Quantifying the Impact of Fatigue on Player Performance in Soccer

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Fatigue is a critical yet complex factor affecting player performance in professional soccer. Traditional methods of fatigue assessment often rely on invasive biomarkers or subjective measures, which limit their scalability across an entire season. In this study, we propose a data-driven framework that leverages event-level soccer data to quantify fatigue and assess its impact on individual player performance. Using detailed match data from the 2019–20 La Liga season, we construct fatigue indicators such as days since last match, total games played, and event intensity, and examine their relationships with key performance metrics — pass accuracy, duel win rate, and shot success rate.

We evaluate multiple modeling approaches including linear regression, random forest, ARIMAX, and LSTM neural networks to predict performance under varying fatigue conditions. Our findings reveal that while historical performance is the strongest predictor of match outcomes, fatigue-related features — particularly match intensity — add measurable explanatory power. Clustering analysis further identifies distinct fatigue-resilience profiles among players. This study demonstrates the feasibility of using non-invasive, tracking-derived indicators to model fatigue, offering valuable insights for match planning, squad rotation, and player management in elite soccer contexts.

I. Introduction

Fatigue is an inevitable consequence of high-performance sports and plays a pivotal role in shaping athletic outcomes. In professional soccer, where athletes are subjected to congested match schedules, intense physical demands, and minimal recovery periods, understanding how fatigue impacts player performance is essential for optimizing player management and maximizing competitive success. Yet, despite its importance, quantifying fatigue in a reliable and scalable manner remains a persistent challenge.

Traditional approaches to fatigue measurement rely heavily on physiological biomarkers (e.g., lactate levels, heart rate variability), subjective self-reports, or simplistic workload metrics like minutes played. While useful, these methods are either invasive, infrequent, or insufficiently granular to capture the dynamic nature of fatigue over a full competitive season. With the rise of event-based and tracking data in soccer analytics, there is now an opportunity to derive non-invasive, data-driven fatigue proxies that reflect players' workload, match intensity, and recovery intervals.

This study aims to bridge the gap between theory and application by developing a comprehensive framework to model the relationship between fatigue and player performance using event-level data from the 2019–20 La Liga season. We construct fatigue indicators such as *days since last match*, *total games played*, and *total events*, and examine their effect on three key performance metrics: *pass accuracy*, *duel win rate*, and *shot success rate*.

To capture the multifaceted relationship between fatigue and performance, we apply a diverse set of statistical and machine learning techniques — including linear regression with engineered features, unsupervised clustering for fatigue profiling, and time-series models (ARIMAX and LSTM) for longitudinal forecasting. By integrating multiple perspectives, we provide both predictive insights and practical implications for workload management in elite soccer.

Our research contributes to the growing field of sports analytics by demonstrating that fatigue can be effectively modeled using non-invasive metrics derived from widely available data, and that doing so can improve both performance prediction and player health management throughout a demanding season.

II. Literature Review

Fatigue is a well-documented factor affecting player performance in soccer, but its quantification has traditionally relied on invasive biomarkers, subjective player surveys, or simple workload metrics like minutes played. However, with the increasing availability of tracking data, there is an opportunity to measure fatigue more accurately and non-invasively. This literature review explores previous research on fatigue in soccer, methodologies for assessing its impact on performance, and potential approaches using tracking data for non-invasive fatigue estimation.

A. Fatigue and Performance in Soccer

Previous studies have examined how fatigue affects physical and technical performance in soccer. Research by Mohr et al. [1] found that players cover significantly less distance and engage in fewer high-intensity sprints in the latter stages of matches, suggesting a measurable impact of fatigue. Similarly, Carling et al. [2] identified a decline in passing accuracy and defensive actions late in games, further supporting the hypothesis that fatigue affects both physical and cognitive performance.

While many studies rely on biomarker analysis (e.g., blood lactate levels, heart rate variability) to assess fatigue [3], these methods are impractical for continuous monitoring across an entire season. Tracking data provides a more scalable and non-invasive alternative, allowing researchers to analyze movement patterns and infer fatigue-related declines in performance.

B. Tracking Data as a Fatigue Estimation Tool

Recent advances in soccer analytics have leveraged tracking data to analyze player movements, workload, and recovery. Link and Hoernig [4] demonstrated that tracking data can effectively measure player workload by quantifying accelerations, decelerations, and changes in direction, which are key indicators of physical fatigue. Additionally, Torres et al. [5] used tracking data to assess tactical behaviors and found that players with high fatigue levels exhibit reduced defensive positioning accuracy and slower reaction times to opposition movements.

By aggregating tracking data on a bi-weekly basis, as suggested in previous research, we can create a longitudinal dataset to track fatigue trends throughout a season. This allows for the identification of fatigue patterns at both individual and team levels, informing coaching decisions on player rotations and recovery strategies.

C. Modeling Approaches

To analyze the relationship between fatigue and performance, various modeling techniques can be employed:

1. Machine Learning Approaches

Long Short-Term Memory (LSTM) models have been widely used in time-series forecasting and may be suitable for modeling fatigue trends based on historical tracking data [6]. LSTMs can capture sequential dependencies, making them useful for predicting fatigue levels based on prior workload and recovery periods.

2. Time Series Analysis

Autoregressive Integrated Moving Average (ARIMA) models and their multivariate extensions have been used in sports analytics to model player performance trends [7]. By incorporating external covariates such as match congestion and training intensity, ARIMA models can provide insights into how fatigue accumulates over time.

3. Hierarchical and Mixed Effects Models

Fatigue likely affects players differently based on individual fitness levels, playing style, and positional demands. Hierarchical or mixed-effects models allow for player-specific variations in fatigue trends [8], providing more personalized fatigue estimations.

D. Research Gaps

Despite the growing body of literature on soccer performance analytics, there are still gaps in understanding fatigue using tracking data. Most existing studies focus on short-term fatigue within a single match rather than cumulative fatigue over a season. Additionally, few studies compare multiple modeling approaches to determine the most effective method for predicting fatigue-induced performance declines. This research aims to bridge these gaps by developing a non-invasive, tracking-based fatigue model and evaluating different statistical techniques for optimal predictive accuracy.

Fatigue is a critical factor in soccer performance, yet existing methods for measuring it are often impractical for large-scale implementation. Tracking data presents a promising alternative, allowing researchers to analyze player movements and infer fatigue levels indirectly. This literature review highlights key findings from past studies and outlines potential modeling approaches for fatigue analysis. By integrating time-series forecasting and machine learning techniques, this research seeks to develop a scalable and actionable fatigue prediction model that can inform player management decisions in professional soccer.

