Textile & Leather Review

ISSN 2623-6281 | www.tlr-journal.com | 10.31881/TLR

The Dynamic Evolution and Reversal Prediction of Momentum in Tennis Matches Based on Bayesian State Space and Risk Rate Models

Haiyang Ding, Mengye Meng, Ziyang Ma, Jianfan Lu

How to cite: Ding H, Meng M, Ma Z, Lu J. The Dynamic Evolution and Reversal Prediction of Momentum in Tennis Matches Based on Bayesian State Space and Risk Rate Models. Textile & Leather Review. 2026; 9:3172-3202. https://doi.org/10.31881/TLR.2026.3172

How to link https://doi.org/10.31881/TLR.2026.3172

Published:25 April 2026

The Dynamic Evolution and Reversal Prediction of Momentum in Tennis Matches Based on Bayesian State Space and Risk Rate Models

Haiyang Ding[1]*, Mengye Meng[2], Ziyang Ma[2], Jianfan Lu[3]

[1]Public Basic Education Branch, Shaoxing Institute of Technology, Shaoxing 312000, Zhejiang, China

[2]School of Artificial Intelligence, Shaoxing Institute of Technology, Shaoxing 312000, Zhejiang, China

[3]School of Architecture and Environmental Engineering, Shaoxing Institute of Technology, Shaoxing 312000, Zhejiang, China

*dinghaiyang@zsit.edu.cn

Article

https://doi.org/10.31881/TLR.2026.3172

Published 25 April 2026

ABSTRACT

This study aims to quantify momentum in competitive sports and its impact on the transparency of match outcomes. Taking the 2023 Wimbledon Men's Singles Final as a case, we construct a multi-dimensional nonlinear prediction framework. First, a Bayesian state-space model is used to define momentum as an unobservable continuous latent variable, and an extended Kalman filter is applied to capture performance fluctuations. Then, the significant local impact of momentum in the late game is verified by comparing the win probability shift model with momentum factors and the benchmark win probability model. The risk rate model further identifies key turning point indicators such as double faults and net errors. Finally, Monte Carlo simulation demonstrates the generalization potential of this framework in badminton and table tennis. The results provide a quantitative tool for understanding the dynamic evolution of complex competitive systems.

KEYWORDS

tennis matches, bayesian state space, risk rate model, reversal prediction

INTRODUCTION

In the 2023 Wimbledon Men's Singles Final, the match between Alcaraz and Nicolas Jarry was marked by multiple dramatic shifts in momentum. Such fluctuations in the course of the game are often attributed to the effect of "momentum," yet in sports science, there remains no consensus on how to precisely measure momentum or the underlying physical mechanisms driving it. Previous research has largely focused on simple winning streak statistics or static score analysis; some perspectives even suggest that momentum is merely an illusion of random fluctuations, lacking a deep deconstruction of momentum as a continuous evolutionary process [1-3]. The innovation of this section lies in abstracting momentum as a continuous latent variable within a state equation. By combining logistic regression with stochastic processes, we achieve a dynamic representation of performance states and distinguish between global fluctuations and local significance mechanisms. It should be emphasized that the benchmark model set in this study not only considers the real-time score, but also integrates multiple core technical statistical indicators screened by Principal Component Analysis (PCA), ensuring that the extracted momentum has explanatory value beyond conventional competitive performance. The general research framework of this section is as follows: First, we establish physical assumptions and a symbolic system for player performance, visualizing performance metrics through a Bayesian framework; second, we formulate null and alternative hypotheses to verify, via statistical tests, the substantive contribution of momentum to win rates; third, we define the crossing of the zero line as a turning point and construct a risk ratio model to identify the core technical indicators driving the reversal of advantage; finally, utilizing multiple evaluation metrics to assess predictive accuracy and exploring the model's generalizability and stability across different sports scenarios [4,5].

ASSUMPTIONS AND SYMBOLIZATION

Assumptions and Justifications

Assumption 1. Assumption that players are in good health. Exclude the effect of new and old injuries to players on the outcome of the match [6,7].

Assumption 2. Assumption that the playing field, time of day, weather conditions, etc., are ideal. Exclude all external influences that have a favorable or unfavorable effect on the players.

Assumption 3. It is assumed that the matches are fair and impartial, the players show their true level of performance, and the data of the matches is true and valid.

Symbol Description

Table 1. Symbol description

Symbol	Description
y_t	Indicates cumulative score
z_t	The implicit function of "momentum"
p_t	Probability of winning a point
s_t	Serving advantage

Symbol	Description
S_t	Watershed
h_t	Hazard rate of turnaround
LogLoss $_m$	Logarithmic discount
Brier $_m$	Brier Score

Symbol description is shown in Table 1.

VISUALIZE PLAYER PERFORMANCE METRICS

Model Overview

This task requires the development of a model capable of capturing various processes during a match to reflect players' performance states at different points in the game. The model development and solution process is illustrated in Figure 1.

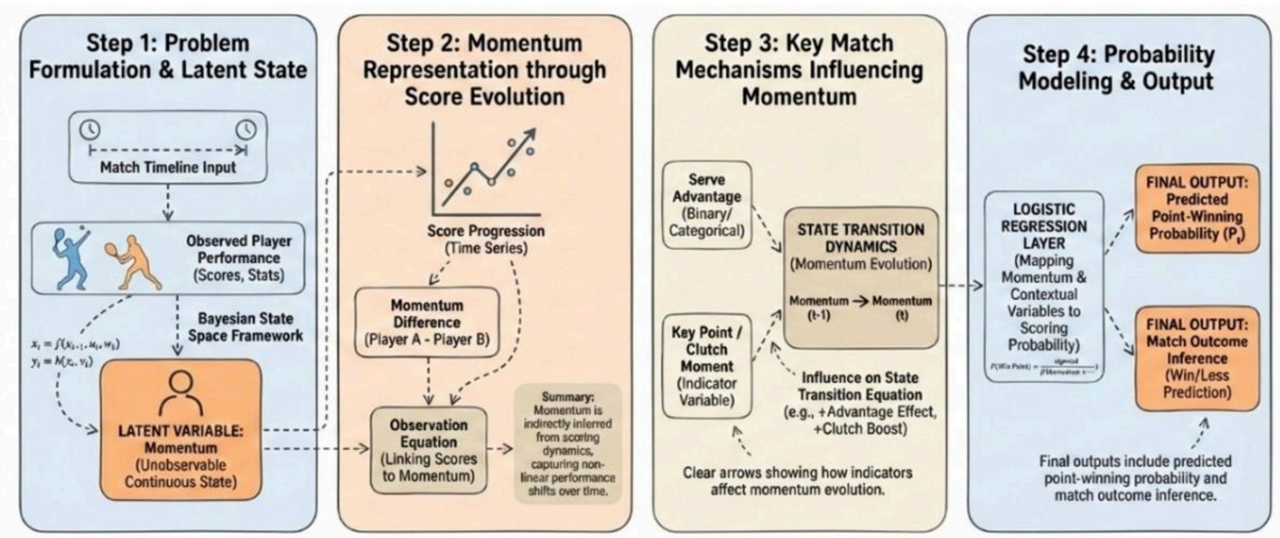

Figure 1. Overview of the model

Modeling

To demonstrate player performance during matches, a Bayesian state space model is established with "momentum" as an unobservable continuous latent variable [8,9]. This model preliminarily reflects the momentum gap between teams based on match scoring conditions. Using the provided match data, the scoring states are mapped to y_t :

$$y_t = \{+1, \text{Carlos Alcaraz Win} \\ -1, \text{Nicolas Jarry Win} \tag{1}$$

Where t denotes the moment of each point in the match.

Based on the scoring status of both players during the match, the hidden function representing "momentum" is denoted as z_t , which signifies the momentum difference between the two players at time t (the intensity of Carlos Alcaraz's performance relative to Nicolas Jarry's). When $z_t > 0$, Carlos Alcaraz holds the advantage, when $z_t < 0$, Nicolas Jarry holds the advantage. The greater the absolute value of z_t , the stronger the advantage [10].

In the game, the serving side typically possesses greater momentum. To incorporate this into momentum calculations, the serving side must be mapped to s_t using the formula:

$$s_t = \{+1, \text{Carlos Alcaraz Service} \\ -1, \text{Nicolas Jarry Service} \tag{2}$$

Establish a logistic regression model for the probability of scoring in a match, as follows:

$$P(y_t = +1 \mid z_t) = \sigma(z_t + \alpha \cdot s_t) \tag{3}$$

Where $\sigma(u) = \frac{1}{1+e^u}$, denotes the contribution of the momentum difference between both sides to winning points in the match, and s_t represents the quantification of the serving advantage [11-13].

To model player performance during matches, establish a state equation incorporating player momentum. Due to momentum's persistence, a player's momentum evolves throughout the match as the game progresses. Factors such as physical exertion, rally duration, and winning points influence whether momentum persists or diminishes. The regression equation is formulated as follows:

$$z_t = \rho z_{t-1} + \beta^T X_{t-1} + \varepsilon_t \tag{4}$$

Where ρ represents the player's momentum inertia, X_{t-1} denotes real-time factors such as physical exertion (distance covered), match intensity (point duration), and winning points, while $\varepsilon_t \sim N(0, \sigma^2)$.

The contest for crucial points significantly impacts players' psychology and strategy. Key events such as break points, match points, and tiebreak points drive momentum shifts. Translating the importance of these critical points into weighting directly influences the scoring dynamics of a match. The weighting for crucial points is expressed as:

Where P_b denotes the break point indicator, P_g denotes the match point indicator, and P_s denotes the tiebreak point indicator [14].

Combining key score weights, an autoregressive equation incorporating key score impact terms was established, namely:

$$z_t = \rho z_{t-1} + \beta^T X_{t-1} + \kappa \omega_{t-1} y_{t-1} + \varepsilon_t \tag{5}$$

This equation can be understood as: winning a point shifts the momentum in one's favor, and seizing crucial points grants even greater momentum.

To visualize players' performance during matches, the posterior distribution under the Bayesian state space model is calculated—specifically, the probability distribution $p(z_t \mid y_{1:t})$ of momentum z_t at time t . The mean of this posterior distribution, $\hat{z}_t$, is taken as the "instantaneous momentum difference." When $\hat{z}_t > 0$, Carlos Alcaraz holds the advantage; when $\hat{z}_t < 0$, Nicolas Jarry holds the advantage. The greater the value of $\mid \hat{z}_t \mid$, the stronger the advantage [15].

