects are therefore estimands of that process rather than descriptions confined to the specific fixtures observed. This model-based (super-population) framing is what licenses interval estimation and equivalence testing in a near-census design.

Model structure and variance components: Observations were not independent by design, and clustering could arise at two levels. Each team contributed up to 36 observations (mean 34.8), and each match contributed exactly two observations, one for each competing team. Both levels were therefore modelled simultaneously in a crossed random-effects specification with random intercepts for match and for team, and the proportion of variance attributable to each level was computed by partitioning the variance components (Nakagawa & Schielzeth, 2013). Marginal and conditional R-squared were obtained by the same approach.

Variance components were verified across five optimisation algorithms (L-BFGS, BFGS, conjugate gradient, Powell and Nelder–Mead). This step is reported because it proved consequential: in a team-only specification the L-BFGS algorithm reported successful convergence while returning a boundary solution of exactly zero team variance, whereas the four remaining algorithms agreed on a non-zero estimate. Estimates from the four concordant algorithms were adopted, and all reported models were fitted with Powell's method. We recommend this verification as routine practice wherever a variance component is estimated at or near zero, since a boundary solution accompanied by a convergence flag is otherwise indistinguishable from a genuine null.

To assess whether venue-fixed factors contributed to the match-level variance, the variance-components model for each outcome was additionally augmented with a random intercept for the home stadium, identified from the fixture record. Because every match is played at a single venue, this partitions the match-level variance into a between-stadium component, which absorbs any factor common to all matches at a given venue — including the

fixed camera geometry, calibration and image-processing of that installation as well as genuine physical venue characteristics such as pitch surface and dimensions — and a within-stadium component, which reflects variation among different matches recorded by the same fixed installation. Stadium-fixed measurement characteristics are constant within a venue and can therefore contribute only to the between-stadium component; the within-stadium component is by construction free of stadium-fixed processing artefact. This decomposition was verified across the same five optimisation algorithms.

Fixed effects, marginal means and contrasts: Each outcome was modelled as a function of match result, match venue and opponent quality simultaneously, so that each factor is evaluated after adjustment for the other two. Omnibus fixed effects were tested by Wald statistics on the relevant coefficient blocks. Effect size was expressed as the semi-partial marginal R-squared, that is, the reduction in marginal R-squared when a factor is removed from the model; partial eta-squared was not used because it is not defined for mixed models. Estimated marginal means were computed from the fitted model by averaging the design matrix over a balanced grid of the remaining factors, with standard errors obtained from the fixed-effect covariance matrix; they are therefore adjusted estimates, not raw group means, and both are reported side by side for transparency. Pairwise contrasts across opponent-quality strata were estimated from the same model and adjusted by the Holm procedure, which controls the family-wise error rate without assuming the balanced, equal-variance structure required by Tukey's procedure. Standardised mean differences between strata are reported as Cohen's *d* computed from the raw group data (Lakens, 2013).

Evaluation of null findings: A non-significant test does not establish the absence of an effect. Where an omnibus factor was not associated with an outcome, the constituent pairwise contrasts were therefore additionally submitted to two one-sided tests of equivalence against a smallest effect size of interest of 0.2 standard deviations, the conventional threshold for a small effect (Cohen, 1988). A contrast was declared statistically equivalent only when its 90% confidence interval fell entirely within the equivalence bounds. A sensitivity power analysis was also conducted to establish the smallest effect the design could have detected with 80% power at an alpha level of 0.05.

Assumptions and robustness: Residual distributions were examined by skewness, kurtosis and the Shapiro–Wilk statistic, and homogeneity of variance by Levene's test. Residuals were acceptable for the AD ratio (skewness 0.32; *W* = 0.990) and mildly positively skewed for HIM (skewness 0.83; *W* = 0.962). Levene's test indicated unequal variances across opponent-quality

strata for HIM ($W = 4.58$, $p = 0.003$) but not for the AD ratio ($W = 0.21$, $p = 0.887$). Three robustness analyses were therefore pre-specified: ordinary least squares with cluster-robust standard errors at match level; re-analysis of HIM after natural log transformation; and re-derivation of the entire dataset using a more restrictive 80-minute inclusion threshold. A finding was regarded as robust only if preserved across all three.

RESULTS

Observation flow and sample characteristics

The derivation of the analytical dataset is summarised in Table 1. Of 11,351 raw records, 1,138 were provider-generated summary rows and 676 were goalkeeper observations; a further 3,261 outfield observations did not meet the 60-minute criterion. The final file comprised 6,276 player-match observations, aggregated to 662 team-match observations spanning 331 matches and all 19 clubs. The design was balanced by construction for venue (331 home and 331 away observations) and near-balanced for result (253 wins, 253 losses and 156 draws).

Table 1. Derivation of the analytical dataset.

Step	Criterion applied	Excluded (n)	Remaining (n)
1	Raw provider export	—	11,351
2	Remove per-team seasonal totals	569	10,782
3	Remove per-team seasonal averages	569	10,213
4	Remove goalkeepers	676	9,537
5	Retain players completing ≥ 60 minutes	3,261	6,276
6	Retain single-position records	0	6,276
7	Aggregate to team-match level	—	662

Note: Player-match observations at step 6 derive from 427 unique outfield players (mean playing time 91.7, SD 12.3 minutes). Team-match observations at step 7 derive from 331 unique matches and 19 clubs, with a mean of 9.5 (SD 0.8) eligible players per team-match value.

Descriptive characteristics and the structure of the two outcomes

Descriptive statistics and the correlation matrix are presented in Table 2. High-intensity acceleration distance exceeded high-intensity deceleration distance by approximately threefold, giving a mean AD ratio of 2.997 (SD 0.311). The two raw variables were strongly collinear ($r = 0.890$, 95% CI 0.873 to 0.905), which would have made their separate analysis largely redundant. The two derived outcomes were only moderately correlated ($r = 0.393$, 95% CI 0.327 to 0.456), confirming that the magnitude and balance components capture substantially separate information and justifying their joint reporting.

Table 2. Descriptive statistics and correlations for team-match physical variables (n = 662).

Variable	Mean $\pm$ SD	Range	Accel	Decel	HIM	AD ratio
High-intensity acceleration distance ($\text{m} \cdot \text{min}^{-1}$)	2.073 $\pm$ 0.479	1.074–4.162	—	0.890	0.995	0.483
High-intensity deceleration distance ($\text{m} \cdot \text{min}^{-1}$)	0.691 $\pm$ 0.137	0.401–1.233	0.890	—	0.932	0.042
HIM ($\text{m} \cdot \text{min}^{-1}$)	2.764 $\pm$ 0.605	1.491–5.270	0.995	0.932	—	0.393
AD ratio (dimensionless)	2.997 $\pm$ 0.311	2.193–4.619	0.483	0.042	0.393	—

Note: Values to the right of the range column are Pearson correlation coefficients. HIM, high-intensity movement; AD ratio, acceleration-to-deceleration ratio. Key correlations with 95% confidence intervals: acceleration with deceleration $r = 0.890$ [0.873, 0.905]; HIM with AD ratio $r = 0.393$ [0.327, 0.456].