III. Data

A. Data Collection and Variables

This study utilizes event data from **StatsBomb** [9], one of the most comprehensive and widely used soccer analytics datasets. StatsBomb provides highly detailed event data for professional soccer leagues, covering player actions, match context, and advanced performance metrics.

For this analysis, we focus on data from the **2019-20 La Liga season** (Competition ID: 2, Season ID: 27). This dataset contains **detailed event-level records for every match played in the league**, including passes, shots, tackles, duels, and other player actions. The availability of precise timestamps and event locations enables us to construct a detailed understanding of player workload and performance trends.

A key objective of this study is to analyze how **fatigue impacts player performance** over a season. To achieve this, we extract a set of relevant **fatigue indicators** and **performance metrics** from the event dataset.

1. Fatigue Indicators:

Fatigue is an essential factor in soccer performance, affecting decision-making, reaction time, and execution of skills. In this study, we quantify player fatigue using the following indicators:

- **Days Since Last Match:** This variable represents the number of days elapsed since a player's last recorded match.
  - Players with shorter rest periods between matches are expected to experience higher levels of fatigue due to limited recovery time.
  - Conversely, players with longer breaks may return with better fitness but might also experience a drop in match sharpness.
  - Understanding the relationship between rest days and performance can help optimize player rotation strategies.
- **Total Games Played:** This variable represents the total number of games a player has participated in up to the current match within the season.
  - As the number of matches increases, cumulative fatigue builds up, potentially leading to decreased performance or increased injury risk.

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  – High match volume can lead to **chronic fatigue**, defined as the gradual accumulation of physical and mental stress over an extended period without sufficient recovery. This condition is characterized by persistent tiredness, reduced neuromuscular function, and impaired cognitive processing, all of which can negatively impact consistency in passing accuracy, duels, and shooting efficiency.
  – This variable helps in assessing whether players who frequently feature in matches show a decline in performance over time.

2. Performance Metrics:

To evaluate the impact of fatigue on player effectiveness, we define three key performance metrics. These metrics are selected based on their **fundamental role in soccer gameplay**:

- **Pass Accuracy:** Defined as the proportion of successful passes completed by a player relative to their total pass attempts.
  – Passing is a core aspect of soccer, and fatigue is expected to impact a player's ability to execute accurate passes under pressure.
  – Higher fatigue levels may lead to **increased mispasses**, slower decision-making, and reduced precision in ball distribution.
  – This metric allows us to investigate whether players with fewer rest days struggle with maintaining passing accuracy.
- **Duel Win Rate:** Represents the percentage of successful duels won by a player out of their total duel attempts.
  – Duels involve **physical and mental exertion**, requiring quick reflexes and strength to win one-on-one battles.
  – Fatigue is expected to **negatively affect duel performance**, making players slower to react and less effective in challenges.
  – Analyzing duel win rates across different fatigue levels provides insights into **how well players maintain their competitive edge under fatigue**.
- **Shot Success Rate:** Defined as the proportion of goals scored relative to the total shots taken by a player.
  – Shooting requires precision, quick decision-making, and proper technique. Fatigue may reduce a player's ability to strike the ball cleanly.
  – Players experiencing high fatigue might take **more inaccurate shots** or struggle with **finishing under pressure**.
  – This metric helps assess whether players with greater match congestion show **a decline in shooting efficiency**.

The combination of **fatigue indicators** and **performance metrics** provides a comprehensive framework to analyze the relationship between workload and player effectiveness. By examining these variables, we aim to uncover patterns that could aid in optimizing squad rotation, training loads, and recovery strategies in professional soccer.

B. Exploratory Analysis

Understanding the distribution of rest days between matches is crucial in assessing how frequently players experience short recovery periods and how often they get extended breaks. Figure 1 illustrates the distribution of **days since last match** for all players in the dataset.

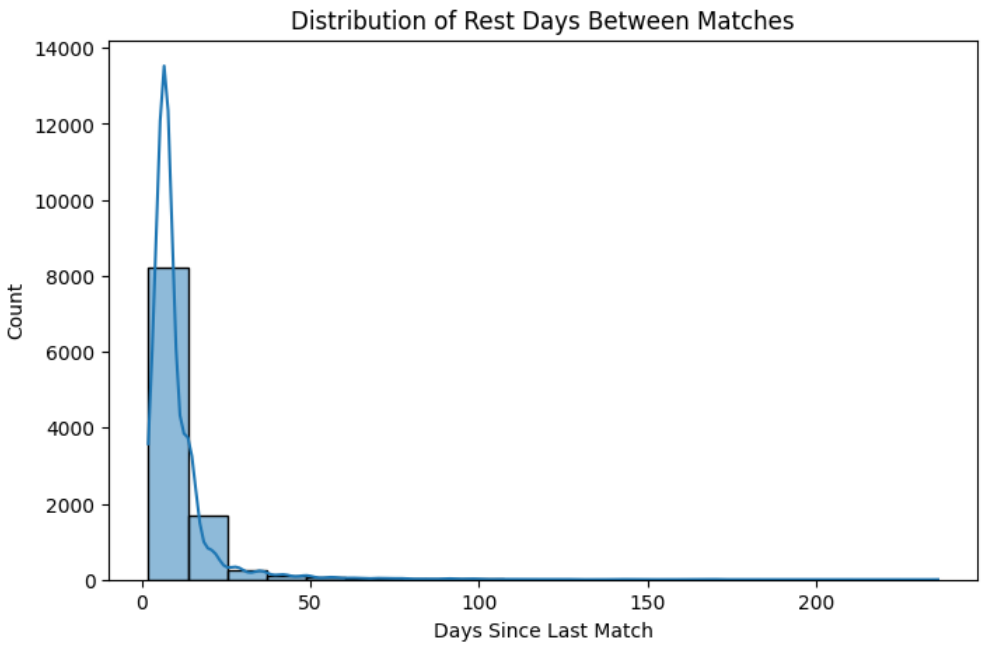

Fig. 1 Distribution of Rest Days Between Matches

The histogram shows that the vast majority of matches are played within **0 to 10 days** after a player's previous game. This highlights the congested scheduling in professional soccer, where players often compete with limited recovery time. A long right tail is observed, representing cases where certain players have extended breaks, possibly due to injuries, rotations, or international duty.