Analysis of Results

Using the 2023 Wimbledon men's tournament data and applying the Bayesian state space model established above, we employed an extended Kalman filter to analyze the performance metrics of both players in the match. Key performance indicators are presented in Table 2.

Table 2. Outcome data

Outcome Indicators	value
Average momentum difference	0.980
Carlos Alcaraz's Lead Time Percentage	0.830
Nicolas Jarry's Lead Time Percentage	0.167
Carlos Alcaraz's Momentum	3.701
Nicolas Jarry's Momentum	1.232

Throughout the entire match, Carlos Alcaraz's peak momentum reached 3.701, significantly higher than Nicolas Jarry's. Moreover, Alcaraz maintained the momentum lead for 0.830 of the match duration. Simultaneously, his average winning percentage stood at 0.688, clearly demonstrating his dominant advantage in this contest [16-19].

Based on the momentum difference function and the probability of winning points, the momentum difference between Carlos Alcaraz and Nicolas Jarry at various stages of the match, along with its 95% confidence interval, and Carlos Alcaraz's probability of winning points in that match can be derived, as shown in Figure 2 and Figure 3. In this model, the intercept term of the state equation (Equation 5) aims to absorb the players' baseline skill level, while the latent variable z_t focuses on characterizing short-term performance deviations caused by psychological pressure or changes in competitive rhythm. This design effectively avoids misjudging the inherent advantage of high-level players as continuous momentum growth.

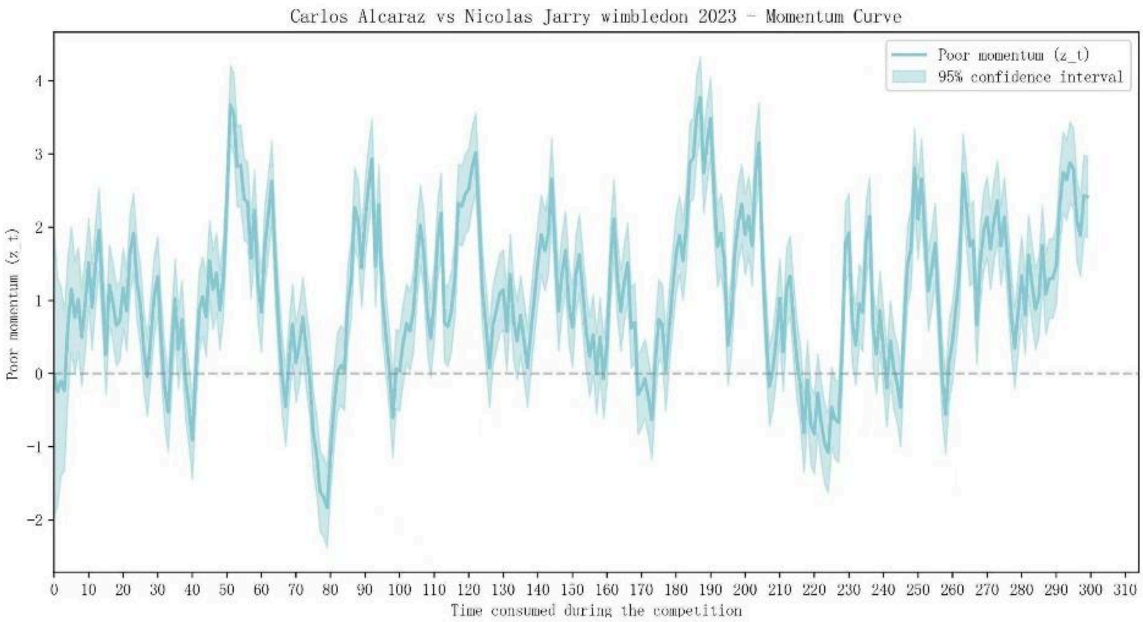

Figure 2. Momentum curve and carlos alcaraz real-time winning score probability

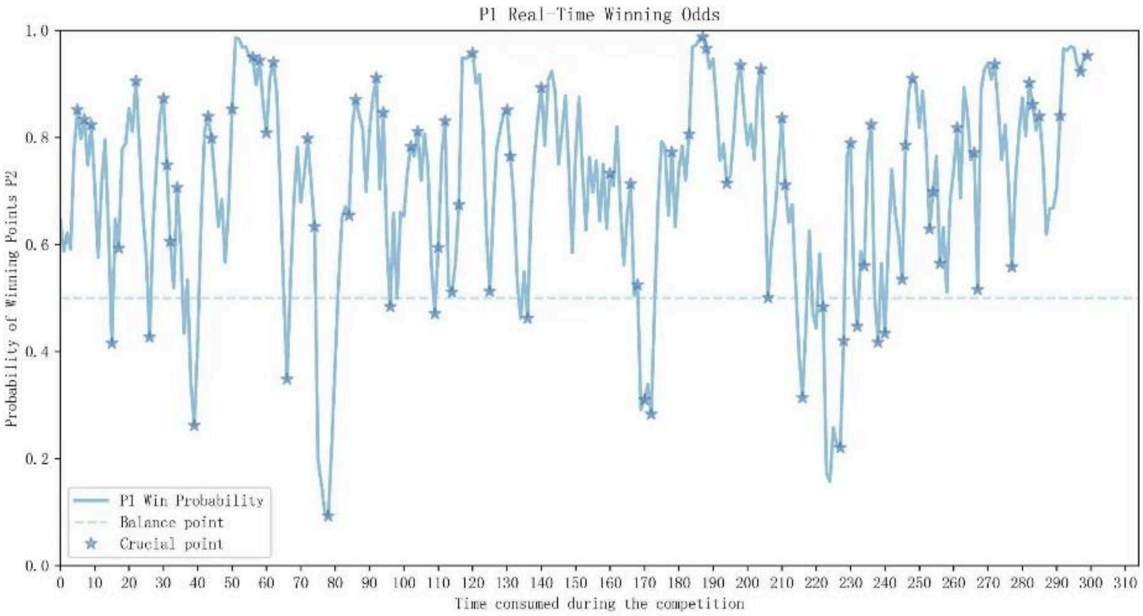

Figure 3. Smoothing curves of "momentum differences"

Observe the chart above: The momentum curve remains above the zero axis for most match intervals, and the 95% confidence interval for a significant portion of these intervals also consistently exceeds zero. This indicates that in the vast majority of cases, Carlos Alcaraz maintains a high probability of winning points in real time and holds a clear advantage throughout the match.

From a segmented perspective of the match progression, the momentum gap and Carlos Alcaraz's point-winning probability did not rise steadily but rather in a seesaw pattern: the number of momentum inflection points reached 51. Furthermore, Alcaraz's real-time point-winning probability curve exhibited multiple instances of rapid decline followed by swift recovery. It also experienced noticeable pullbacks—even briefly turning negative—in corresponding intervals, accompanied by widening confidence intervals, indicating increased uncertainty [20].

The entire match demonstrated that crucial points or phase transitions often trigger short-term fluctuations and frequent turning points. However, Carlos Alcaraz typically managed to reestablish a higher winning probability after such fluctuations, pulling his advantage back into positive momentum territory. This pattern revealed a match rhythm characterized by "short-term fluctuations, long-term bias toward Carlos Alcaraz."

DOES MOMENTUM AFFECT THE OUTCOME OF THE GAME?

Model Overview

Whether momentum influences match outcomes requires further analysis of game data based on the Bayesian state space model. The modeling and solution flow is shown in Figure 4.

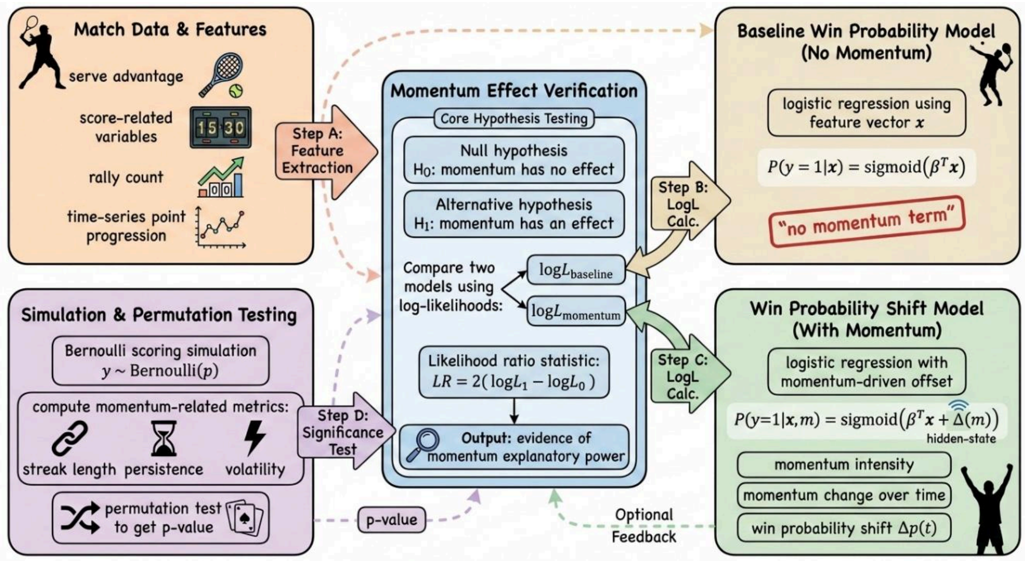

Figure 4. Overview of the model

Modeling

To investigate the impact of momentum on match progression and outcomes, we modified the Bayesian state space model. By distinguishing between scenarios with and without momentum effects on winning probability, we established a baseline win rate model (without momentum) and a win rate offset model (with momentum).

Establish a feature equation influencing scoring probability. Process the influencing factors in the data list via Principal Component Analysis to identify the primary factors: dominance of first serves and game scores, rhythm of extended rallies during second serves, and pressure during critical break point moments.

Benchmark Win Rate Model M_0

By modeling win rates without incorporating momentum effects through logistic regression, the baseline win rate model is obtained as follows:

$$\text{logit}\ (p_t) = \beta^T X_t \tag{6}$$

Simplifying yields the win rate for P1 at t points:

$$p_t = \sigma(\beta^T X_t) = \frac{1}{1 + e^{-\beta^T X_t}} \tag{7}$$

Win Rate Shift Model M_1

Building upon the baseline win rate model, we introduce the momentum influence term m_t to derive the logistic regression equation for Carlos Alcaraz's win rate under momentum effects:

$$\text{logit } (p_t) = \beta^T X_t + m_t \tag{8}$$

When $m_t > 0$, Carlos Alcaraz holds the upper hand, the probability of winning points increases; when $m_t < 0$, Nicolas Jarry holds the upper hand.