Where the variance sits

The variance decomposition is presented in Table 3 and displayed in Figure 1, panel A. For HIM, two-thirds of the total variance was attributable to the match (66.3%), with only one-tenth attributable to the team (10.1%) and the remainder residual (23.6%). The conditional R-squared of 0.770 indicates that match and team identity together with the contextual factors accounted for the large majority of variance in this outcome, while the marginal R-squared of 0.027 shows that the contextual factors themselves explained little of it. The AD ratio behaved differently: match-level variance was modest (13.8%), team-level variance small (4.2%), and most variance was residual (82.0%), with a conditional R-squared of 0.195.

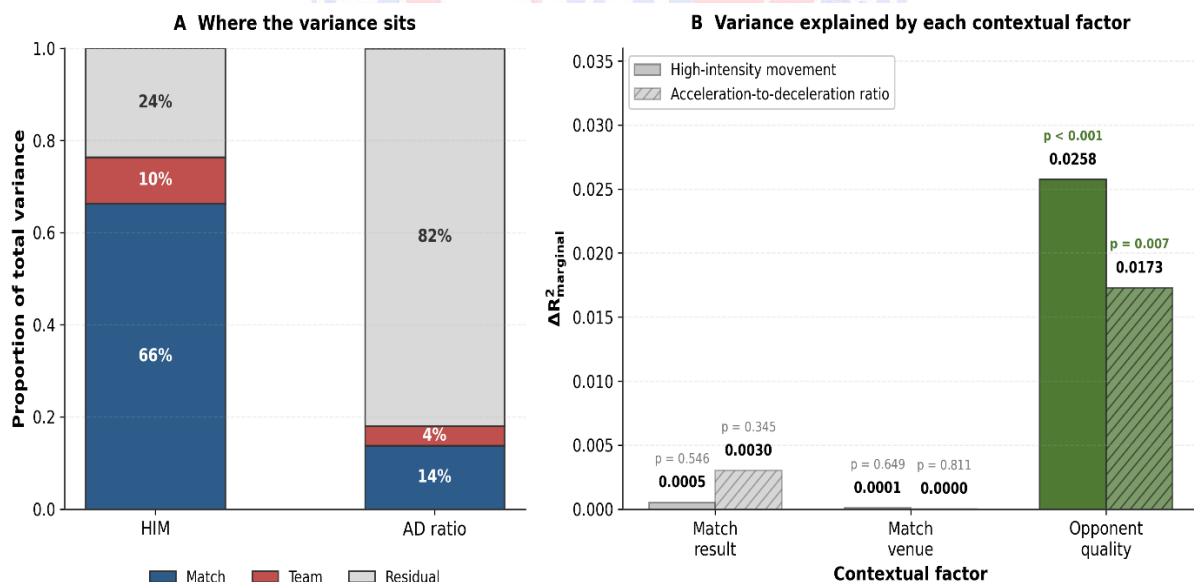


Figure 1. Panel A: proportion of total variance in each outcome attributable to the match, to the team and to residual error, estimated from the crossed random-effects model. Panel B: reduction in marginal R-squared when each contextual factor is removed from the model, with the corresponding p values. Solid bars denote high-intensity movement and hatched bars the acceleration-to-deceleration ratio; green indicates $p < 0.05$.

Augmenting the model with a random intercept for the home stadium partitioned this match-level variance into a between-stadium and a within-stadium component. For HIM, the

within-stadium component (variation among different matches recorded by the same fixed camera installation) accounted for 71.4% of the match-level variance, and the between-stadium component for 28.6%; this split was stable across all five optimisers. Because stadium-fixed measurement characteristics cannot vary between matches at the same venue, the predominance of the within-stadium component indicates that the match-level clustering in HIM is not an artefact of venue-fixed processing. For the AD ratio, whose match-level variance was small to begin with, the split was more even (within-stadium 46.4%, between-stadium 53.6%).

The verification of these components across optimisation algorithms is reported in Table 3. In a team-only specification the L-BFGS algorithm returned a team variance of exactly zero while reporting successful convergence, whereas BFGS, conjugate gradient, Powell and Nelder–Mead all returned 0.066, corresponding to an intraclass correlation of 0.184. The concordant estimate was adopted.

Table 3. Variance decomposition from the crossed random-effects model, and optimiser verification.

Outcome	Source	Variance	% of total	R ² marginal	R ² conditional
HIM	Match	0.23100	66.3%	0.027	0.770
	Team	0.03534	10.1%		
	Residual	0.08229	23.6%		
AD ratio	Match	0.01318	13.8%	0.019	0.195
	Team	0.00404	4.2%		
	Residual	0.07858	82.0%		

Optimisation algorithm	Team variance	ICC (team)	Convergence reported
L-BFGS	0.00000	0.000	Yes
BFGS	0.06640	0.184	Yes
Conjugate gradient	0.06640	0.184	Yes
Powell	0.06640	0.184	Yes
Nelder–Mead	0.06641	0.184	Yes

Note: Upper panel: crossed random-effects model with match and team random intercepts, fitted by Powell's method. Lower panel: team-only specification for HIM, fitted by five algorithms. The L-BFGS solution lies on the parameter boundary and was not adopted.

Contextual Effects

The fixed-effect tests are presented in Table 4. Neither match result nor match venue was associated with either outcome. For HIM the result factor produced $\chi^2(2) = 1.21$, $p = 0.546$, with a semi-partial marginal R-squared of 0.0005, and venue produced $\chi^2(1) = 0.21$, $p = 0.649$, $\Delta R^2 \text{marginal} = 0.0001$. The same pattern held for the AD ratio, with $\chi^2(2) = 2.13$, $p = 0.345$,

$\Delta R^2_{\text{marginal}} = 0.0030$ for result and $\chi^2(1) = 0.06$, $p = 0.811$, $\Delta R^2_{\text{marginal}} < 0.0001$ for venue. The distributions underlying these tests are displayed in Figure 2.