This distribution raises an important question: **Does playing with fewer rest days significantly impact a player's passing accuracy, duel win rate, or shot success rate?**

To explore this, we first compute the correlation between fatigue-related variables (*days since last match* and *total games played*) and key performance metrics. As shown in Figure 2, there are weak or negligible linear correlations between fatigue and performance indicators. For instance, *days since last match* has a near-zero correlation with pass accuracy ($r = -0.04$), duel win rate ($r = 0.02$), and shot success rate ($r = 0.03$). The correlations are generally weak, but still provide informative patterns about which performance metrics are more sensitive to fatigue.

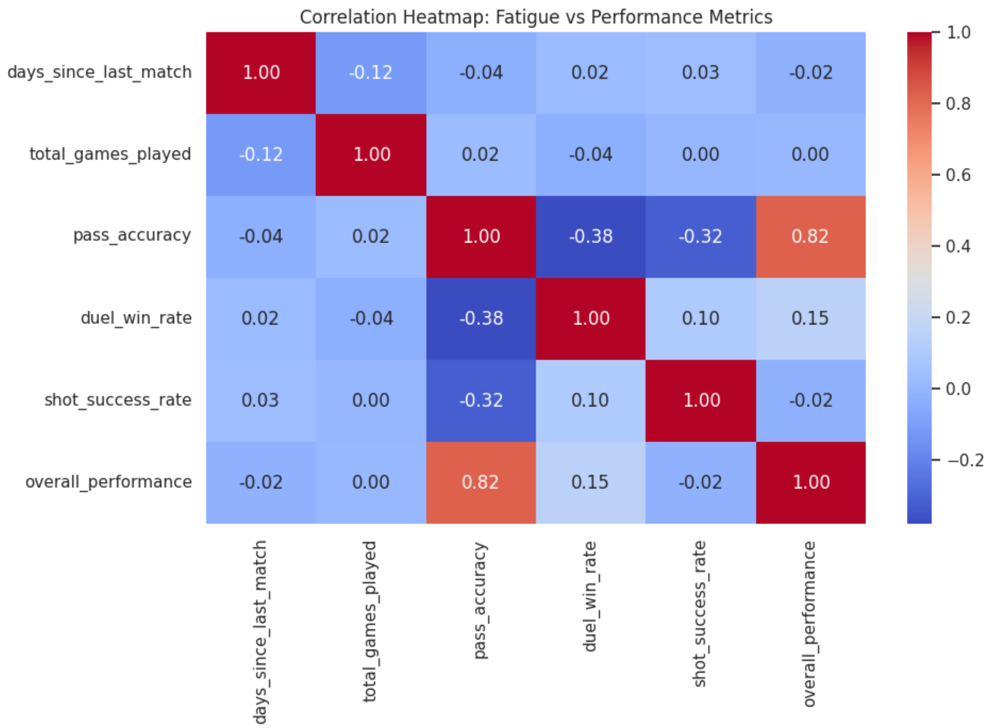

Fig. 2 Correlation Heatmap: Fatigue vs Performance Metrics

Several insights can be drawn from the heatmap:

- **Pass accuracy** shows moderate negative correlations with both duel win rate ($r = -0.38$) and shot success rate ($r = -0.32$), suggesting that players who pass more accurately tend to engage in fewer duels or take fewer high-risk shots — possibly due to positional roles or tactical discipline.
- **Overall performance** is strongly correlated with pass accuracy ($r = 0.82$), underscoring the dominant influence of technical execution in defining overall effectiveness.
- **Fatigue indicators** (i.e., `days_since_last_match` and `total_games_played`) have weak but consistent negative correlations with most performance metrics. For instance, days since last match shows negative correlations with pass accuracy ($r = -0.04$) and overall performance ($r = -0.02$), hinting at mild performance decline after short rest periods.
- **Total games played** has the most pronounced fatigue correlation: a negative relationship with `days_since_last_match` ($r = -0.12$), indicating that players who participate in more matches tend to do so with shorter rest intervals. This supports the hypothesis that high-volume players face cumulative fatigue stress.

While these linear correlations are small, their consistency across metrics and directions justifies further investigation using more expressive modeling techniques (e.g., regression with interaction terms, tree-based models) to uncover nonlinear and player-specific fatigue effects.

While the correlation heatmap shows minimal linear relationships, scatter plots in Figure 3 help visualize potential nonlinear patterns. Notably, performance metrics tend to cluster more tightly at lower rest intervals (under 30 days), suggesting more variability when players have longer breaks.

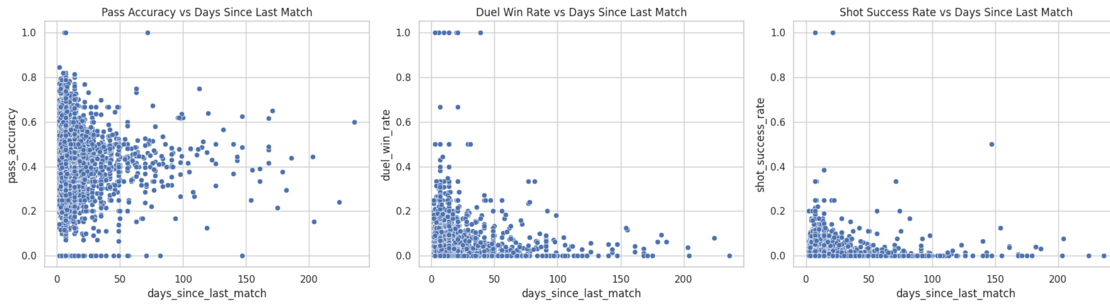

Fig. 3 Scatter Plots: Days Since Last Match vs. Individual Performance Metrics

Figure 4 illustrates how fatigue levels evolve over time for several sample players. It reveals that even within a season, players experience both high-frequency play and long breaks, indicating fluctuating recovery patterns that might influence match readiness.