Considering the persistence of momentum in the game, the autoregressive equation describing the effect of momentum is:

$$m_t = \phi m_{t-1} + \eta_t \tag{9}$$

When $\phi \in (0, 1)$ indicates the persistence of momentum, with values closer to 1 signifying stronger persistence; $\eta_t \sim N(0, \sigma^2)$, where σ represents the intensity of momentum change.

According to this model, the "momentum" intensity obtained at the t minute mark is:

$$m_t = E[m_t \mid y_{1:t}] \tag{10}$$

The null hypothesis $H_0 : m_t = 0$ posits that momentum has no effect, meaning that after controlling for factors such as serve advantage and score, no momentum effect exists. Additionally, the alternative hypothesis $H_1 : m_t \neq 0$ asserts that a sustained momentum effect over time is present in the match.

To assess the impact of "momentum," a likelihood ratio test was conducted on the two models, calculating the log-likelihood values using the following formula:

$$l(M) = \sum_t [y_t \log p_t + (1 - y_t) \log(1 - p_t)] \tag{11}$$

Substituting the two models into the above equation yields the statistic A , whose formula is:

$$A = l(M_1) - l(M_0) \tag{12}$$

When A is used to evaluate the explanatory power of the model. A higher A value indicates that the model incorporating "momentum" has stronger explanatory power, while a lower A value indicates weaker explanatory power.

To better illustrate the occurrence of strong winning or losing streaks in random matches with or without momentum effects, we randomly generate Carlos Alcaraz's scores in matches such that:

$$y_t^{(b)} \sim \text{Bernoulli } (p_t^{(0)}) \tag{13}$$

When $p_t^{(b)}$ denotes the conditional probability of score Carlos Alcaraz under the null hypothesis H_0 , $b = 1, ..., B$, and B represents the number of permutation tests.

In simulated data, the maximum winning streak length $T_{\max}$ serves as a feature statistic for "momentum." Its role is illustrated through consecutive winning and losing streaks, while the persistence or intensity of momentum can also be treated as a feature statistic. The formula for calculating the maximum winning streak length is:

$$T_{\max} = \max\{T_+, T_-\} \tag{14}$$

When T_+ denotes the length of Carlos Alcaraz's consecutive scoring streak, while T_- denotes the length of Nicolas Jarry's consecutive scoring streak.

Combining the win rate deviation model, calculate the p -value using the permutation test. The formula is as follows:

$$p = \frac{1 + \sum_{b=1}^{B} 1\{T(y^{(b)}) \geq T(y)\}}{B+1} \tag{15}$$

When $\sum_{b=1}^{B} 1\{T(y^{(b)}) \geq T(y)\}$ denotes the maximum length of streaks occurring under the influence of momentum, exceeding the number of streaks without momentum. Therefore, when the p -value is small, it indicates that under random conditions, it is difficult for strong winning or losing streaks to emerge, suggesting that the progression and outcome of the game are significantly influenced by momentum.

Analysis of Results

By combining the match data from a certain bureau for Carlos Alcaraz and Nicolas Jarry, we solve the permutation test results for both models and visualize them, as shown in Figure 5.

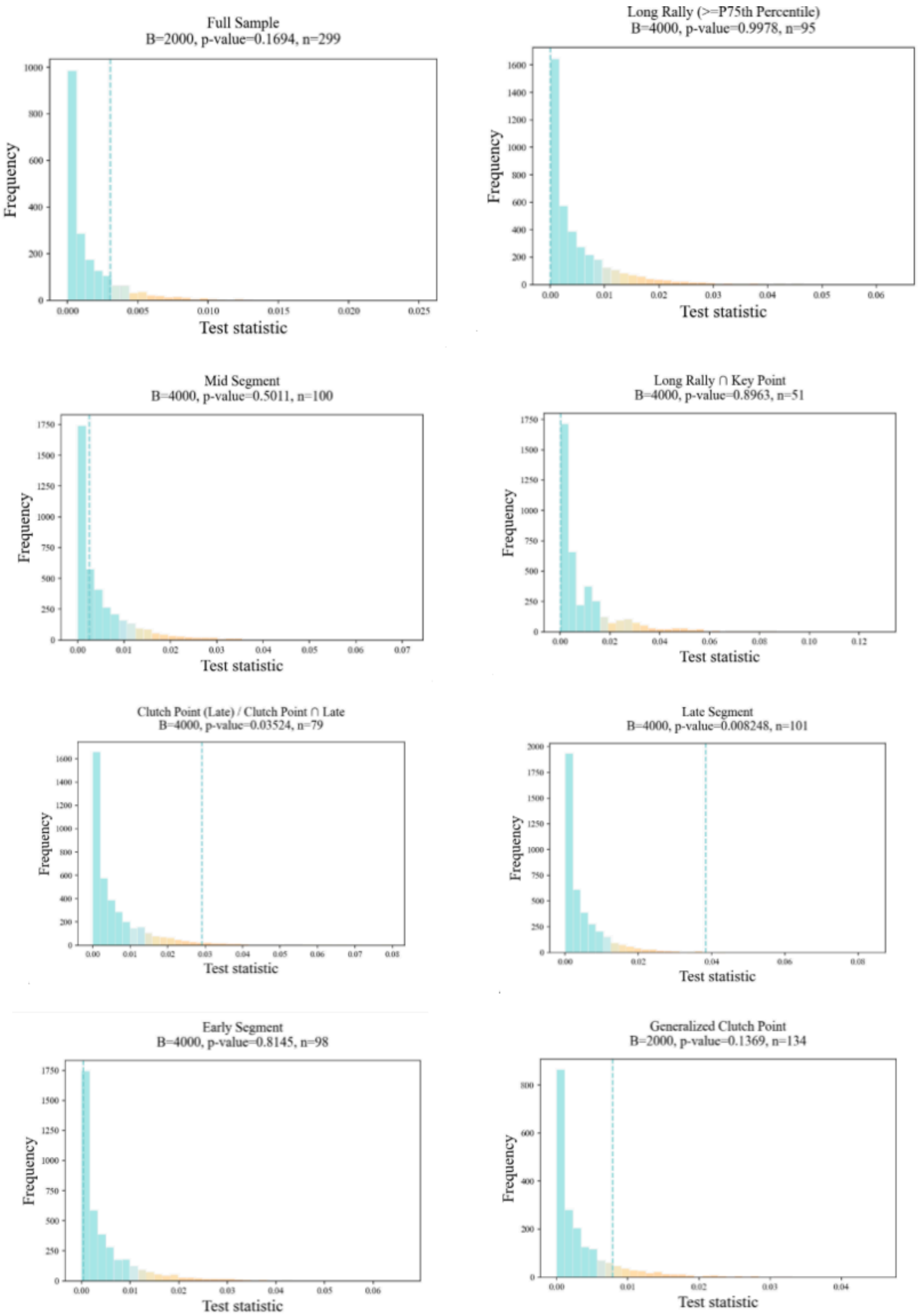

Figure 5. Relationship between p-values and test statistics in each round

From the overall results, this match provides no strong evidence supporting a "universal momentum effect." When momentum exists, A should be significantly positive and concentrated in the right tail of the distribution. Even the "Long rallies," "Early Segment," and "Mid Segment" factors showed no significance (with large p -values). This indicates that after controlling for structural factors like serve, second serve, break point, rally count, running difference, and point difference, the outcome of the previous point does not consistently influence the next point's outcome, and the "momentum" effect is not significant. Therefore, from a holistic perspective, the claim that "momentum = random fluctuation" cannot be readily dismissed.

However, analysis of the game's local progression reveals that momentum is not sustained throughout but is influenced by the latter stages and pressure. Within segment hierarchies, "Late Segments" showed significant effects ($p = 0.008$, $\Delta = 0.038$), and "Key points&Late Segments were also significant ($p = 0.035$, $\Delta = 0.029$). The test statistics for these segments fell markedly in the extreme right tail of the replacement distribution. This indicates that in the latter stages of the match—particularly when pressure from key points intensified—the outcome of the previous point exerted a stronger influence on the subsequent point. Psychological, physical, and strategic risk preferences were amplified during the final stages of the match. Consequently, while evidence for "momentum" was weak at the global level, statistically significant short-term dependencies emerged during the latter stages and under pressure points. This suggests that "momentum" is more likely a context-triggered localized mechanism rather than a consistent pattern spanning the entire match.

By solving the particle filter to obtain the continuous variation of the momentum difference during the match, we derive the hidden state of the momentum difference variation and its 95% confidence interval, as shown in Figure 6.

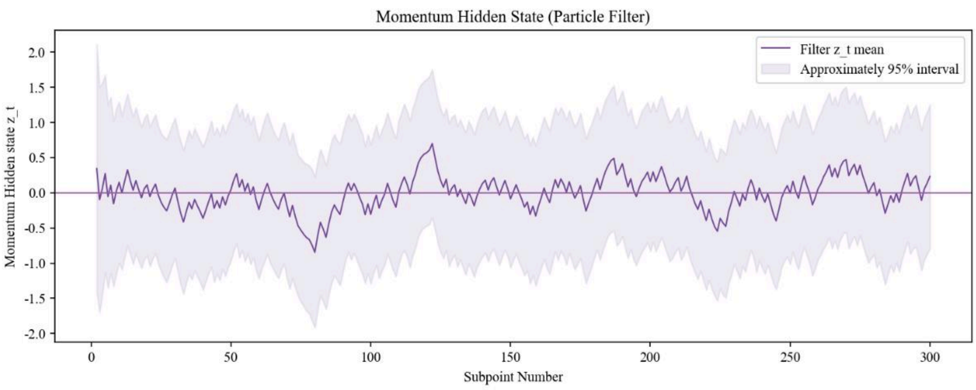

Figure 6. "Momentum difference" hidden state changes with 95% confidence intervals

Observing the chart above reveals that the estimated "momentum" fluctuates around zero for most of the time, with the 95% confidence interval crossing zero at the vast majority of data points. This indicates that after controlling for structural factors such as first serves, second serves, break points, rally length, running distance, and point difference, the model exhibits no significant bias toward "momentum." Many fluctuations can likely be attributed to the inherent randomness of the match. Consecutive wins or losses are more likely to result from explainable factors and natural fluctuations caused by noise, rather than a strong, persistent process influenced by momentum.