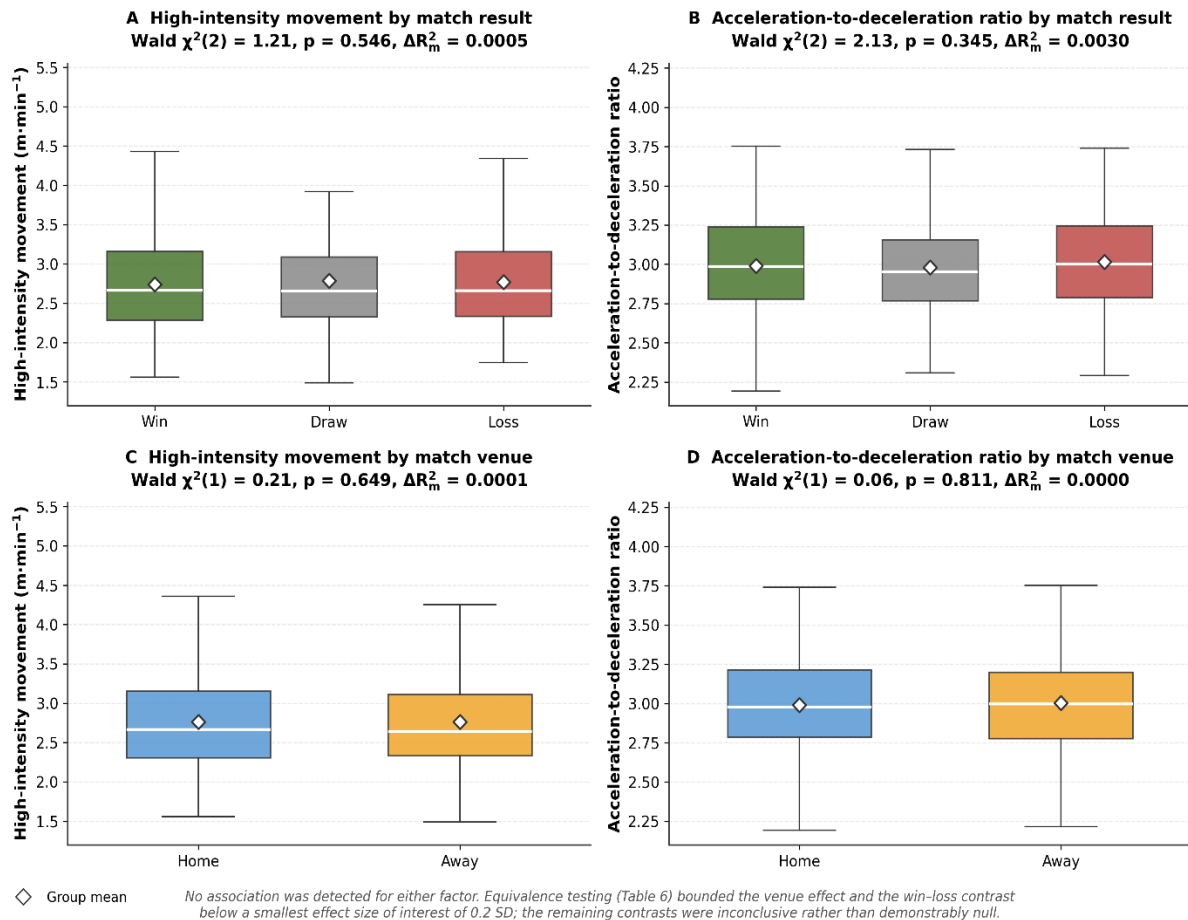


Figure 2. Distribution of high-intensity movement and the acceleration-to-deceleration ratio across match-result categories (panels A and B) and match venues (panels C and D). Boxes show the median and interquartile range, whiskers extend to 1.5 times the interquartile range, and diamonds denote group means. Test statistics are Wald tests from the crossed random-effects model. Neither factor was associated with either outcome; equivalence testing (Table 7) bounded the venue contrasts and the win-loss contrast for high-intensity movement below a smallest effect size of interest of 0.2 SD, whereas the remaining contrasts were inconclusive.

Opponent quality was associated with both outcomes: $\chi^2(3) = 19.09$, $p < 0.001$, $\Delta R^2_{\text{marginal}} = 0.0258$ for HIM, and $\chi^2(3) = 12.23$, $p = 0.007$, $\Delta R^2_{\text{marginal}} = 0.0173$ for the AD ratio. Distributions across opponent-quality strata are displayed in Figure 3, and the variance explained by each contextual factor is compared in Figure 1, panel B.

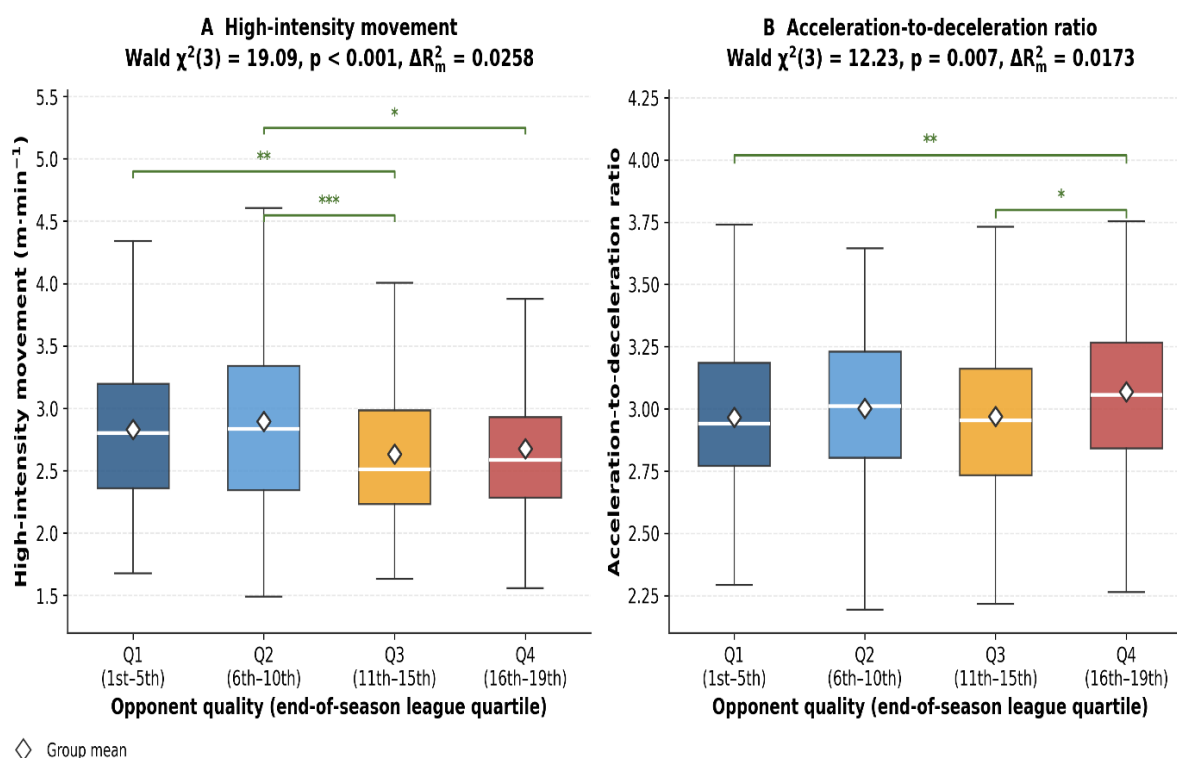


Figure 3. Distribution of high-intensity movement (panel A) and the acceleration-to-deceleration ratio (panel B) across opponent-quality strata, defined as quartiles of the opponent's end-of-season league position. Boxes show the median and interquartile range, whiskers extend to 1.5 times the interquartile range, and diamonds denote group means. Brackets indicate Holm-adjusted pairwise contrasts from the crossed random-effects model: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Fixed-effect tests from the crossed random-effects model.

Outcome	Factor	Wald χ^2	df	p	ΔR^2 marginal	Conclusion
HIM	Match result	1.21	2	0.546	0.0005	Not associated
	Match venue	0.21	1	0.649	0.0001	Not associated
	Opponent quality	19.09	3	<0.001	0.0258	Associated
AD ratio	Match result	2.13	2	0.345	0.0030	Not associated
	Match venue	0.06	1	0.811	<0.0001	Not associated
	Opponent quality	12.23	3	0.007	0.0173	Associated

Note: Each factor is adjusted for the remaining two. ΔR^2 marginal is the reduction in marginal R-squared when the factor is removed.