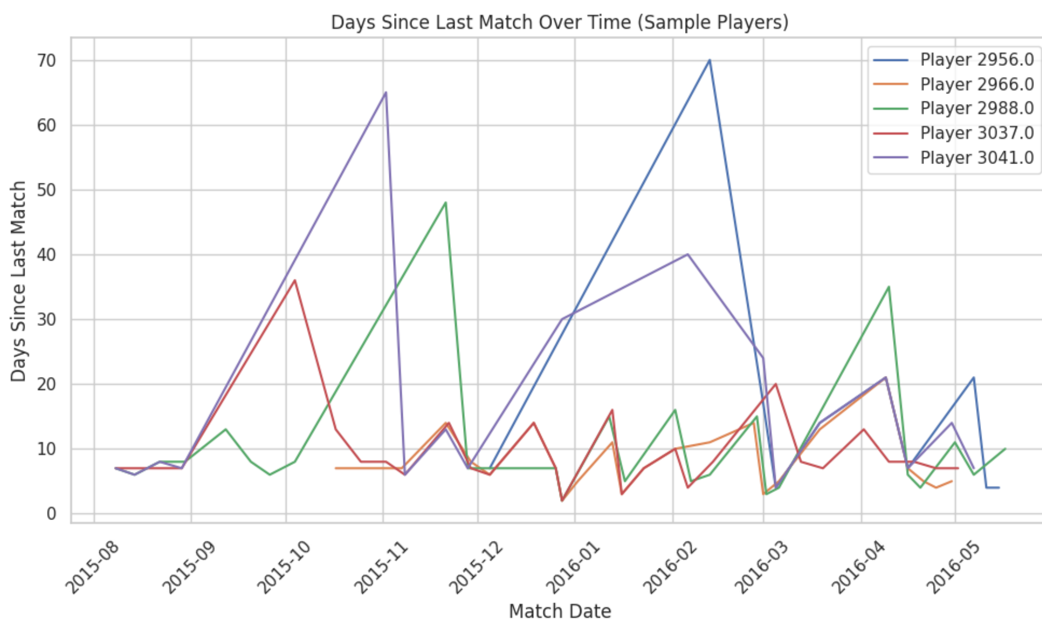

Fig. 4 Days Since Last Match Over Time (Sample Players)

Taken together, these visualizations underscore the importance of modeling fatigue alongside historical player form. The weak linear relationships call for more advanced methods (e.g., regression with nonlinear features, or interaction terms) to properly capture how fatigue interacts with performance.

IV. Methodology

To analyze the relationship between fatigue and performance, we employ a combination of **regression models, clustering methods, and time-series forecasting techniques**. These methods serve distinct purposes:

1) **Regression models** are used to quantify the direct impact of fatigue indicators on player performance metrics.
2) **Clustering methods** allow us to classify players based on their ability to maintain performance despite fatigue, identifying fatigue-resilient and fatigue-vulnerable groups.
3) **Time-series forecasting models** help predict future trends in player fatigue levels, assisting in squad rotation and workload optimization.

By using multiple modeling approaches, we can **not only measure the effect of fatigue on performance but also understand patterns in fatigue resilience** across players and forecast future fatigue trends.

A. Regression Models for Fatigue Impact

To quantify the effect of fatigue on player performance, we implement a series of regression models, starting with a baseline linear regression using historical metrics and extending to more expressive models that incorporate nonlinear transformations and interaction terms.

Baseline Linear Regression: We begin with a simple **Ordinary Least Squares (OLS) regression** using historical performance metrics (e.g., a player's previous pass accuracy) as predictors. This establishes a baseline for how well past performance alone predicts current match outcomes.

Extended Linear Model with Fatigue Features: To assess the added predictive power of fatigue-related variables, we augment the baseline model with three key features:

- **Days Since Last Match**: a short-term fatigue indicator.
- **Total Games Played**: a long-term accumulation of workload.
- **Total Events Per Match**: a proxy for match intensity.

To capture potential nonlinear effects and interaction between variables, we apply the following feature engineering strategies:

- **Nonlinear transformations** including the square root, square, and log transformations of each fatigue-related feature.
- **Interaction terms** such as the product of rest days and games played (rest_x_games) to account for conditional fatigue effects.

The expanded feature space allows the model to better capture diminishing returns, thresholds, or compounding fatigue effects that a purely linear formulation might miss. These models are trained separately for each performance metric — pass accuracy, duel win rate, and shot success rate — enabling a detailed understanding of how fatigue influences different aspects of player performance.

Finally, we extract and visualize the learned **regression coefficients** to interpret the relative impact of each factor. This not only quantifies the importance of fatigue indicators but also reveals whether their effect is direct, nonlinear, or conditioned on player workload.

B. K-Means Clustering for Fatigue Resilience

To identify patterns of **fatigue resilience among players**, we apply **K-Means clustering** using a combination of fatigue-related and performance indicators. The goal is to group players based on their ability to maintain performance under varying levels of fatigue and workload.

Feature Selection: We construct a feature set that includes:

- **Days Since Last Match** (short-term fatigue),
- **Total Games Played** (long-term fatigue accumulation),
- **Total Events Per Match** (match workload intensity),
- **Pass Accuracy** (a technical performance measure).

Preprocessing: Before clustering, all features are standardized using **z-score normalization** to ensure comparability across different units and scales. We handle missing and infinite values by dropping incomplete records to maintain cluster integrity.

Clustering Algorithm: We apply the **K-Means algorithm** with $k = 3$ clusters to partition players into distinct groups. Each cluster represents a different profile of fatigue-performance interaction, helping us differentiate between:

- **Fatigue-resilient players** who maintain performance under heavy workload,
- **Fatigue-sensitive players** whose performance drops with high intensity or short rest,
- and **Moderate responders** who fall between these extremes.

These clusters offer actionable insights into how different players respond to fatigue, which can inform player rotation, recovery planning, and personalized workload management.

C. Random Forest Regression for Nonlinear Fatigue Modeling

To capture potential **nonlinear interactions** between fatigue indicators and performance outcomes, we implement a **Random Forest regression model**. Unlike linear models that assume additive relationships, Random Forests are **ensemble-based tree models** that recursively partition the feature space to minimize prediction error.

Feature Set: The model incorporates both historical performance and fatigue-related features:

- **Historical Pass Accuracy** — a player's recent form.
- **Days Since Last Match** — a short-term fatigue signal.
- **Total Games Played** — a proxy for long-term fatigue accumulation.
- **Total Events** — representing match intensity and workload.

Modeling Approach: We use a **RandomForestRegressor** with 100 decision trees to predict each player's match-level performance (e.g., pass accuracy). The model is trained and evaluated using an 80/20 train-test split, and its accuracy is assessed via the R^2 metric.

Interpretability: To understand the relative influence of each feature, we extract and analyze the model's **feature importances**, which indicate how frequently and effectively each variable contributes to the reduction in prediction error across all trees. This allows us to assess whether fatigue indicators add meaningful predictive value beyond historical performance alone.