For this match, after smoothing the latent state changes of "poor momentum" based on player performance and match results, the outcome is shown in Figure 7.

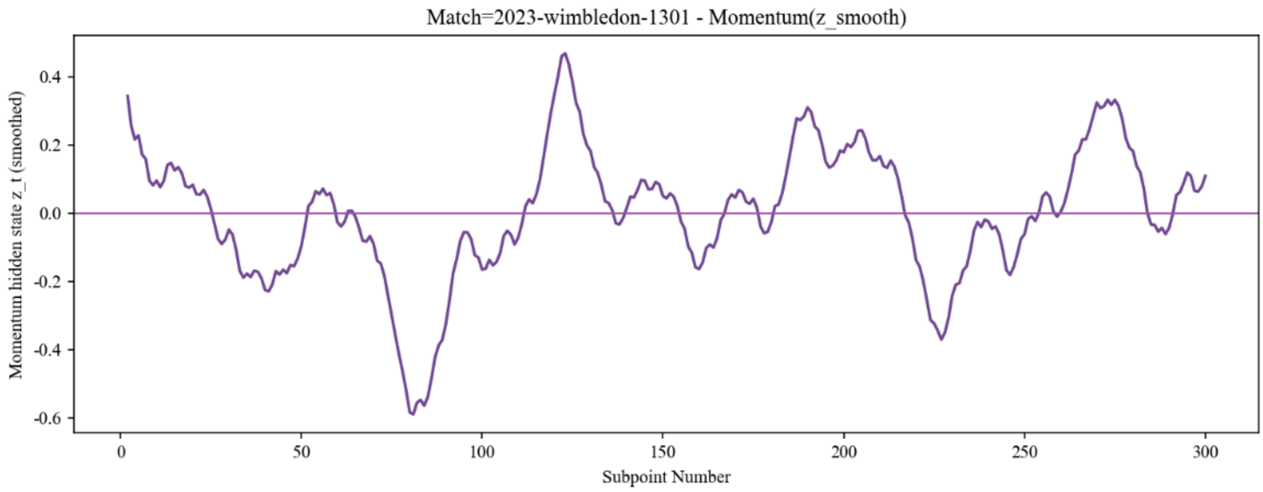

Figure 7. Smooth presentation of "momentum difference" hidden state changes

After smoothing out the "short-cycle noise" in the competition data, several distinct trend segments spanning dozens of sub-points become clearly visible. These trend segments precisely align with findings from the stratified analysis: the Late Segment is significant ($p = 0.008$) and the "Key points & Late Segments" factor is also significant ($p = 0.035$). This further validates the role of "momentum" as a localized mechanism—not a universal rule governing the entire field.

Particle filtering yields overall weak momentum (confidence intervals frequently span 0), yet smoothing reveals the presence of persistent segments. These segments tend to cluster toward the latter stages of matches and around critical points, explaining why the full sample shows no significance while "Late Segments" and "Critical points & Late Segments" demonstrate statistical significance.

INDICATORS AFFECTING ADVANTAGEOUS TURNAROUND

Model Overview

Combining the Bayesian state space model with the concept of momentum, this analysis examines key indicators for shifting competitive advantage and predicts turning points. By evaluating player performance metrics and risk rates, it identifies pivotal moments and proposes optimal strategies. The established model and solution process are illustrated in Figure 8.

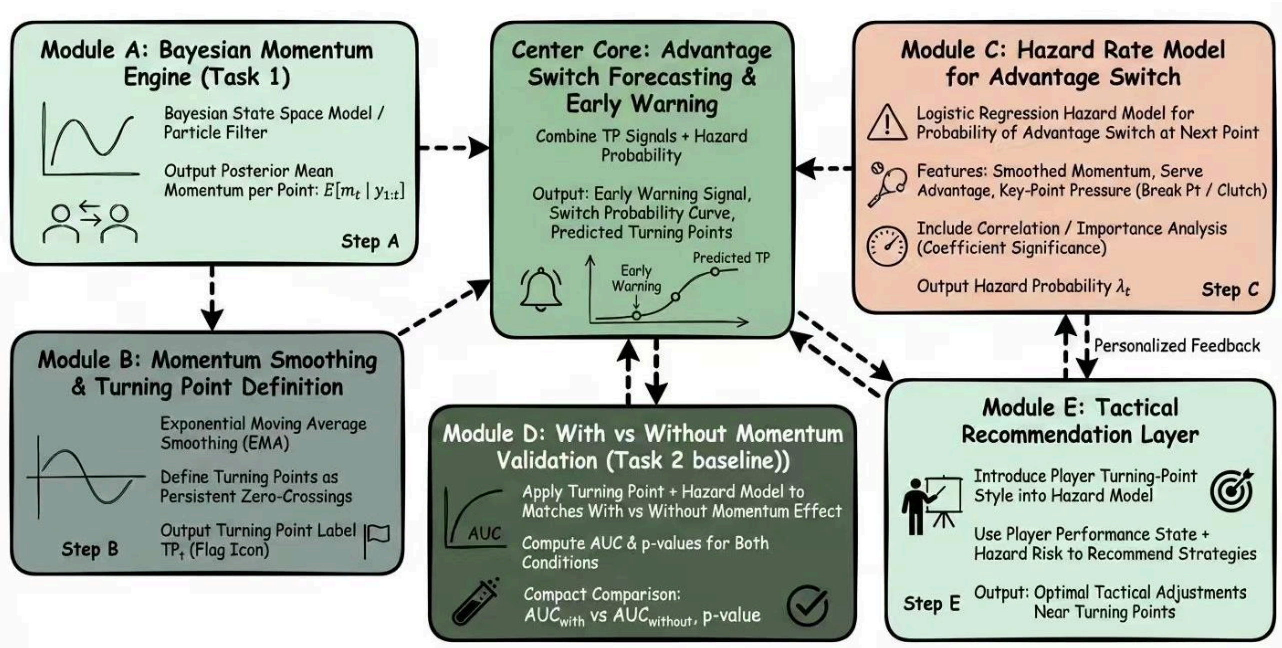

Figure 8. Overview of the model

Modeling

To investigate whether certain indicators can help identify turning points where the dominant team shifts in a match, we define a turning point as the moment when momentum crosses zero. A simple reversal might merely reflect momentum fluctuations, whereas a turning point signifies a change in dominance rather than the outcome of a single point. Based on the Bayesian state space model incorporating momentum effects, and utilizing the posterior probability of momentum difference at each scoring instance, the smoothed momentum $\tilde{z}_t$ is calculated via exponential moving average as follows:

Where η denotes the smoothing coefficient, and its autoregressive equation is $EMA_t = \eta \cdot \hat{z}_t + (1-\eta) \cdot EMA_{t-1}$

The timing of the turning point is represented as:

$$S_t = I(\tilde{z}_{t-1} > 0, \tilde{z}_t < 0) \vee I(\tilde{z}_{t-1} < 0, \tilde{z}_t > 0) \tag{16}$$

Based on the timing of turning points and the smoothing of "momentum," a hazard rate model is established to predict the next turning point where "momentum" occurs. Using a logistic regression model, the hazard rate calculation formula is derived as follows:

Where $|\ \tilde{z}_t\ |$ represents the current momentum stability, where a lower value indicates greater ease for the dominant side to shift momentum. $\Delta\tilde{z}_t$ reflects changes in smoothed momentum, with lower values signifying greater susceptibility to reversal. s_t denotes serve advantage, P_t represents pressure at key points, and f_t indicates other characteristic metrics.

The scores without the "momentum" effect are introduced to train the risk rate model and compute the inflection point data. Simultaneously, the risk rate model and inflection point calculations are applied to real match data to compare their predictive performance regarding advantage shifts. This comparative analysis transcends the mere existence of "momentum," advancing to the possibility of anticipating momentum shifts in advance.

Apply hierarchical transfer to historical dominant team transitions, stratifying by match progression to analyze dynamic shifts in momentum across different stages of the game. Utilize the risk rate model as the parameter for hierarchical transfer, defined as:

Where (i, j) denotes our player versus the opponent, $u_i \sim N(0, \sum_u)$ represents our style bias in momentum conversion, $v_j \sim N(0, \sum_v)$ indicates the opponent's style bias in transition, and g_t signifies characteristics such as momentum stability, rate of change, pressure at critical points, and rally length.

Based on layered transitions, preliminary indications can be provided according to the risk rate. For instance, when smooth momentum emerges after critical points or extended rallies, a surge in the risk rate indicates that the point is highly susceptible to shifting in favor of the dominant player.

Given the historical turning points, applying this further to tactical choices and abstracting real-time tactical decisions into a_t can alter the probability of winning the next point and the evolution of momentum. The following principles can be derived: If our side holds the advantage but h_t is high, the advantage may shift, necessitating more stable tactics to minimize errors and maintain control. Conversely, if the opponent holds the advantage but h_t is high, we can proactively create volatility by adopting more aggressive tactics to seize points. When the critical point is significant, tactics with fewer turning points and lower risk should be employed.

Analysis of Results

Key Indicators

Based on the above model, the curves depicting the evolution of momentum and risk rate throughout the match are obtained, as shown in Figure 9.