Estimated marginal means

Estimated marginal means, together with the raw group means for comparison, are presented in Table 5; the opponent-quality estimates are displayed in Figure 4. Point estimates from the two approaches differed little, as expected in a near-balanced design, but the model-based standard errors are appreciably larger because they incorporate match-level and team-level clustering. Estimated marginal HIM was near-identical across result categories (2.742 to

2.779 $\text{m} \cdot \text{min}^{-1}$) and across venues (2.758 versus 2.768 $\text{m} \cdot \text{min}^{-1}$), separations smaller than one twentieth of a standard deviation. Across opponent-quality strata, estimated marginal HIM ranged from 2.641 $\text{m} \cdot \text{min}^{-1}$ against third-quartile opponents to 2.872 $\text{m} \cdot \text{min}^{-1}$ against second-quartile opponents. The pattern was non-monotonic: estimates were elevated against opponents from the top two quartiles, lowest against third-quartile opponents, and slightly higher again against bottom-quartile opponents.

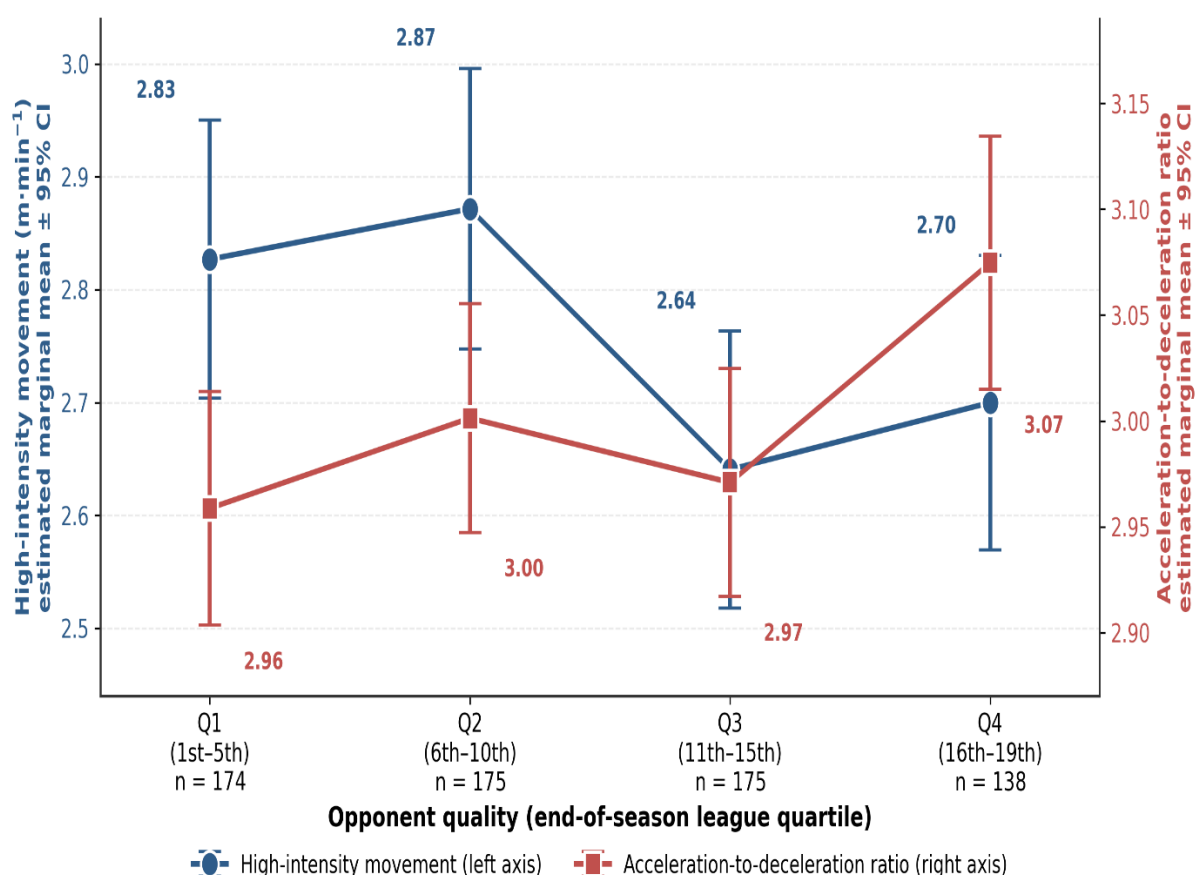


Figure 4. Estimated marginal means with 95% confidence intervals for high-intensity movement (left axis) and the acceleration-to-deceleration ratio (right axis) across opponent-quality strata. *Estimates are adjusted for match result and match venue and derive from the crossed random-effects model, so the intervals account for match-level and team-level clustering and are wider than intervals computed from raw group means.*

The AD ratio followed a different contextual pattern, with the highest estimate against bottom-quartile opponents (3.075) and the lowest against top-quartile opponents (2.959). Inspection of the component variables indicates that this shift arose principally from the deceleration term, which was highest against first- and second-quartile opponents (0.714 and 0.722 $\text{m} \cdot \text{min}^{-1}$) and lowest against fourth-quartile opponents (0.657 $\text{m} \cdot \text{min}^{-1}$).

Table 5. Estimated marginal means and raw group means by contextual factor.

Outcome	Factor	Level	n	Raw mean (SD)	EMM	SE	95% CI
HIM	Match result	Win	253	2.742 (0.572)	2.742	0.056	2.632–2.852
		Draw	156	2.786 (0.693)	2.779	0.073	2.635–2.923
		Loss	253	2.771 (0.579)	2.774	0.056	2.664–2.885
	Match venue	Home	331	2.765 (0.609)	2.768	0.053	2.664–2.872
		Away	331	2.763 (0.601)	2.758	0.053	2.654–2.862
	Opponent quality	Q1	174	2.831 (0.568)	2.827	0.063	2.704–2.950
		Q2	175	2.894 (0.678)	2.872	0.063	2.747–2.996
		Q3	175	2.634 (0.573)	2.641	0.063	2.518–2.763
		Q4	138	2.677 (0.547)	2.700	0.067	2.570–2.830
	AD ratio	Match result	Win	253	2.990 (0.303)	2.984	0.025
Draw			156	2.980 (0.342)	2.981	0.030	2.922–3.040
Loss			253	3.015 (0.300)	3.021	0.025	2.972–3.070
Match venue		Home	331	2.991 (0.313)	2.995	0.022	2.951–3.038
		Away	331	3.004 (0.310)	3.000	0.022	2.956–3.044
Opponent quality		Q1	174	2.965 (0.301)	2.959	0.028	2.903–3.014
		Q2	175	3.002 (0.306)	3.001	0.028	2.947–3.055
		Q3	175	2.969 (0.298)	2.971	0.028	2.917–3.025
		Q4	138	3.068 (0.339)	3.075	0.031	3.015–3.134

Note: EMM, estimated marginal mean from the crossed random-effects model, adjusted for the other two factors. Q1–Q4 denote quartiles of opponent final league position; the fourth quartile contains four clubs because the league comprised 19 teams.

Pairwise contrasts

Holm-adjusted contrasts across opponent-quality strata are presented in Table 6. For HIM, three of six comparisons reached significance: second versus third quartile (difference $0.231 \text{ m} \cdot \text{min}^{-1}$, $p = 0.001$, $d = 0.42$), first versus third quartile ($0.186 \text{ m} \cdot \text{min}^{-1}$, $p = 0.007$, $d = 0.35$) and second versus fourth quartile ($0.172 \text{ m} \cdot \text{min}^{-1}$, $p = 0.029$, $d = 0.35$). Neither the comparison between the two upper quartiles nor that between the two lower quartiles approached significance, consistent with a contrast between stronger and weaker opposition rather than a graded relationship with league position.