D. ARIMAX for Fatigue-Adjusted Performance Forecasting

To forecast **how player performance evolves over time under fatigue**, we implement an **ARIMAX (Auto-Regressive Integrated Moving Average with Exogenous Variables) model**. Unlike previous approaches that model fatigue directly, this method treats **overall player performance** as the target variable, allowing us to assess the predictive impact of fatigue-related indicators over time.

Target Variable: We define a composite **overall performance score** as the weighted sum of pass accuracy, duel win rate, and shot success rate. This single performance metric provides a holistic view of a player's technical and physical effectiveness in a match.

Exogenous Variables: To model the influence of fatigue, we incorporate the following match-level indicators as exogenous inputs:

- **Days Since Last Match** — short-term recovery or fatigue level.
- **Total Games Played** — long-term workload accumulation.
- **Total Events** — in-game intensity or physical demand.

Model Structure: The ARIMAX model captures both temporal and external influences on performance:

- **Auto-Regressive (AR) terms** model historical performance trends.
- **Integrated (I) terms** account for non-stationarity in performance levels.

- **Moving Average (MA) terms** address autocorrelated shocks or randomness.
- **Exogenous (X) variables** bring in external fatigue signals.

This structure enables us to forecast future player performance while explicitly modeling the role of fatigue indicators, providing insight into how rest, workload, and match intensity affect trends in performance over time.

E. LSTM Model for Fatigue-Adjusted Performance Prediction

To capture complex temporal and nonlinear relationships between fatigue indicators and player performance, we implement a **Long Short-Term Memory (LSTM)** neural network model. LSTMs are particularly suited for sequence modeling and are capable of learning dependencies across time, making them ideal for modeling fatigue effects across successive matches.

Target Variable: We construct a composite **overall performance score** by summing three key performance indicators: pass accuracy, duel win rate, and shot success rate. This provides a unified target for evaluating player effectiveness across multiple dimensions.

Input Features: The input to the LSTM consists of six features:

- Three historical performance indicators: `hist_pass_accuracy`, `hist_duel_win_rate`, and `hist_shot_success_rate`,
- Three fatigue-related features: `days_since_last_match`, `total_games_played`, and `total_events`.

All features are standardized using z-score normalization after filtering out any records containing missing or infinite values.

Model Architecture and Training: The LSTM model consists of a single LSTM layer with 50 hidden units followed by a fully connected linear layer for final output. We apply Xavier uniform initialization to all weights to prevent gradient explosion. The model is trained using the Adam optimizer with a learning rate of 10^{-4}, and gradients are clipped to a maximum norm of 1.0 to stabilize training.

Sequence Format and Inference: Each input is structured as a one-step sequence with six features, allowing the LSTM to treat each match as an individual timestep while retaining its ability to capture temporal dependencies. The model is trained for 100 epochs to minimize mean squared error (MSE) between predicted and actual performance scores.

This LSTM setup enables us to model more complex interactions between fatigue and performance than traditional regression approaches, offering a flexible framework to detect subtle patterns that evolve over time.

V. Results and Discussion

To evaluate how well each modeling approach captures the relationship between fatigue and player performance, we assess model performance using metrics such as Mean Absolute Error (MAE) and R^2 (coefficient of determination). We also analyze feature importances and regression coefficients to interpret the contribution of fatigue indicators.

The results are organized in alignment with the methodology: we begin with regression models that quantify direct relationships, followed by clustering-based insights on player resilience, and then report on the predictive accuracy of time-series and deep learning models.

A. Regression Models for Fatigue Impact

We compare the performance of two linear regression models for each performance metric: a baseline model that uses only historical performance indicators, and an extended model that incorporates fatigue-related features through nonlinear transformations.

1. Pass Accuracy:

The baseline model using only historical pass accuracy achieved an R^2 score of 0.355 and an MAE of 0.062. When fatigue features were added, the R^2 improved slightly to 0.363 with the same MAE of 0.062, indicating a small but measurable improvement in predictive power.

The learned coefficients in the extended model reveal that historical pass accuracy remains the dominant predictor ($\beta = 0.709$), while fatigue-related features such as log-transformed total events ($\beta = 0.011$) and days since last match ($\beta = 0.0007$) have smaller but positive contributions. Interestingly, total games played exhibits a negative coefficient ($\beta = -0.0013$), suggesting a mild decline in passing performance with increasing match load.

Interpretation: For every additional game played in the season, a player's pass accuracy is predicted to decrease by approximately 0.13 percentage points, holding other factors constant. Conversely, each additional day of rest before a match is associated with a very slight increase of 0.07 percentage points in pass accuracy.

2. Duel Win Rate:

The duel win rate model showed a greater improvement from adding fatigue indicators. The baseline model achieved an R^2 of 0.123 (MAE = 0.028), while the fatigue-enhanced model reached an R^2 of 0.176 with the same MAE.

Historical duel win rate was again the most influential predictor ($\beta = 0.397$), but fatigue variables also played meaningful roles. Total events ($\beta = -0.010$) and days since last match ($\beta = -0.0012$) both had negative coefficients, indicating reduced duel performance under higher physical demand and shorter rest. In contrast, total games played had a small positive effect ($\beta = 0.0006$), potentially reflecting match experience benefits.

Interpretation: A one-unit increase in match intensity (as measured by total events) corresponds to a 1 percentage point decrease in duel win rate. Each additional day of rest is associated with a 0.12 percentage point decline in duel success — potentially reflecting a loss in sharpness. Interestingly, playing more matches is associated with a slight increase in duel success rate (0.06 percentage points), possibly due to improved timing or resilience built through experience.

3. Shot Success Rate:

The shot accuracy model showed the smallest gain from including fatigue indicators, with the baseline model achieving an R^2 of 0.047 (MAE = 0.014) and the full model reaching 0.061 (MAE = 0.015). This suggests that shot performance may be less sensitive to fatigue, or more influenced by contextual or tactical factors not captured by current features.

Historical shot success rate had the largest weight ($\beta = 0.360$), while all fatigue indicators had very small coefficients, indicating only minor influence. Days since last match and total games played had coefficients near zero, reinforcing the minimal explanatory power of fatigue in this context.

Interpretation: Fatigue features had negligible predictive power for shot success. For example, playing one more game or resting one more day would only affect shot success rate by less than 0.01 percentage points, which is likely not practically significant.

These results demonstrate that while historical performance remains the strongest predictor, fatigue-related metrics—particularly total match intensity and rest duration—contribute additional explanatory power, especially for duels and passing outcomes.