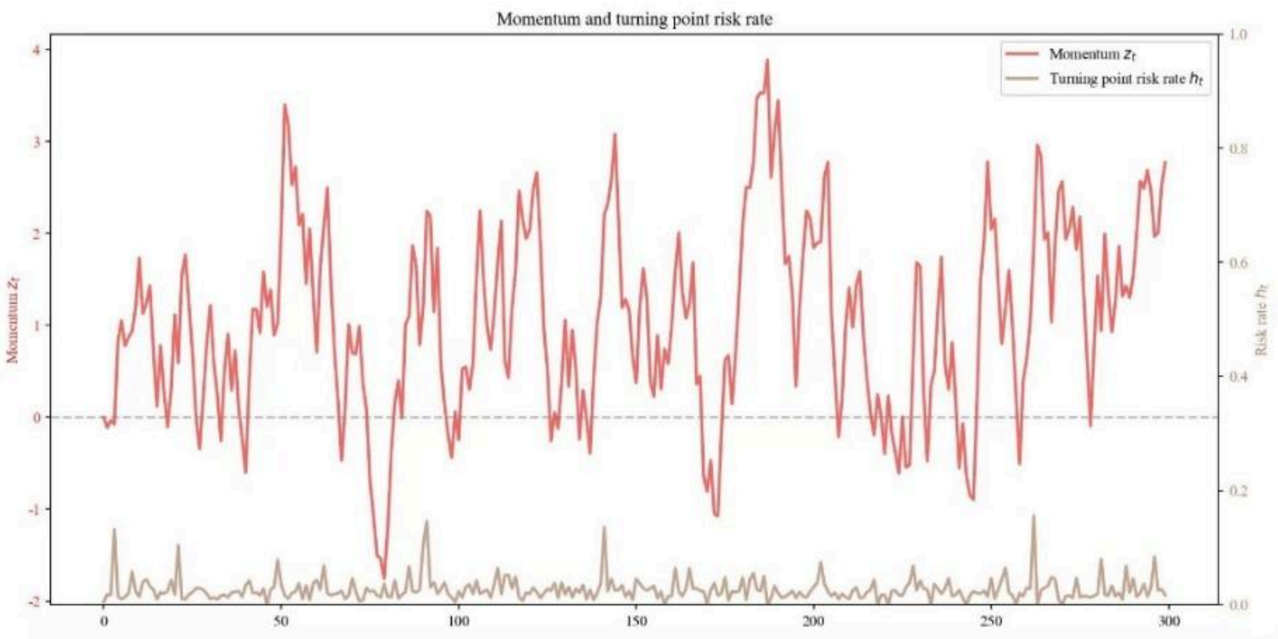

Figure 9. Momentum and hazard rate curves

Observations reveal that indicators capable of anticipating impending shifts in match dynamics do indeed exist. However, these indicators are not singular variables but function in predictions as a combination of "momentum state" and "technical behavior changes." In the Carlos Alcaraz vs. Nicolas Jarry match, only 5-9 turning points were detected, with a frequency of approximately 2%–3%. This indicates that genuine momentum shifts are sparse yet structured events—not random fluctuations—and can be anticipated through certain indicators.

Further analysis at the prediction level reveals that the turning point prediction model trained solely on technical features (i.e., incorporating the "momentum" effect) achieves an AUC of approximately 0.7 to 0.88 in real matches, significantly outperforming random guessing. This indicates that before a turning point occurs, "momentum"-driven behaviors exhibit systematic changes that can be captured by the turning point prediction model. Although overall significance is weak in the absence of "momentum," the prediction of turning points based on technical behaviors in real matches is not coincidental.

Therefore, the turning point of the match is predictable, but the focus of prediction is not "the outcome of the next point," but rather "whether the course of the match is shifting (whether the advantage is changing hands)."

Observing Figure 10 and Figure 11 reveals that the most significant factors influencing match turning points are concentrated in "risky behaviors" rather than "stable technical abilities." Among these, the difference in double faults, the difference in net approaches, and the difference in winners exhibit the largest absolute coefficients in the model, with clear directionality. The difference in double faults shows a strong negative correlation, indicating that a sudden increase in unforced errors by one player often signals an impending reversal in momentum. Net approaches and point differential reflect shifts in tactical initiative, frequently occurring during attempts to break a stalemate. Winner differential, meanwhile, captures short-term leaps in offensive efficiency rather than long-term skill advantages.

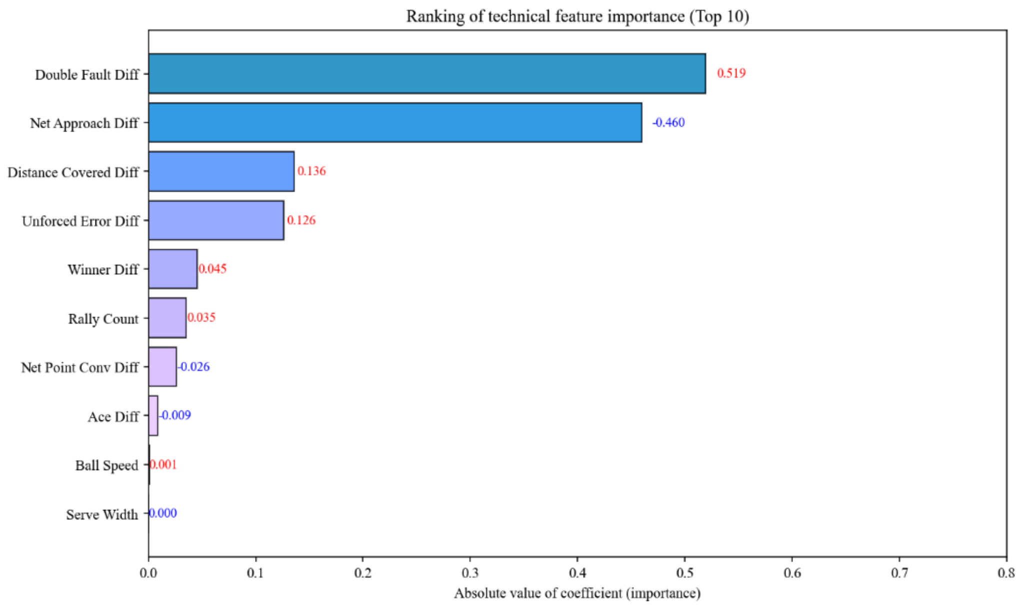

Figure 10. Ranking of the importance of characteristic indicators

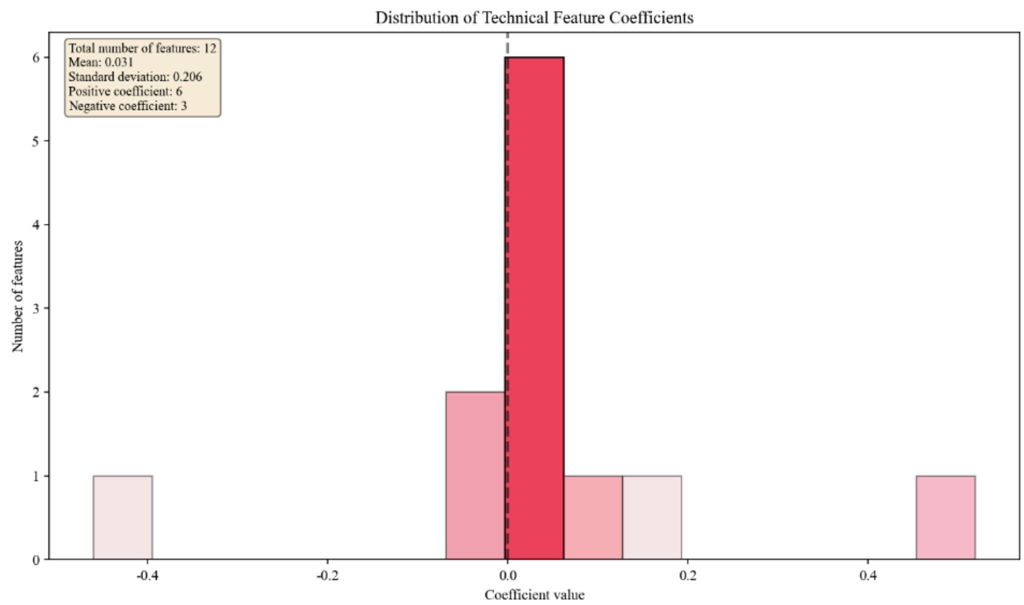

Figure 11. Distribution of the importance of characterization indicators

In contrast, traditional metrics such as ball speed, number of rallies, and serve width play a significantly weaker role in predicting turning points. This indicates that turning points stem more from "changes in strategic choices" than "fluctuations in technical skill." That is, matches are unlikely to see reversals primarily due to shifts in playing styles; rather, shifts in advantage during a match are more often driven by tactical decisions—adopting riskier or more conservative approaches.

Furthermore, analyzing the correlations between various characteristics and momentum reveals that these key technical features exhibit significant correlations with both the momentum variable z and the point-winning probability p_t . This indicates that they serve as both trigger points for reversals and amplification points for momentum shifts. This precisely validates the conclusion that momentum is not purely psychological but is driven by technical behavior. The risk behaviors identified by the model (e.g., increased double faults) often coexist with aggressive attacking strategies in tennis tactics. However, when these behaviors cause the momentum axis to cross the zero point (Turning Point), they more reflect the collapse of the players' psychological defense or physical bottleneck rather than active tactical adjustment. Therefore, the risk rate model provides an early warning signal to help coaches identify when tactical risk-taking evolves into systemic collapse.

Analyze the correlations among technical features in the match and visualize these relationships, as shown in Figure 12.

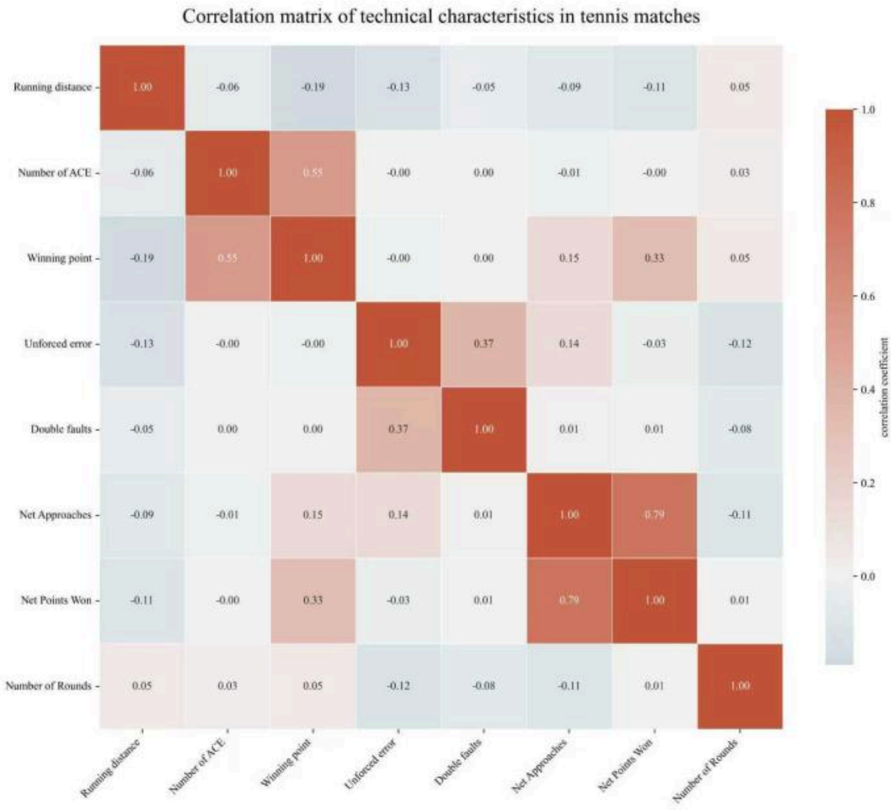

Figure 12. Heat map of the correlation of characteristic indicators

Observing the chart above reveals a strong positive correlation between net point differential and net point frequency, indicating high tactical and technical consistency among players, resulting in high success rates at the net. This demands an integrated approach to tactics and technique. The difference in unforced errors correlates positively with the difference in double faults, reflecting a chain reaction of errors under pressure. This indicates that scoring stability is influenced by a player's concentration. The difference in running distance correlates negatively with the difference in winners. This indirectly shows that players who generate more winners while covering less ground control the match's rhythm, forcing opponents into a defensive stance where they struggle to produce winners.