For the AD ratio, two comparisons reached significance, both involving bottom-quartile opponents: first versus fourth quartile (difference -0.116 , $p = 0.009$, $d = 0.32$) and third versus fourth quartile (-0.104 , $p = 0.014$, $d = 0.31$). The locus of this effect therefore lies specifically in matches against the weakest opposition.

Table 6. Holm-adjusted pairwise contrasts across opponent-quality strata.

Outcome	Contrast	Difference	SE	95% CI	p (Holm)	Cohen's d
HIM	Q1 vs Q2	-0.045	0.059	-0.161 to 0.072	0.665	0.10
	Q1 vs Q3	0.186	0.058	0.073 to 0.300	0.007	0.35
	Q1 vs Q4	0.127	0.063	0.004 to 0.250	0.128	0.28
	Q2 vs Q3	0.231	0.060	0.114 to 0.348	0.001	0.42
	Q2 vs Q4	0.172	0.064	0.046 to 0.297	0.029	0.35
	Q3 vs Q4	-0.059	0.061	-0.179 to 0.061	0.665	0.08
AD ratio	Q1 vs Q2	-0.043	0.033	-0.108 to 0.022	0.597	0.12
	Q1 vs Q3	-0.012	0.033	-0.077 to 0.053	0.712	0.02
	Q1 vs Q4	-0.116	0.036	-0.187 to -0.045	0.009	0.32
	Q2 vs Q3	0.030	0.033	-0.033 to 0.094	0.700	0.11
	Q2 vs Q4	-0.073	0.035	-0.142 to -0.005	0.145	0.21
	Q3 vs Q4	-0.104	0.035	-0.172 to -0.036	0.014	0.31

Note: Contrasts are estimated from the crossed random-effects model, with the second-named stratum subtracted from the first. Cohen's d is computed from the raw group data and reported as an absolute value. Significant contrasts are shown in bold.

Equivalence and sensitivity

Because a non-significant test does not by itself establish the absence of an effect, the constituent contrasts of the two unassociated factors were submitted to equivalence testing (Table 7). Three of eight contrasts were statistically equivalent at a smallest effect size of interest of 0.2 SD: the venue contrast for HIM ($p = 0.006$), the venue contrast for the AD ratio ($p = 0.022$) and the win-loss contrast for HIM ($p = 0.037$). The remaining five contrasts, all involving draws or the AD ratio result factor, were inconclusive: their confidence intervals did not exclude effects as large as the equivalence bound, and they should therefore be interpreted as an absence of evidence rather than as evidence of absence. The sensitivity analysis indicated that the design could detect effects corresponding to a partial eta-squared of approximately 0.012 to 0.016 with 80% power, so the observed null effects lie below that detectable range.

Table 7. Equivalence tests for the unassociated factors, and sensitivity power.

Outcome	Contrast	SESOI	Difference	90% CI	TOST p	Verdict
HIM	Win vs loss	0.121	-0.029	-0.113 to 0.055	0.037	Equivalent
	Win vs draw	0.121	-0.043	-0.153 to 0.066	0.121	Inconclusive
	Draw vs loss	0.121	0.014	-0.095 to 0.124	0.055	Inconclusive
	Home vs away	0.121	0.002	-0.076 to 0.079	0.006	Equivalent
AD ratio	Win vs loss	0.062	-0.025	-0.069 to 0.019	0.082	Inconclusive
	Win vs draw	0.062	0.010	-0.045 to 0.065	0.059	Inconclusive
	Draw vs loss	0.062	-0.035	-0.090 to 0.020	0.205	Inconclusive
	Home vs away	0.062	-0.013	-0.053 to 0.027	0.022	Equivalent

Note: SESOI, smallest effect size of interest, set at 0.2 standard deviations. A contrast is declared equivalent when its 90% confidence interval falls entirely within $\pm$ SESOI. Sensitivity power analysis ($\alpha = 0.05$, power = 0.80, $n = 662$): minimum detectable effects corresponded to partial eta-squared of 0.014 for match result, 0.012 for match venue and 0.016 for opponent quality.

Robustness

All three robustness analyses reproduced the primary conclusions (**Table 8**). Under ordinary least squares with cluster-robust standard errors at match level, opponent quality remained associated with HIM ($p < 0.001$) and the AD ratio ($p = 0.010$), while result and venue remained unassociated. Log transformation of HIM reduced residual skewness from 0.83 to 0.24 and left the opponent effect essentially unchanged ($p < 0.001$). Re-deriving the dataset with an 80-minute inclusion threshold preserved the opponent effect for both outcomes ($p = 0.002$ and $p = 0.017$). The violation of variance homogeneity for HIM therefore did not materially influence any inference.

Table 8. Robustness analyses.

Outcome	Analysis	p (result)	p (venue)	p (opponent)
HIM	Primary crossed random-effects model	0.546	0.649	<0.001
	Cluster-robust OLS (match clusters)	0.826	0.942	<0.001
	Natural log transformation	0.501	0.691	<0.001
	80-minute inclusion threshold	0.939	0.440	0.002
AD ratio	Primary crossed random-effects model	0.345	0.811	0.007
	Cluster-robust OLS (match clusters)	0.176	0.908	0.010
	80-minute inclusion threshold	0.201	0.889	0.017

DISCUSSION and CONCLUSION

This study asked where the variance in team-level high-intensity change-of-speed load resides, and whether that load responds to match context. Across a complete season of the Turkish Super League, two-thirds of the variance in high-intensity movement was attributable to the individual match rather than to either competing team. Within that structure, neither the result of the match nor the venue at which it was played was associated with the magnitude or the accelerative-decelerative balance of the load, whereas opponent quality was associated with both, with effects that were statistically reliable, robust to alternative specifications, and small in magnitude.

High-intensity load as a property of the contest

The dominance of match-level variance is the most consequential finding and, to our knowledge, has not previously been quantified for acceleration and deceleration metrics in football. Two opposing teams share a pitch, a referee, a tempo and a tactical exchange, and their high-intensity change-of-speed loads rose and fell together to a striking degree: knowing which match an observation came from accounted for 66.3% of the variance in high-intensity movement, whereas knowing which club produced it accounted for 10.1%. The natural

interpretation is that transition-dense, end-to-end contests impose elevated braking and re-acceleration demands on both teams simultaneously, while controlled, low-tempo contests suppress them for both. This is coherent with the documented magnitude of match-to-match variability in high-intensity activity within a single team (Carling et al., 2016) and with the argument that physical metrics reported without tactical context are poorly interpretable (Bradley & Ade, 2018).

This interpretation requires one important qualification. The match random effect absorbs everything shared by the two teams in a fixture - not only the tempo and tactical exchange of the contest, but also any factor fixed to the venue at which it was played, including the geometry and calibration of that stadium's camera installation. Because the derived acceleration and deceleration metrics carry appreciable measurement error and the specific system has not been independently validated (see Methods), the 66.3% match-level share is best read as an upper bound on the contribution of genuine match dynamics rather than a pure estimate of it. To bound this threat we partitioned the match-level variance by home stadium (Results): the predominant within-stadium component (71.4%), reflecting variation among matches recorded by the same fixed installation and therefore free of venue-fixed processing, indicates that the match-level clustering reflects real match-to-match variation in the demands of the contest rather than an artefact of where it was measured, while the non-trivial between-stadium component is acknowledged as a residual source of uncertainty.