B. K-Means Clustering for Fatigue Resilience

To identify patterns in how players maintain performance under varying levels of fatigue, we applied K-Means clustering using four features: days since last match, total games played, total events per match, and pass accuracy. This unsupervised learning approach grouped players into three distinct clusters based on their fatigue-performance profiles.

Figure 5 visualizes the clustering results in the two-dimensional space defined by event intensity (x-axis) and pass accuracy (y-axis), with each color representing a different fatigue-resilience cluster.

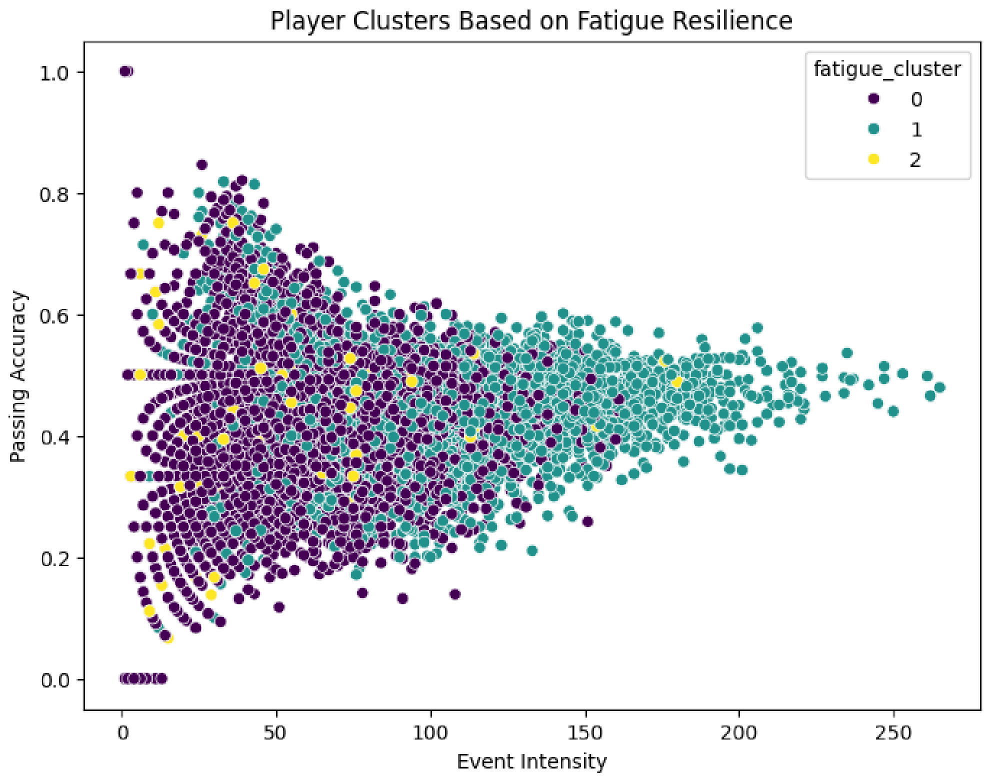

Fig. 5 Player Clusters Based on Fatigue Resilience

The plot reveals several clear patterns:

- **Cluster 0** (purple) contains players with high event intensity and relatively lower pass accuracy, suggesting this group may be more **fatigue-sensitive**, struggling to maintain technical performance under heavier workloads.
  - *Example players:* Sadio Mané, James Morrison, Nathan Redmond
  - These players frequently engaged in high-tempo matches and physical actions but showed greater variability in technical accuracy, possibly due to aggressive playing styles or demanding positional roles.
- **Cluster 1** (teal) exhibits moderate-to-high pass accuracy across a wide range of event intensities. These players appear to be **fatigue-resilient**, maintaining performance even under physically demanding conditions.
  - *Example players:* David Silva, Mesut Özil, Jordan Henderson
  - Known for consistency and tactical discipline, these midfielders often delivered high technical output regardless of match frequency or workload.
- **Cluster 2** (yellow) represents a smaller group with mixed characteristics. These players tend to cluster near the lower end of event intensity and accuracy, potentially indicating less playing time or roles with different tactical demands.
  - *Example players:* Rob Elliot, Maya Yoshida, Glenn Murray
  - Often defensive or rotational squad members, these players had fewer match events and less frequent

involvement in build-up play, making fatigue impacts harder to observe.

Overall, the clustering highlights that while many players experience performance degradation with increased workload, a significant subset maintains consistent accuracy — potentially due to superior conditioning, tactical awareness, or recovery strategies. These insights could be useful for identifying players suitable for high-intensity roles or in need of more recovery time.

C. Random Forest Regression for Nonlinear Fatigue Modeling

To evaluate the nonlinear relationship between fatigue indicators and player performance, we trained a Random Forest regression model using historical performance metrics and fatigue-related features. Two model variants were tested: one using only historical performance as input, and another augmented with fatigue features.

The baseline model, which included only historical indicators (pass accuracy, duel win rate, and shot success rate), achieved an R^2 score of 0.120. Feature importance analysis showed that historical pass accuracy had the strongest predictive power (52.6%), followed by duel win rate (28.7%) and shot success rate (18.7%). These results reinforce the finding that recent performance history is a strong predictor of future outcomes.

When fatigue-related features were added — including days since last match, total games played, and total events — the model's performance improved to an R^2 of 0.191. The importance of historical pass accuracy decreased (to 36.1%) as new features contributed explanatory power: event intensity (20.6%), duel win rate (16.4%), and both long-term and short-term fatigue indicators (e.g., total games played at 9.9% and days since last match at 7.3%).

These results demonstrate that while recent performance remains the dominant signal, fatigue-related metrics do provide meaningful predictive value. In particular, match intensity (total events) emerged as a significant nonlinear predictor of performance decline, highlighting the importance of modeling workload effects in a more flexible, nonparametric framework.

D. ARIMAX for Fatigue-Adjusted Performance Forecasting

To investigate how fatigue influences performance trends over time, we implemented an ARIMAX model with both autoregressive components and exogenous fatigue-related variables. The model was trained on match-level average overall performance and used fatigue indicators — including days since last match, total games played, and total events — as external predictors.

The best-fitting model, determined using information criteria, was specified as SARIMAX(2,1,2) with seasonal terms SARIMAX(1,1,1,12). The model achieved a high log-likelihood of 894.55 and an Akaike Information Criterion (AIC) of -1769.10, indicating a strong fit to the observed performance trend over time.