Different Match Recommendations

Based on our match-turning prediction model, combined with players' historical turning-point styles, we can provide more personalized tactical preferences for players during matches.

Based on the results of this model combined with historical data, momentum is not globally sustained but rather triggered under specific conditions. The no-momentum world test indicates that the momentum effect is not significant at the full sample level. However, when combined with scenarios involving the latter stages of matches and critical points, the momentum difference becomes statistically significant. This implies that players need not chase momentum throughout the entire match but should instead focus their efforts on the latter stages and moments when critical points accumulate.

Combining the tactical decision-making module, the optimal strategy in the Alcaraz–Jarry match was to adopt a conservative approach, only recommending increased aggression when the risk of a turning point significantly rose or when trailing. This outcome demonstrates that against different opponents, the key lies not in sustained offense, but in "timing the shift in risk level"—that is, altering the timing of turning points. For instance, against "consistent players," one should proactively create variations in the latter stages of the match to maintain a stable advantage. Conversely, when facing "high-volatility players," reducing one's own errors and waiting for the opponent to trigger a turning point is advisable, thereby shifting the advantage in one's favor.

Therefore, when facing different opponents, players should understand their historical patterns of momentum shifts—specifically, at which stages these shifts typically occur and what technical behaviors trigger them. Once these signals emerge during a match (such as a sudden surge in double faults or frequent net approaches), they should be interpreted as the opponent's intent. To prevent a reversal of overall advantage, players must immediately adjust their tactical intensity rather than passively reacting after the score has already shifted.

ACCURACY AND GENERALIZABILITY OF FORECASTS

Model Overview

Based on the mode, a model evaluation process is developed to assess the accuracy and predictive effectiveness of this model in forecasting shifts in match dynamics, while also analyzing its generalizability. The workflow for model establishment and solution is illustrated in Figure 13.

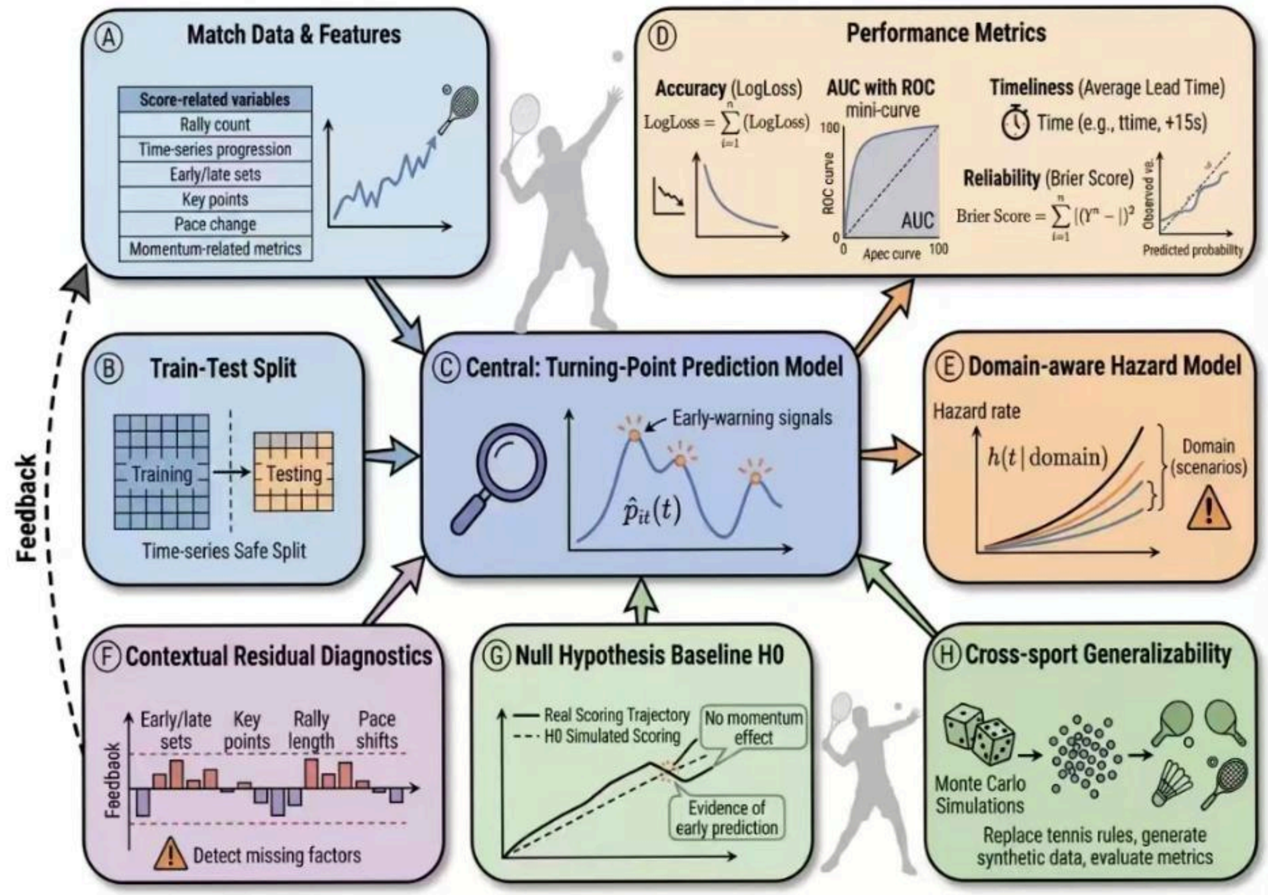

Figure 13. Overview of the model

Modeling

Establishment of Evaluation Indicators

Based on the persistent zero-crossing of the momentum curve, turning events are identified, and the match data is divided into the model's training set M and test set m . The risk rate model is integrated, consolidating all technical indicators into a feature matrix, yielding the following formula:

$$\text{logit }(h_t) = \theta_0 + \theta^T g_t \tag{17}$$

Based on the match turning point prediction model, the match data is divided into training and testing sets. Three evaluation metrics are established: accuracy assessment (log loss, AUC), timeliness of early warnings (average lead time), and overall reliability (Brier score).

Accuracy Metrics

The accuracy of predicting the probability of advantage-side switching is evaluated using a log-loss model, with the log-loss formula given as:

$$\mathrm{logLoss}_m = -\frac{1}{T_m}\sum_{t=1}^{T_m}[S_{t+1}\log h_t + (1 - S_{t+1})\log(1 - h_t)] \tag{18}$$

By assessing the relationship between the predicted probability and the actual occurrence probability, the closer the two are, the higher the accuracy; conversely, the lower the accuracy.

Evaluate the accuracy of the advantage-side conversion judgment in the turning point prediction model using AUC, specifically the accuracy of determining the level at which the advantage shifts during the match.

Timeliness of early warnings

Using actual match data, the set of turning point timestamps during the game serves as a reference. The turning point warning issued at time $t - k$ is recorded as the advance notice. The timeliness of the warning is assessed by calculating the average advance notice, determined by the following formula:

$$\mathrm{lead}_m(\tau) = \frac{1}{\mid T_m \mid}\sum_{t \in T_m}\max\{k \geq 0 : h_{t-k} > \tau\} \tag{19}$$

Where τ represents the threshold for the early warning. The lower the threshold, the more sensitive the detection of turning points becomes. A larger advance notice period allows for earlier detection of events, providing more ample time to prepare for shifts in competitive advantage.

Overall reliability

The accuracy of a predictive model is assessed by calibrating the probability of prediction through the Brier score, calculated as follows:

$$\mathrm{Brier}_m = \frac{1}{T_m}\sum_{t=1}^{T_m}(S_{t+1} - h_t)^2 \tag{20}$$

A value of 0 or 1 for this metric indicates a perfect model, meaning it delivers flawless predictions with extremely high reliability. A significant increase in the Brier score suggests the model cannot be applied to new domains and exhibits poor reliability.

Compatibility

To further demonstrate the accuracy of this model, domain variables are introduced to establish a hazard rate model with random domain existence, which is applied to competitions in different scenarios. The formula for incorporating domain variables into the hazard rate model is as follows:

$$\text{logit }(h_t) = \theta_0 + \theta^T g_t + a_D + b_D^T g_t \tag{21}$$

Where a_D denotes the domain intercept, $a_D \sim N(0, \sigma_a^2)$, while b_D represents the rate of change of the domain feature index, $b_D \sim N(0, \sum_b)$.

In different scenarios, such as the beginning or end of a set, crucial points, the number of rallies, or changes in pace, the residual is calculated and predicted to analyze whether relevant factors are missing in a given scenario. The formula is as follows:

$$r_t = S_{t+1} - h_t \tag{22}$$

When the residual mean exhibits a positive or negative bias, it indicates that relevant factors are missing in that scenario. The accuracy of the model's predictions can be improved by incorporating additional relevant indicators.

Introducing the baseline win rate model without momentum effects (i.e., H_0), we apply both actual scores and H_0 -based scores to a hazard rate model with domain randomization, then compare their accuracy.

The accuracy on real data is denoted as AUC_m , while the accuracy without momentum is $AUC_m^{H_0}$. When $AUC_m \gg AUC_m^{H_0}$, it indicates that early warnings of advantage shifts exist in the competition, rather than random outcomes.

Extend to other competitions

To analyze the universality of the hazard rate model with domain randomization, the model was extended to other sports by replacing tennis rules with those of other games, such as table tennis and badminton. This adaptation included key features like scoring systems, critical points, and pivotal rallies. Relevant data for these sports were obtained through Monte Carlo simulations and substituted into the model, yielding:

$$\text{logit }(h_t) = \theta_0 + \theta^T G_t \tag{23}$$

Where G_t denotes the values of the feature vectors from other competitions.