Two further qualifications are important. First, the finding does not show that clubs have no physical identity; it shows that, within a single season and for these particular metrics, club identity accounted for approximately one-tenth of the variance while the contest accounted for two-thirds. Second, the AD ratio behaved quite differently, with only 13.8% of variance at match level and 82.0% residual. The balance between accelerating and braking therefore appears far more idiosyncratic than the total magnitude of change-of-speed load and is correspondingly harder to predict from either the identity of the teams or the character of the fixture. Reporting a magnitude term and a balance term separately made this divergence visible; it would have been concealed by analysing acceleration and deceleration as two collinear outcomes.

There is also a design consequence worth stating. All three contextual factors vary within match: venue always, and opponent quality and match result in approximately four-fifths and three-quarters of matches respectively. The contextual estimates are therefore identified from within-match contrasts, which controls implicitly for the shared conditions of the fixture.

Substantial match-level clustering does not undermine these estimates; it makes them cleaner, and it explains why cluster-robust standard errors changed the inferences so little.

Opponent quality and the magnitude of high-intensity load

The association between opponent quality and high-intensity movement aligns with the most consistent strand of the situational-variable literature. Serie A teams of lower standing covered greater total distance but less high-intensity distance with the ball than stronger teams (Rampinini et al., 2009); opponent ranking modulated running output across five seasons of English professional football (Morgans et al., 2025); and in the Turkish first division opponent quality affected medium- and high-intensity running with standardised differences of 0.21 to 0.31 (Plakias & Michailidis, 2024). The magnitude we observed is closely comparable, with the largest pairwise contrast yielding $d = 0.42$. These findings extend an established speed-zone result into the acceleration and deceleration domain, in a league for which such data had not previously been reported.

The pattern across strata was not a simple gradient. High-intensity movement was elevated against opponents from the upper two quartiles, lowest against third-quartile opponents, and marginally higher again against the bottom quartile. The significant pairwise contrasts, however, were confined to comparisons with third-quartile opponents (Q1 versus Q3 and Q2 versus Q3) and to the Q2 versus Q4 contrast, whereas neither the two upper strata nor the two lower strata differed from each other, and the Q1 versus Q4 contrast did not reach significance (Table 6). This pattern is therefore more consistent with a threshold-like contrast between stronger and weaker opposition than with a dose-response relationship to league position. A plausible reading is that fixtures against upper-half opponents are more contested in transition, generating frequent bidirectional changes of speed, whereas fixtures against lower-half opponents permit greater control of tempo. The slight elevation against bottom-quartile opponents is consistent with a different mechanism, namely sustained attacking initiative, and this reading is supported by the divergent behaviour of the AD ratio. These interpretations remain inferential, because no possession, pressing or formation covariates were available; work in the same league has shown that high-pressing behaviour exerts effects on running output of comparable magnitude to opponent quality (Plakias & Michailidis, 2024), so such variables plausibly mediate part of what is attributed here to opposition standard.

The acceleration-to-deceleration balance

The AD ratio effect was localised to matches against bottom-quartile opponents, where the profile became relatively more acceleration-oriented, and inspection of the components shows that this was driven principally by reduced deceleration distance rather than by increased acceleration distance. Against the weakest opposition, teams appear to accumulate proportionally less high-intensity braking, consistent with fewer defensive recovery and pressing-recovery actions when the opponent poses a lesser attacking threat. Matches against top-quartile opponents produced the most deceleration-weighted profile, in keeping with a greater defensive and transitional braking burden.

One feature of the ratio requires careful interpretation. Its mean of approximately 3.0 indicates that high-intensity acceleration distance exceeded high-intensity deceleration distance roughly threefold, which may appear to contradict the meta-analytic finding that football exhibits more high-intensity decelerations than accelerations (Harper et al., 2019). The two observations are compatible because they are expressed in different units. That meta-analysis quantified effort counts, whereas the present ratio is based on distance. For a given intensity threshold, braking is completed over a shorter displacement than acceleration, so a sport can simultaneously record more deceleration efforts and less deceleration distance. The informative signal in the AD ratio is accordingly not its absolute level, which is a property of the metric, but its variation across contexts. This variation should nonetheless be interpreted with restraint. Contextual factors accounted for only 1.7% of the variance in the AD ratio ($\Delta R^2_{\text{marginal}}$), and 82% of its variance was residual, so the ratio is best treated here as a descriptive, hypothesis-generating outcome rather than one supporting firm mechanistic conclusions. Within those limits, the effect was not an artefact of the season's single incomplete club: excluding the mid-season withdrawing side (the only bottom-quartile club without a complete fixture record) as an opponent left the localisation to bottom-quartile opponents essentially unchanged (first-versus-fourth-quartile difference -0.116 with and without it, and the opponent-quality omnibus significant in both, $p = 0.006$ and $p = 0.015$). Consistent with this modest and more venue-linked signal, the between-stadium partition of the AD ratio's already small match-level variance (Results) was proportionally larger than for high-intensity movement.

Interpreting the absence of result and venue effects

The absence of a detectable match-result effect is consistent with the Bundesliga finding that running performance was insufficient to determine victory (Hoppe et al., 2015), with the Turkish first-division analysis reporting that running performance was not a strong determinant

of winning (Plakias et al., 2025), and with the broader conclusion that the running–success relationship is weak and context-dependent (Andrzejewski et al., 2022). It stands in contrast to reports associating sprinting with outcome (Andrzejewski et al., 2018) and, most directly, to the finding that an English club recorded its highest acceleration and deceleration frequencies in matches it won (Rhodes et al., 2021). Several design differences plausibly account for the divergence: that study examined a single club, in which a stable tactical approach can allow outcome-linked patterns to emerge, whereas the present analysis pooled 19 clubs; it analysed effort counts rather than distance normalised to playing time, and per-minute normalisation removes the volume component through which a team chasing a deficit accumulates more actions; and the direction of any such association is ambiguous, since score-line state is known to alter team behaviour during the match (Lago et al., 2010).

Equivalence testing allows these null findings to be stated with more precision than significance testing alone permits. The venue contrasts for both outcomes, and the win–loss contrast for high-intensity movement, were statistically equivalent at a bound of 0.2 SD: for these comparisons the data support the conclusion that any true difference is smaller than a small effect. The remaining contrasts, principally those involving draws, were inconclusive; the data neither demonstrate an effect nor exclude one of practically relevant size, and they should not be read as evidence of absence. This distinction matters because the venue result in particular runs counter to a well-established competitive phenomenon: home advantage is firmly documented in points and scoring terms (Pollard & Gomez, 2014), and a single-club study in this same league reported venue-related differences in high-speed running by position (Coskun & Torun, 2025). Our results suggest that whatever produces home advantage in this competition is not expressed through the magnitude or balance of team-level change-of-speed load, at least not at a scale exceeding a small effect.