Model Specification: We use a Seasonal AutoRegressive Integrated Moving Average model with exogenous regressors, denoted as **SARIMAX(2,1,2)(1,1,1,12)**. This specification can be broken down as follows:

- **(2,1,2)** — the non-seasonal ARIMA terms:
  - $p = 2$: two autoregressive lags (performance depends on values from two previous matches),
  - $d = 1$: first differencing is applied to ensure stationarity,
  - $q = 2$: two lagged forecast errors are used to adjust predictions.
- **(1,1,1,12)** — the seasonal component:
  - $P = 1$: one seasonal autoregressive lag (performance depends on its value one "season" ago),
  - $D = 1$: first seasonal differencing,
  - $Q = 1$: one seasonal moving average term,
  - $s = 12$: seasonality is assumed to repeat every 12 matches.

The seasonal lag of 12 was chosen based on empirical match spacing in professional leagues (e.g., approximately one month of match play or three fixture cycles), capturing medium-term performance rhythms such as monthly rotation patterns or fatigue cycles.

Model Equation (Simplified): The SARIMAX model with exogenous inputs can be written as:

$$Y_t = c + \sum_{i=1}^{2} \phi_i Y_{t-i} + \sum_{j=1}^{2} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{3} \beta_k X_{k,t} + \text{Seasonal Terms} + \varepsilon_t \tag{1}$$

Where:

- Y_t is the differenced overall performance at time t,
- ϕ_i are the autoregressive coefficients,
- θ_j are the moving average coefficients,
- ε_t is the white noise error term,
- $X_{k,t}$ are the fatigue-related exogenous variables: `days_since_last_match`, `total_games_played`, and `total_events`,
- β_k are the coefficients for those fatigue predictors.

This model structure allows us to simultaneously model:

- **Short-term memory** (via AR and MA terms),
- **Seasonal dynamics** (capturing periodic fatigue or form cycles),
- **External fatigue influences** (via the exogenous regressors).

Figure 6 shows the in-sample performance and out-of-sample forecast. While short-term variability remains high, the model captures overall downward trends and predicts a continued modest decline in performance.

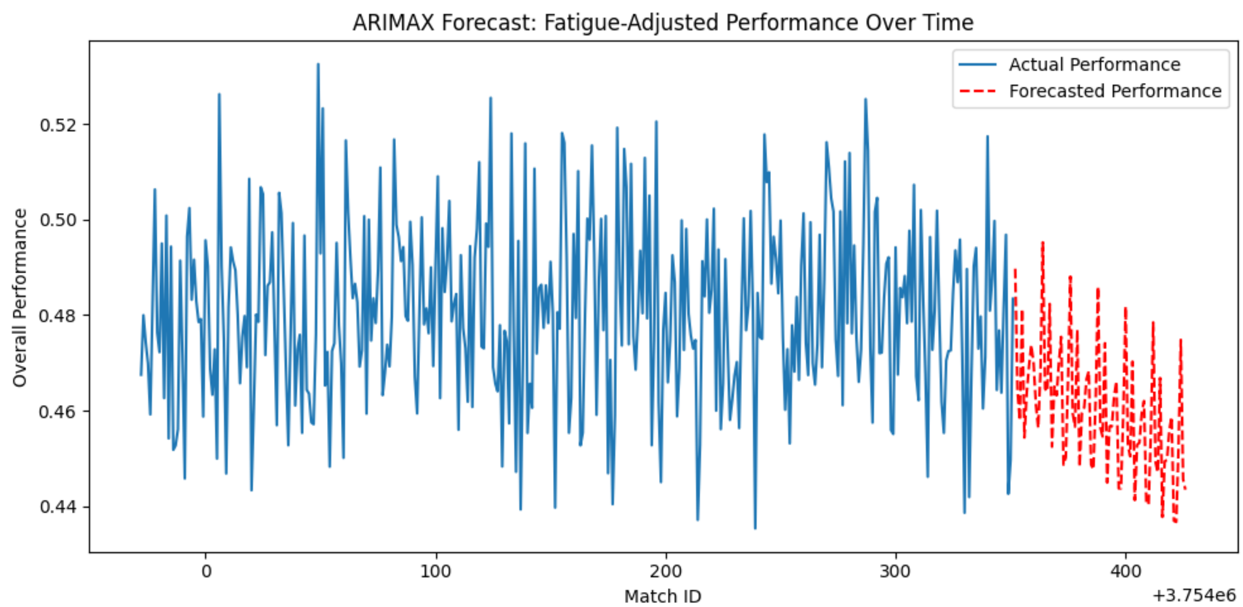

Fig. 6 ARIMAX Forecast: Fatigue-Adjusted Performance Over Time

Coefficient Interpretation: The model's learned coefficients offer insight into the temporal and fatigue-based drivers of performance:

- **Total Events** had a significant negative coefficient ($\beta = -0.0007$, $p < 0.001$), indicating that matches with higher intensity are associated with subsequent declines in performance.
- **Total Games Played** also had a negative impact ($\beta = -0.0003$, $p = 0.023$), suggesting a cumulative fatigue effect across the season.
- **Days Since Last Match** was not statistically significant ($p = 0.675$), implying that short-term rest may have limited predictive value for team-level performance in this context.
- Seasonal autoregressive (`ar.S.L12`) and moving average (`ma.S.L12`) terms were both highly significant, capturing cyclical trends likely related to match scheduling.

These results support the hypothesis that performance fluctuations are not only temporal but also linked to underlying fatigue signals — particularly those associated with cumulative workload and match intensity.

1. LSTM Model for Fatigue-Adjusted Performance Prediction

To evaluate the ability of deep learning models to capture temporal and nonlinear relationships between fatigue indicators and player performance, we trained a Long Short-Term Memory (LSTM) network using both historical performance and fatigue-related features.

The model was trained on six input features — three historical metrics (pass accuracy, duel win rate, shot success rate) and three fatigue indicators (days since last match, total games played, total events) — to predict a composite overall performance score.

Prediction Accuracy: Figure 7 illustrates the LSTM's predictions against the actual match-level performance scores. While the model is able to capture overall distributional tendencies, the predictions tend to be compressed and fail to fully reflect the variance in real outcomes. This suggests that, despite its capacity, the LSTM may be limited by noise in the input data or insufficient sequential context (since each match was treated as a single time step).