By applying the model to badminton, table tennis, and other sports competitions, we evaluate its accuracy metrics through computational analysis. Comparing these calculated metrics with actual performance data allows us to assess the applicability of the domain-specific random risk rate model in these sports, thereby reflecting its generalizability.

Analysis of Results

Accuracy of the Turning Point Prediction Model

Based on the evaluation model, the accuracy metrics, momentum curve, and turning points of the match turning point prediction model are shown in Table 3 and Figure 14, respectively.

Table 3. Stability of the model (tennis)

Type of Exercise	AUC	LogLoss	Brier Score
Tennis	0.78	0.44	0.14

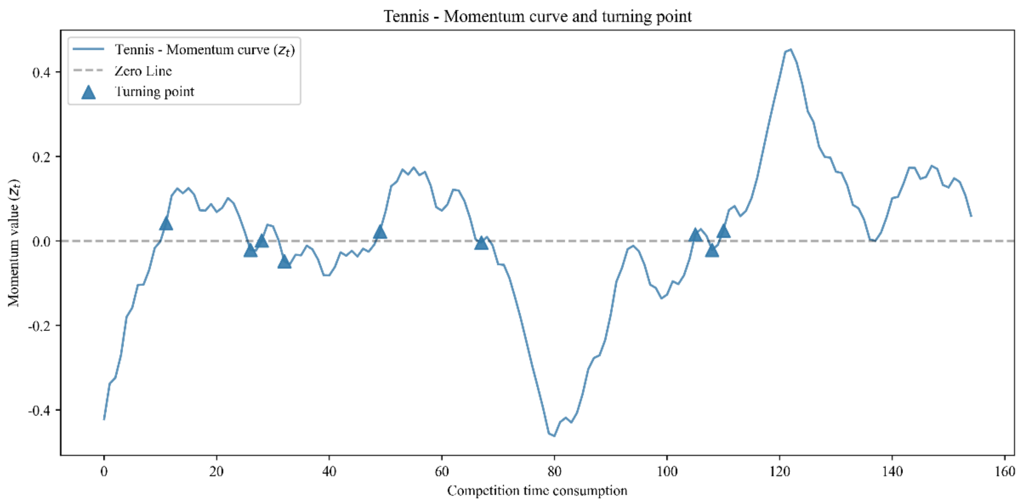

Figure 14. Tennis-momentum curve and turning point

Analysis of Table 3 and Figure 14 reveals that using AUC, LogLoss, and Brier Score as evaluation metrics, the model performs well in tennis matches, significantly outperforming the random baseline. This indicates the model can accurately distinguish moments when "the momentum is about to shift" from those when "the momentum remains stable." The alignment between the probability curves and actual turning points reveals that the model's high probability predictions in tennis matches frequently coincide with periods of score changes or critical games, demonstrating strong interpretability.

Regarding the reasons for the model's suboptimal performance, feature expansion experiments clearly reveal areas for improvement: incorporating the difference in winning points between players and the difference in consecutive points scored significantly enhances the model's ability to capture nonlinear shifts in match dynamics. Particularly in tennis, these two features elevated the AUC from 0.78 to 0.96, indicating that short-term scoring bursts and key-point advantages are core drivers of sudden match transitions. Future models could further incorporate serving quality, rally length distributions, or psychological pressure proxy variables to enhance stability in complex match scenarios.

From a modeling perspective, this model relies on score evolution, momentum shifts, and their temporal structure rather than gender-specific or event-specific rules. Therefore, it theoretically exhibits strong cross-competition applicability. Testing on other match datasets indicates the model possesses robust capability in identifying game-changing moments, though its performance varies significantly across sports. For women's competitions or events at different levels, the model can be directly applied without structural adjustments as long as the scoring system and round structure remain consistent. The primary differences lie in parameter distributions and threshold settings for transition probabilities.

However, different court surfaces—such as hard courts, clay courts, and grass courts—may indirectly alter the shape of momentum curves by influencing rally length, winning shot percentage, and break point frequency. Therefore, when applying these metrics across court surfaces, it is advisable to introduce court-specific adjustment factors or perform lightweight recalibration to avoid systematic bias. This issue also exists in women's competitions but can be effectively mitigated through data-driven approaches.

Generalizability of Breakpoint Prediction Models

Using Monte Carlo simulations, we obtained relevant match data for badminton and table tennis. By inputting this data into the model, we derived momentum curves and turning rates for table tennis and badminton matches, respectively. Combining these with the evaluation model, we compared the accuracy of the three ball sports, as shown in Figure 15, Figure 16, and Figure 17.

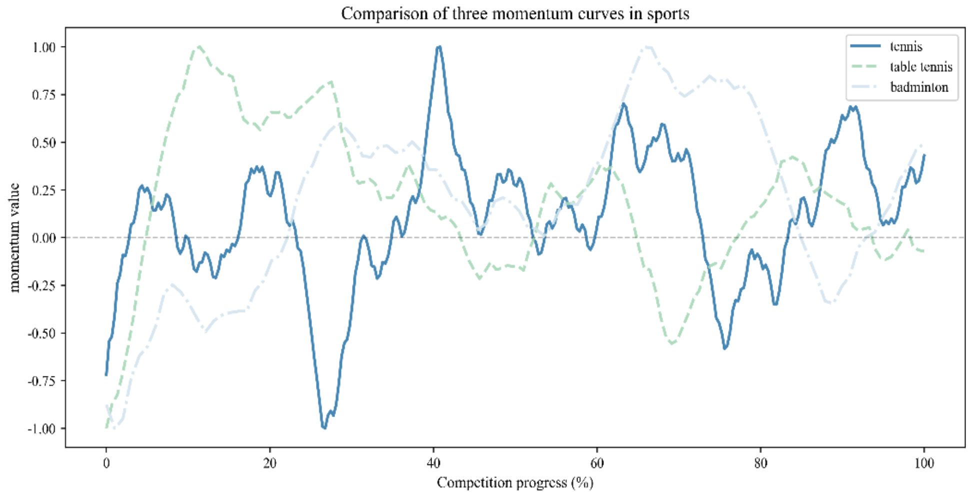

Figure 15. Momentum curves for the three movements

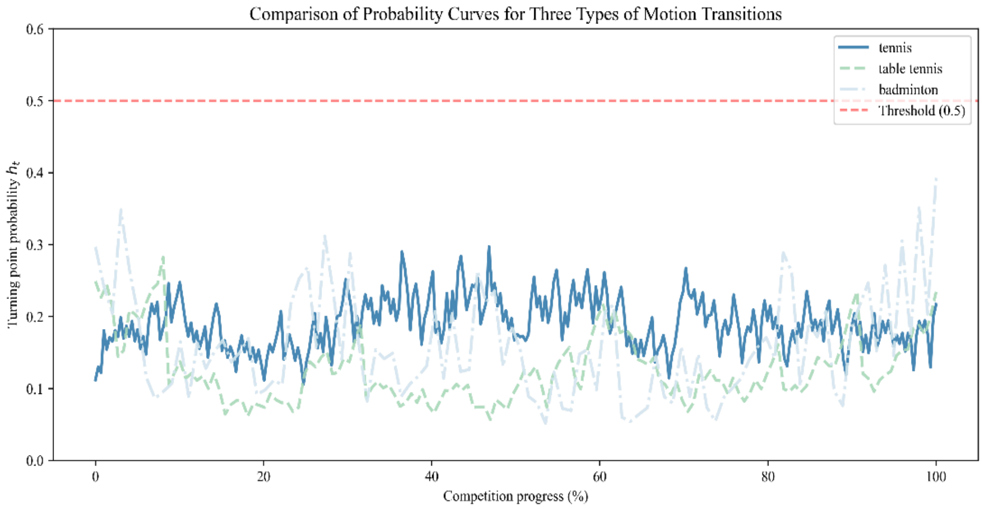

Figure 16. Momentum-turning curves for three movements

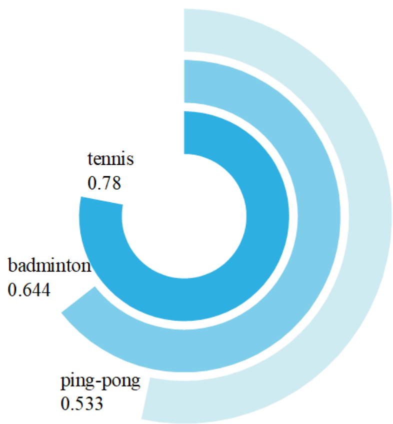

Figure 17. Accuracy of the three sports

Cross-sport experimental results show that the model achieves AUC values of approximately 0.64 and 0.53 for table tennis and badminton, respectively. While still outperforming random predictions, its discriminative capability significantly declines, reflecting differing levels of adaptation to distinct sport rhythms and scoring mechanisms. This demonstrates that the "modeling framework based on momentum and turning point probability" possesses a degree of cross-sport generalization capability. This demonstrates that momentum shifts, as an abstract dynamic phenomenon, share common structural elements across different competitive sports. In table tennis and badminton matches, the probability of momentum shifts fluctuates more frequently but exhibits less pronounced peaks, leading to insufficient model confidence in identifying true turning points. This suggests the model performs better in slower-paced competitions with clearly segmented structures.

Meanwhile, the model's diminished performance in these projects exposed its limitations: when match paces are extremely fast and scoring rallies are exceptionally brief, relying solely on smoothed momentum curves proves insufficient to accurately capture genuine turning points. To achieve greater cross-sport generalizability, the model must further integrate sport-specific key variables—such as serve-receive rotations and consecutive attack points—thereby enhancing adaptability to sport-specific variations while maintaining a unified framework.

SENSITIVITY ANALYSIS

In this section, we perturb each feature factor based on the original model, recalculate the model's AUC value, and examine the model's stability, as shown in Figure 18 and Figure 19, respectively.