Practical applications

Because acceleration-based variables are the external-load metrics practitioners prioritise (Akenhead & Nassis, 2016), the question of what moves them has operational relevance. Among the contextual factors examined, the answer is the opponent, and two implications follow. First, of the three contextual factors examined, only the standard of the forthcoming opposition was associated with change-of-speed load, whereas the outcome of the previous fixture and whether the team was travelling were not. Any anticipatory planning might therefore be oriented to opponent standard rather than to the previous result or the venue, provided such anticipation is treated with appropriate caution given the small size of the association and the

observational design. Relative to third-quartile opponents, high-intensity movement was greater against first- and second-quartile opponents, and it was also greater against second-quartile than against fourth-quartile opponents; these were the only pairwise contrasts to reach significance (Table 6). In parallel, the acceleration-to-deceleration profile became relatively more acceleration-oriented against fourth-quartile opponents, indicating a lower share of high-intensity braking against the weakest opposition (Table 6). Because eccentric braking carries a distinctive neuromuscular and tissue cost (Harper et al., 2022), the scheduling of braking-intensive work within the microcycle and the recovery afforded after the more demanding fixtures may be adjusted accordingly, in keeping with the small magnitude of the differences observed.

Second, these adjustments should be proportionate. The largest between-stratum difference in high-intensity movement was $0.231 \text{ m} \cdot \text{min}^{-1}$, corresponding over a full match to roughly 22 metres of additional high-intensity change-of-speed distance per player. This is a meaningful signal in aggregate and across a congested calendar, but it does not warrant restructuring a training week. The variance decomposition tempers expectations further: since the contest accounts for two-thirds of the variance and the contextual factors for under 3% of it, the load a team will actually incur in a given fixture remains substantially unpredictable in advance. Opponent standard shifts the expected value; it does not determine the outcome.

Strengths and limitations

The principal strengths of this study are the near-completeness of its coverage and its analytical transparency. Rather than drawing a probability sample of matches or clubs, it analyses a near-complete season census of an entire first division, covering 331 of 342 scheduled fixtures (96.8%). The design therefore minimises, rather than eliminates, competition-level sampling and coverage error: because no probability sampling was performed, the classical error of sampling from a finite population does not arise, while the small residual uncertainty introduced by the 11 absent fixtures is mitigated by their diffuse, study-factor-independent pattern of loss (see Methods). Consistent with the model-based inferential framing adopted here, process-level uncertainty is retained by design and is quantified through the reported confidence intervals and equivalence bounds. The clustering structure was examined rather than assumed, and the variance components were verified across five optimisation algorithms after one algorithm was found to return a boundary solution while reporting convergence. Null findings were evaluated by equivalence testing rather than asserted

from non-significance. Reporting a magnitude and a balance metric, rather than two collinear raw variables, allowed two distinct contextual patterns to be identified.

Several limitations qualify the findings. The study covers one season of one league, so generalisation is unwarranted until replicated. No peer-reviewed validation of the specific tracking system has been published; although validation of technologically equivalent multi-camera systems supports the measurement of total accelerations and decelerations, agreement is weaker at higher intensity thresholds and error for acceleration exceeds that for distance (Linke et al., 2020; Gonzalez-Rodenas et al., 2025), which is likely to attenuate rather than manufacture contextual effects. A stadium-augmented decomposition indicated that the match-level variance was predominantly within-stadium and therefore not attributable to venue-fixed processing; however, the between-stadium component cannot be fully separated into measurement and genuine venue effects, and the within-stadium component may still contain match-day factors such as weather or operator differences, so the exact partition of the match-level variance between contest dynamics and measurement should be regarded as bounded rather than fully resolved. Absolute rather than individualised thresholds were applied, so a given value represents a different relative intensity for players of differing capacity (Gualtieri et al., 2023). Opponent quality was indexed by end-of-season position, which is stable and objective but retrospective. Because a club's final position is itself shaped in part by the fixtures analysed here, this indexing carries a mild circularity. Its practical impact is minimal, however: any focal team contributes only two of an opponent's thirty-six results, league position reflects match outcomes rather than physical output, and the coarse quartile classification is insensitive to the small shifts in points that those two fixtures could produce. Aggregation to the team mean removes within-squad dispersion, so positional and individual differences, which are substantial in football (Paul et al., 2015), are invisible here. No possession, pressing, formation or fixture-congestion covariates were available, and evidence from the same league indicates that at least the first two influence running output materially (Plakias & Michailidis, 2024). The 60-minute threshold excludes substitutes. Because each team value is a mean over the outfield players meeting this threshold, differential substitution across contexts could in principle render the included subset context-dependent. The number of eligible players per team-match was, however, essentially invariant to opponent quality (means of 9.5 across all four quartiles; Kruskal–Wallis $p = 0.94$), indicating that the opponent-quality effects do not arise from a shift in the composition of the players contributing to each mean. Minor differences were present by venue (9.6 home versus 9.4 away) and by result (9.6 after wins versus 9.3 after losses, consistent

with earlier substitution when trailing); both were small in magnitude (no more than 0.34 of approximately 9.5 players) but are acknowledged as a potential source of mild selection in the venue and result contrasts specifically. Finally, the design is observational and cross-sectional: the relationship between physical output and match events is bidirectional (Lago, 2009), and the associations reported here describe patterns rather than mechanisms.

Future directions

Four extensions follow directly. Replication across multiple seasons would establish whether the dominance of match-level variance is a stable structural feature or an artefact of a single competitive year, and whether the modest team-level component grows when squads are observed over longer horizons. Incorporating possession, pressing intensity and formation as covariates would determine how much of the match-level variance is tactical in origin and how much of the opponent effect is mediated by tactical behaviour rather than opposition standard per se. Decomposing the analysis by playing position would recover the within-squad variance that team-level aggregation discards and identify which roles absorb the additional braking load imposed by strong opposition. Finally, because deceleration is the mechanically costly component, linking match-level braking load to prospective injury surveillance would test whether the contextual pattern described here has consequences for player availability.

Conclusions

In a near-complete season census of the Turkish Super League, high-intensity change-of-speed load at team level was primarily a property of the individual contest: two-thirds of the variance in high-intensity movement was attributable to the match and one-tenth to the team. Within that structure, neither match result nor match venue was associated with the magnitude or the accelerative-decelerative balance of the load, and equivalence testing bounded the venue effect and the win–loss contrast below a small effect. Opponent quality was associated with both outcomes: high-intensity movement was greater against first- and second-quartile opponents than against third-quartile opponents, and greater against second- than against fourth-quartile opponents, while the profile became relatively more acceleration-oriented against the weakest opposition through reduced high-intensity braking. These contextual differences were small in magnitude. Load planning may reasonably be informed by the standard of the forthcoming opponent, but the small magnitude of these effects and the dominance of match-level variance argue against treating team physical profiles as stable and predictable club characteristics.