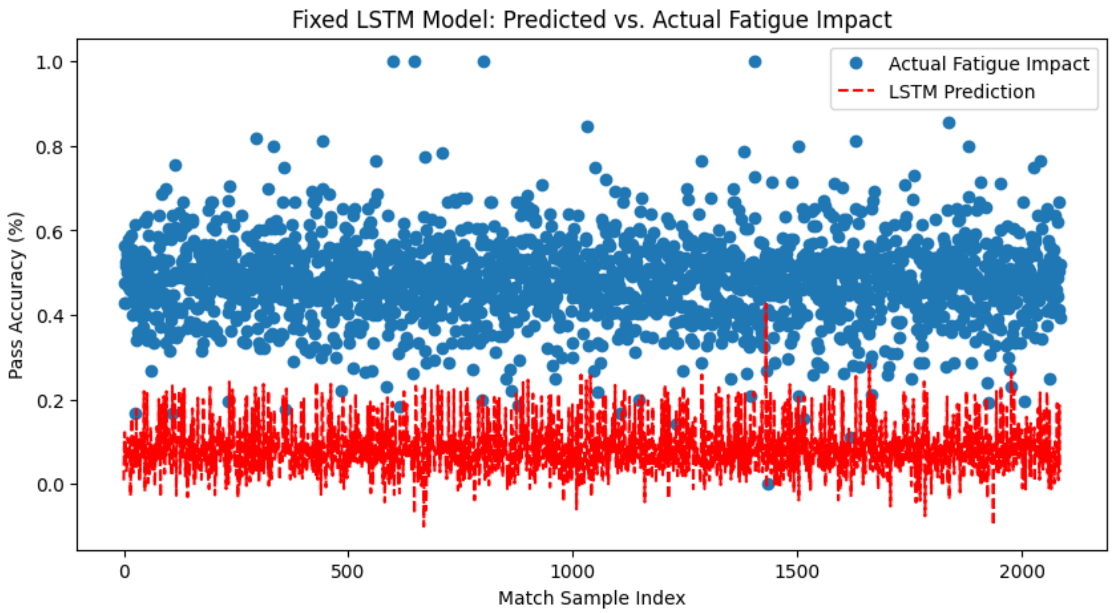

Fig. 7 Fixed LSTM Model: Predicted vs. Actual Fatigue Impact

Model Performance: The LSTM model achieved a Mean Absolute Error (MAE) of **0.399** and a Mean Squared Error (MSE) of **0.168**. While these error rates indicate the model captures general performance levels, they also highlight substantial room for improvement — potentially through incorporating longer sequences, richer contextual features, or recurrent player embeddings.

Feature Importance via Permutation: To interpret the model's predictions, we applied permutation-based feature importance, measuring the drop in R^2 when each feature was randomly shuffled. Table 1 reports the relative importance of each input feature.

Feature	Importance Score
Hist. Duel Win Rate	0.438
Hist. Shot Success Rate	0.339
Hist. Pass Accuracy	0.311
Total Events	0.091
Total Games Played	0.072
Days Since Last Match	0.055

Table 1 LSTM Feature Importances via Permutation-Based R^2 Drop

Historical metrics were consistently the most influential, with duel win rate and shot success rate contributing more than pass accuracy. Among fatigue indicators, total events emerged as the most important, followed by long-term load (total games played) and recent rest (days since last match). These results suggest that the LSTM did learn meaningful fatigue-related patterns, but their influence remains secondary to historical performance in driving model predictions.

VI. Conclusion

This study investigates the relationship between fatigue and individual performance in professional soccer using non-invasive, event-based data from the 2019–20 La Liga season. By engineering interpretable fatigue indicators — including days since last match, total games played, and match event intensity — and combining them with historical performance metrics, we evaluated their impact across three key dimensions of player effectiveness: pass accuracy, duel win rate, and shot success rate.

Our analysis reveals several important insights. First, historical performance remains the most powerful predictor of match-level outcomes, yet fatigue-related features provide meaningful additional explanatory power, particularly for physical actions such as duels. Extended linear models showed that match intensity and accumulated game load are associated with declines in performance. Random forest regressions confirmed the nonlinear influence of these features, with event intensity emerging as the most important fatigue indicator.

Clustering analysis uncovered clear variation in player resilience to fatigue, highlighting that some athletes maintain high performance even under intense workloads, while others show notable declines. Time-series modeling using ARIMAX and LSTM provided complementary insights, with ARIMAX capturing season-long fatigue-performance dynamics, and LSTM learning subtle temporal patterns from match-level sequences — albeit with limited prediction accuracy.

Taken together, these findings demonstrate the value of integrating fatigue indicators into performance modeling pipelines. While more work is needed to refine fatigue estimation and incorporate richer tracking data, our results underscore the potential for data-driven fatigue monitoring to enhance decision-making in player rotation, workload planning, and injury prevention.

A. Key Findings Summary

- **Fatigue indicators, especially match intensity (total events), improve prediction accuracy** across multiple modeling approaches, with the most significant gains observed in duel win rate.
- **Regression models confirm that fatigue has a measurable, if subtle, impact on technical performance metrics**, particularly when nonlinear transformations and interaction terms are included.
- **Random forest models highlight the nonlinear influence of fatigue**, with fatigue-related features contributing nearly half the predictive power in the extended model.
- **K-means clustering identifies distinct groups of fatigue-resilient and fatigue-sensitive players**, offering practical insights for squad management.
- **ARIMAX models reveal that cumulative fatigue (games played and intensity) negatively affects performance trends over time**, while short-term rest (days since last match) is less predictive at the aggregate level.
- **LSTM models capture broad trends but struggle with performance variance**, indicating the need for deeper sequence context or personalized learning.

B. Future Work

While this research provides a foundation for fatigue-aware performance modeling in soccer, several directions remain open for future exploration:

- **Sequence-aware modeling**: Future LSTM implementations could incorporate multi-step sequences of player performance and fatigue indicators, enabling better temporal generalization and richer memory of recent trends.
- **Contextual factors**: Integrating match context (e.g., opposition strength, home/away status, tactical roles) may help explain variance in performance not captured by current models.
- **Player-specific modeling**: Mixed-effects or hierarchical models could account for individual variability in fatigue response, offering personalized fatigue management tools.
- **Positional and role analysis**: Segmenting analysis by position or tactical role may reveal differential fatigue effects among defenders, midfielders, and forwards.
- **Incorporating biometric and GPS tracking data**: Combining event data with physiological metrics (if available) could enable more accurate and holistic modeling of player readiness and fatigue.
- **Real-time applications**: Developing live forecasting tools that integrate updated fatigue estimates could support dynamic substitution, training loads, and injury risk management.

By pursuing these extensions, future studies can build more robust, interpretable, and actionable fatigue modeling frameworks for use in elite soccer environments and beyond.

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