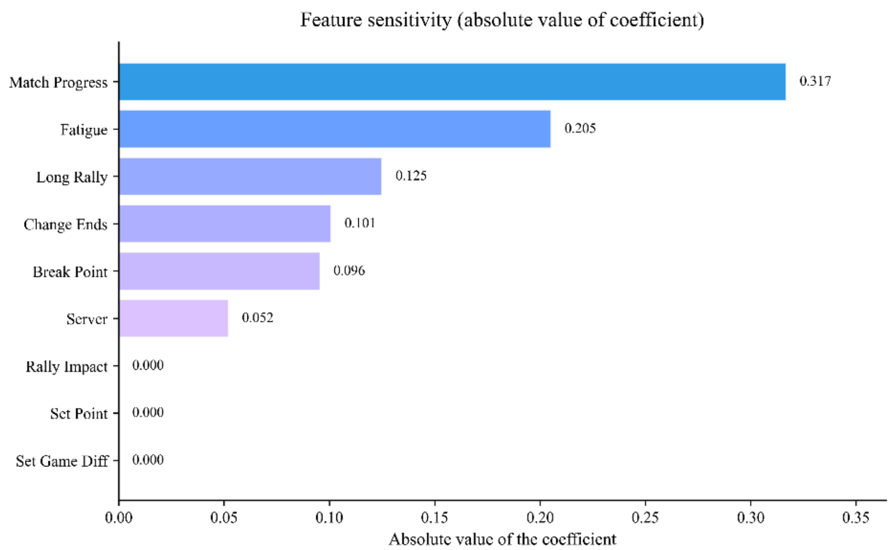

Figure 18. Feature sensitivity (absolute value of coefficient)

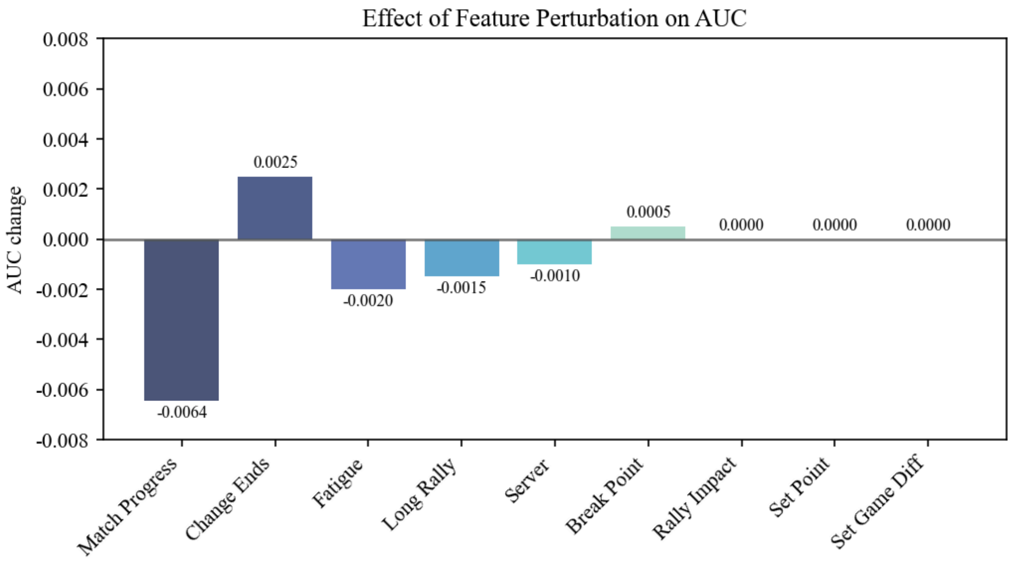

Figure 19. Influence of various factors on the model and AUC perturbation

The feature sensitivity analysis results in the figure above reveal that among all influencing factors, the match progression and fatigue value exert the most significant impact on the model, with absolute coefficient values reaching 31.7% and 20.5%, respectively. Meanwhile, the AUC variation values following feature perturbations remain at relatively low levels, with the maximum change amounting to only 0.0064. This indicates that the model exhibits minimal susceptibility to fluctuations in individual features, demonstrating robust stability.

CONCLUSIONS

Through Bayesian state-space modeling and multilevel statistical tests, this study systematically deconstructed the patterns of momentum evolution in competitive sports. The research confirmed that momentum is not a monotonically accumulating process that spans the entire game, but rather a localized warning signal triggered in the latter stages of a match and under high-pressure conditions, essentially manifesting as an instantaneous characteristic of the system's tendency toward instability. By identifying risk indicators such as double faults and net-rushing strategies, the study successfully reconstructed momentum shifts, providing scientific grounds for a shift in coaching philosophy from "chasing momentum" to "managing momentum risk." However, the current study has certain limitations, such as the model's inability to directly observe players' psychological thresholds or fatigue levels, and its adaptability in extremely fast-paced matches remains to be improved. Future research should focus on integrating real-time wearable sensor data and incorporating sport-specific key variables (such as service rotation changes) to construct a more robust cross-scenario predictive framework. Although the current empirical analysis of this study focuses on a single top-level match (the 2023 Wimbledon Final), its significance lies in providing a reusable dynamic monitoring logic. The rich data dimensions of this match provide a high-resolution slice for verifying the local momentum trigger mechanism. Future research will strive to apply this framework to a wider database of professional events to enhance the statistical generality of the conclusions. Although this study has made significant progress in model prediction accuracy and generalization, there are still limitations: the current framework has not directly integrated real-time physiological indicators of players (e.g., heart rate, fatigue). Future research will focus on two points: first, introducing real-time biofeedback data based on wearable devices; second, conducting nonlinear corrections for the impact of different court types (grass, clay, hard court) on momentum transmission rate, so as to build a more robust full-scenario prediction system.

Author Contributions

Conceptualization – Haiyang Ding; methodology – Haiyang Ding; formal analysis – Mengye Meng; investigation – Ziyang Ma; resources – Haiyang Ding; writing-original draft preparation – Mengye Meng and Ziyang Ma; writing-review and editing – Haiyang Ding and Jianfan Lu; visualization – Mengye Meng; supervision – Jianfan Lu. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding.

Acknowledgements

Not applicable

REFERENCES

[1] Qiu M, Zhang K, Chao Y, et al. Interrupt or reinforce? The impact of timeout on momentum in basketball game. Frontiers in Psychology. 2025; 16:1673186. doi: 10.3389/FPSYG.2025.1673186.

[2] Tenenbaum G, Zion B T, Lev A. Technical fouls as a trigger of momentum change: analysis of two decades of NBA data. International Journal of Sport and Exercise Psychology. 2025; 23(6):905-922. doi: 10.1080/1612197X.2024.2369219.

[3] Lev A, Maymon K Y, Zion B T, et al. Strategic impact: Technical fouls and momentum shifts in basketball games – unveiling insights across quarters of two decades of NBA data. International Journal of Sports Science & Coaching. 2025; 20(4):1598-1607. doi: 10.1177/17479541251333926.

[4] Á.S. Machado, C. De la Fuente, A. Javaloyes, et al. Exploratory analysis of cumulative fatigue derived from volume and intensity indicators in stage races of professional cycling. Science et Sports. 2025; 40(5-6):387-396. doi: 10.1016/J.SCISPO.2024.12.005.

[5] Li B, Deng Z, Gupta G, et al. Predicting tennis match outcomes mid-game using machine learning on psychological and physical data. Journal of Big Data. 2025; 12(1):159-159. doi: 10.1186/S40537-025-01216-4.

[6] Wei C, Li X. Research on the Performance Evaluation and Momentum Analysis of Athletes in Matches Based on the Entropy Weight Method. Academic Journal of Computing & Information Science. 2025; 8(6). doi: 10.25236/AJCIS.2025.080613.

[7] Wang L, Chen P, Sabir A U Q. Tennis Game Dynamic Prediction Model Based on Players' Momentum. AppliedMath. 2025; 5(3):77-77. doi: 10.3390/APPLIEDMATH5030077.

[8] Nigro F, Biondi G, Sirocchi P, et al. Changes in Sprint Momentum in Elite Rugby Union Players over a Three-Season Period. Applied Sciences. 2025; 15(13):7087-7087. doi: 10.3390/APP15137087.

[9] Liu H, Huang X, Gu J, et al. TCDformer-based momentum transfer model for long-term sports prediction. Expert Systems With Applications. 2025; 289:128310-128310. doi: 10.1016/J.ESWA.2025.128310.

[10] Wang D, Zhang X, Xie Y, et al. Quantifying momentum and influencing factors of tennis players using the XGBoost model. Scientific Reports. 2025; 15(1):17297-17297. doi: 10.1038/S41598-025-02465-2.

[11] Wu S, Diao M, Wang J, et al. A Study on the Optimisation of Tennis Players' Match Strategies from the Perspective of Momentum. Applied Sciences. 2025; 15(10):5624-5624. doi: 10.3390/APP15105624.

[12] Tenenbaum G, Maymon K Y, Zion B T, et al. The Effect of Technical Fouls on Momentum Change in Basketball: A Comparison of Regular Season vs. Playoffs in the NBA. Information. 2025; 16(4):307-307. doi: 10.3390/INFO16040307.

[13] Douchet T, Michel A, Verdier J, et al. Intensity vs. Volume in Professional Soccer: Comparing Congested and Non-Congested Periods in Competitive and Training Contexts Using Worst-Case Scenarios. Sports. 2025; 13(3):70-70. doi: 10.3390/SPORTS13030070.

[14] Zhou X, Ke Z, Zhou H. Research on Tennis Match Momentum Based on Dynamic Quantitative Model. Transactions on Computational and Applied Mathematics. 2025; 5(1). doi: 10.23977/TRACAM.2025.050101.

[15] Xia Y, Li C, Zhang T. Analyzing Momentum Shifts in Tennis: A Machine-Learning Approach to Predicting Match Outcomes. Applied Sciences. 2025; 15(4):2018-2018. doi: 10.3390/APP15042018.

[16] Chen Y, Wang H. Momentum Prediction of the Tennis Match Flow. Journal of Medicine and Physical Education. 2025; 2(1). doi: 10.62517/JMPE.202518104.

[17] Xia Y, Gong Z, Wei F. An Exploration of Ball Game Momentum Fluctuations Based on Multiple Regression Analysis and Convolutional Neural Networks. Journal of Electronics and Information Science. 2025; 10(1). doi: 10.23977/JEIS.2025.100102.

[18] Goldschmied N, Mauldin K, Thompson B, et al. NBA game progression of extreme score shifts and comeback analysis: A team resilience perspective. Asia Journal of Sport and Exercise Psychology. 2024; 4(3):75-81. doi: 10.1016/J.AJSEP.2024.10.011.

[19] Yang D, Zhang Q, Luan B. Study on Dynamic Prediction Model for Tennis Matches Based on Multi-Dimensional Indicator Evaluation. Academic Journal of Computing & Information Science. 2024; 7(8). doi: 10.25236/AJCIS.2024.070805.

[20] Nan S, Wang S, Jiao D, et al. Research on the impact of momentum based on quantitative models. Advances in Computer, Signals and Systems. 2024; 8(5). doi: 10.23977/ACSS.2024.080507.