REFERENCES

- Akenhead, R., & Nassis, G. P. (2016). Training load and player monitoring in high-level football: Current practice and perceptions. *International Journal of Sports Physiology and Performance*, 11(5), 587–593. <https://doi.org/10.1123/ijsp.2015-0331>
- Andrzejewski, M., Chmura, P., Konefał, M., Kowalczyk, E., & Chmura, J. (2018). Match outcome and sprinting activities in match play by elite German soccer players. *The Journal of Sports Medicine and Physical Fitness*, 58(6), 785–792. <https://doi.org/10.23736/S0022-4707.17.07352-2>
- Andrzejewski, M., Oliva-Lozano, J. M., Chmura, P., Chmura, J., Czarniecki, S., Kowalczyk, E., Rokita, A., Muyor, J. M., & Konefał, M. (2022). Analysis of team success based on match technical and running performance in a professional soccer league. *BMC Sports Science, Medicine and Rehabilitation*, 14(1), Article 82. <https://doi.org/10.1186/s13102-022-00473-7>
- Bradley, P. S., & Ade, J. D. (2018). Are current physical match performance metrics in elite soccer fit for purpose or is the adoption of an integrated approach needed? *International Journal of Sports Physiology and Performance*, 13(5), 656–664. <https://doi.org/10.1123/ijsp.2017-0433>
- Carling, C., Bradley, P., McCall, A., & Dupont, G. (2016). Match-to-match variability in high-speed running activity in a professional soccer team. *Journal of Sports Sciences*, 34(24), 2215–2223. <https://doi.org/10.1080/02640414.2016.1176228>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Coskun, B., & Torun, M. C. (2025). Evaluation of the differences between home and away matches depending on GPS data from a senior professional football team in the Turkish Super League. *Applied Sciences*, 15(20), Article 11275. <https://doi.org/10.3390/app152011275>
- Felipe, J. L., Garcia-Unanue, J., Viejo-Romero, D., Navandar, A., & Sánchez-Sánchez, J. (2019). Validation of a video-based performance analysis system (Mediacoach) to analyze the physical demands during matches in LaLiga. *Sensors*, 19(19), Article 4113. <https://doi.org/10.3390/s19194113>

- González-Rodenas, J., Nevado, F., López-Del Campo, R., Soler-Aguinaga, A., Agulló, F., Moreno-Pérez, V., & Del Coso, J. (2025). Validity of coupling TRACAB's Gen5 and Mediacoach systems to calculate accelerations and decelerations in professional football. *Sensors*, 25(6), Article 1804. <https://doi.org/10.3390/s25061804>
- Gualtieri, A., Rampinini, E., Dello Iacono, A., & Beato, M. (2023). High-speed running and sprinting in professional adult soccer: Current thresholds definition, match demands and training strategies. A systematic review. *Frontiers in Sports and Active Living*, 5, Article 1116293. <https://doi.org/10.3389/fspor.2023.1116293>
- Harper, D. J., Carling, C., & Kiely, J. (2019). High-intensity acceleration and deceleration demands in elite team sports competitive match play: A systematic review and meta-analysis of observational studies. *Sports Medicine*, 49(12), 1923–1947. <https://doi.org/10.1007/s40279-019-01170-1>
- Harper, D. J., McBurnie, A. J., Dos'Santos, T., Eriksrud, O., Evans, M., Cohen, D. D., Rhodes, D., Carling, C., & Kiely, J. (2022). Biomechanical and neuromuscular performance requirements of horizontal deceleration: A review with implications for random intermittent multi-directional sports. *Sports Medicine*, 52(10), 2321–2354. <https://doi.org/10.1007/s40279-022-01693-0>
- Hoppe, M. W., Slomka, M., Baumgart, C., Weber, H., & Freiwald, J. (2015). Match running performance and success across a season in German Bundesliga soccer teams. *International Journal of Sports Medicine*, 36(7), 563–566. <https://doi.org/10.1055/s-0034-1398578>
- Ju, W., Hawkins, R., Doran, D., Gómez-Díaz, A., Martín-García, A., Evans, M., Laws, A., & Bradley, P. S. (2023). Tier-specific contextualised high-intensity running profiles in the English Premier League: More on-ball movement at the top. *Biology of Sport*, 40(2), 561–573. <https://doi.org/10.5114/biol sport.2023.118020>
- Lago, C. (2009). The influence of match location, quality of opposition, and match status on possession strategies in professional association football. *Journal of Sports Sciences*, 27(13), 1463–1469. <https://doi.org/10.1080/02640410903131681>
- Lago, C., Casais, L., Domínguez, E., & Sampaio, J. (2010). The effects of situational variables on distance covered at various speeds in elite soccer. *European Journal of Sport Science*, 10(2), 103–109. <https://doi.org/10.1080/17461390903273994>

- Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, 4, Article 863. <https://doi.org/10.3389/fpsyg.2013.00863>
- Linke, D., Link, D., & Lames, M. (2018). Validation of electronic performance and tracking systems EPTS under field conditions. *PLOS ONE*, 13(7), Article e0199519. <https://doi.org/10.1371/journal.pone.0199519>
- Linke, D., Link, D., & Lames, M. (2020). Football-specific validity of TRACAB's optical video tracking systems. *PLOS ONE*, 15(3), Article e0230179. <https://doi.org/10.1371/journal.pone.0230179>
- Morgans, R., Di Michele, R., Ceylan, I. H., Ryan, B., Haslam, C., King, M., Zmijewski, P., & Oliveira, R. (2025). Physical match performance of elite soccer players from the English Championship League and the English Premier League: The effects of opponent ranking and positional differences. *Biology of Sport*, 42(1), 29–38. <https://doi.org/10.5114/biolsport.2025.139079>
- Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R^2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, 4(2), 133–142. <https://doi.org/10.1111/j.2041-210x.2012.00261.x>
- Paul, D. J., Bradley, P. S., & Nassis, G. P. (2015). Factors affecting match running performance of elite soccer players: Shedding some light on the complexity. *International Journal of Sports Physiology and Performance*, 10(4), 516–519. <https://doi.org/10.1123/IJSP.2015-0029>
- Plakias, S., & Michailidis, Y. (2024). Factors affecting the running performance of soccer teams in the Turkish Super League. *Sports*, 12(7), Article 196. <https://doi.org/10.3390/sports12070196>
- Plakias, S., Tasoulis, S., Kyranoudis, A. E., Kokkotis, C., & Moustakidis, S. (2025). The limited impact of running performance on football success in the Turkish Super League. *Applied Sciences*, 15(2), Article 637. <https://doi.org/10.3390/app15020637>
- Pollard, R., & Gómez, M. A. (2014). Comparison of home advantage in men's and women's football leagues in Europe. *European Journal of Sport Science*, 14(sup1), S77–S83. <https://doi.org/10.1080/17461391.2011.651490>

- Rampinini, E., Impellizzeri, F. M., Castagna, C., Coutts, A. J., & Wisløff, U. (2009). Technical performance during soccer matches of the Italian Serie A league: Effect of fatigue and competitive level. *Journal of Science and Medicine in Sport*, 12(1), 227–233. <https://doi.org/10.1016/j.jsams.2007.10.002>
- Rhodes, D., Valassakis, S., Bortnik, L., Eaves, R., Harper, D., & Alexander, J. (2021). The effect of high-intensity accelerations and decelerations on match outcome of an elite English League Two football team. *International Journal of Environmental Research and Public Health*, 18(18), Article 9913. <https://doi.org/10.3390/ijerph18189913>
- Silva, H., Nakamura, F. Y., Beato, M., & Marcelino, R. (2022). Acceleration and deceleration demands during training sessions in football: A systematic review. *Science and Medicine in Football*. Advance online publication. <https://doi.org/10.1080/24733938.2022.2090600>
- Trewin, J., Meylan, C., Varley, M. C., & Cronin, J. (2017). The influence of situational and environmental factors on match-running in soccer: A systematic review. *Science and Medicine in Football*, 1(2), 183–194. <https://doi.org/10.1080/24733938.2017.1329589>
- von Elm, E., Altman, D. G., Egger, M., Pocock, S. J., Gøtzsche, P. C., & Vandenbroucke, J. P. (2007). The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: Guidelines for reporting observational studies. *The Lancet*, 370(9596), 1453–1457. [https://doi.org/10.1016/S0140-6736\(07\)61602-X](https://doi.org/10.1016/S0140-6736(07)61602-X)