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# Research on the Performance Evaluation and Momentum Analysis of Athletes in Matches Based on the Entropy Weight Method

**Chaoying Wei, Xuwei Li***

*School of Advanced Manufacturing, Fuzhou University, Quanzhou, China, 362251*
**Corresponding author: sun484173006@163.com*

***Abstract:*** *This study delves into the intricate problem of quantifying and evaluating tennis players' performance during matches and its direct relationship with match outcomes. By employing the Entropy-weight Method, the research constructs a robust and comprehensive evaluation model that meticulously quantifies players' performance across various stages of a match. The model leverages the Pearson Correlation Coefficient and Spearman Rank Correlation Coefficient to rigorously verify the strong correlation between player performance metrics and match results. These statistical tools ensure the reliability and validity of the findings, highlighting the importance of performance consistency and adaptability in determining match success. Additionally, through the integration of real-time data and innovative Boolean operation visualization techniques, the study provides a dynamic analysis of the trend relationship between match fluctuations and player performance. The results reveal a significant correlation between player performance and match fluctuations, with the momentum accumulation process emerging as a critical factor in shaping match outcomes. This model not only equips coaches and players with actionable insights for real-time tactical adjustments but also offers a scientific foundation for predicting match results. By bridging the gap between theoretical analysis and practical application, this research holds substantial value for the sports science community, enhancing both strategic decision-making and performance optimization in competitive tennis.*

***Keywords:*** *Entropy-Weight Method, Pearson Correlation Coefficient, Spearman Rank Correlation Coefficient, Tennis Match Performance Evaluation, Momentum Analysis*

## 1. Introduction

Momentum means that a player benefits from a psychological and/or physiological boost. A psychological boost is a positive change in cognition [1]. In sports psychology, studying momentum can help predict athletes' performances because athletes may feel they have "momentum" during a game, but it is difficult to measure how momentum occurs or changes [2-8]. The present research examines psychological momentum (PM), a perceived force that lay intuition suggests influences performance [9-10].

Previous research has predominantly focused on qualitative descriptions of momentum. For instance, Helmut Dietl and Cornel Nesseler [1] demonstrated that momentum provides a significant advantage to players when they are in control of a match, while Martínez J. A. [9] highlighted through data analysis that momentum often emerges when players initiate attacks or face challenges. However, these studies have not systematically quantified the mechanisms of momentum transfer or identified the critical turning points in momentum shifts. Additionally, although Markman and Guenther [10] proposed a psychological momentum theory based on a Newtonian physics model and applied it to non-sporting contexts, its applicability in competitive sports remains to be further validated. We have carried out the following work. Through data-driven model construction and correlation analysis, we have quantified the performance of players and deeply explored the relationship between momentum and game results. Our work not only provides a basis for coaches and players to make real-time tactical adjustments but also provides scientific support for the prediction of game results. Specifically:

We have quantified the performance of players in the game through the entropy weight method and visualized the dominance of players in different time periods.

We have verified the strong correlation between momentum and game results through Pearson and Spearman correlation coefficients and revealed the influence of momentum changes on the trend of the

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game through the analysis of cumulative momentum.

These works provide a scientific basis for understanding the momentum phenomenon in games and support coaches and players in making more informed decisions during games.

## 2. Evaluation model of tennis players' match performance based on Entropy-Weight Method and Correlation Analysis, with a study on the correlation trend of match fluctuations

### *2.1 Model for evaluating tennis players' match performance*

The entropy-weight method is a multi-attribute decision analysis method. Entropy-weight Method calculates the information entropy of each factor to determine its contribution in decision-making, so as to get the weight allocation, fully considering the information and diversity of each indicator, and more comprehensively reflecting the differences between the indicators. The theoretical framework of the Entropy-weight method is relatively simple and easy to understand and apply. This makes it operable in practical decision-making problems.

$$E_i = -\sum_{j=1}^{m} p_{ij} \cdot \log_2(p_{ij}) \tag{1}$$

Where $p_{ij}$ is the share of the j-th subgroup of the i-th indicator.

$$K_i = \frac{1}{\log_2(m)} E_i \tag{2}$$

Where m is the number of groupings.

$$\omega_i = \frac{1-K_i}{n-\sum_{j=1}^{n} K_j} \tag{3}$$

(1) The BP neural network is linked by different node coefficients. When connecting weights and weights are positive, it indicates that the current link is in an exciting state. Conversely, if the link coefficient is negative, the link state is a state of suppression.

(2) The input signal and the linear signal are the combination of the signals for each input signal.

(3) The function of the nonlinear activation function: making the neuron output signal within a certain range.

### *2.2 Modeling for the correlation analysis between player performance and match fluctuations*

(1) Employing Correlation Coefficient Calculation for Data - Driven Relationship Modeling

A specific model is employed to deeply analyze the relationship between player performance and match results. The data correlation analysis method is mainly utilized, with an emphasis on calculating the Pearson correlation coefficient and the Spearman rank correlation coefficient.

(2) Data standardization

The collected player match data, including various index data such as scores, errors, and serving conditions, undergoes standardization. This process transforms data with different dimensions into a unified standard, ensuring that all index data is on the same comparable scale and eliminating the impact of dimensional differences on the calculation of correlation.

(3) Calculation of Correlation Coefficients

Based on the standardized data, the value of the Pearson correlation coefficient is calculated according to the formula (4) to measure the strength of the linear relationship between variables. Meanwhile, the Spearman run correlation coefficient is calculated according to the formula (5) to capture a broader range of monotonic relationships between variables. Thus, a model framework that can accurately reflect the relationship between the two is constructed.

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$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{4}$$

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \tag{5}$$

Where $d_i$ is the rank difference between the corresponding observed values of the two variables, and n is the sample size.

(4) Modeling of the Analysis of Player Performance Momentum Accumulation Process (Real-time Data Integration Method)

With player performance at the core, the analysis of the momentum accumulation process is carried out using real-time data.

(5) Real-time Data Collection and Organization

During the match, various technical means such as court sensors and video tracking systems are used to collect players' performance data in real-time, including scores, errors, and time intervals between shots. Subsequently, the collected raw data is organized, classified, and labeled according to the match time sequence and specific match events (the start and end of each game and set) to ensure the accuracy and integrity of the data.

(6) Calculation of Positive and Negative Performances and Points

A set of calculation methods is designed. According to the match rules and the evaluation criteria for player performance, the positive and negative performances of players in each time segment are determined. For example, scores can be counted as positive performances, and errors as negative performances. At the same time, point-scoring rules are set, and different point-scoring weights are assigned based on factors such as the importance of scores and the match stage. By continuously accumulating the points corresponding to these positive and negative performances, an integrated accumulation sequence that comprehensively reflects players' match performance is constructed, enabling the evaluation of players' dynamic performance and overall competitive level in the match, and forming a performance momentum accumulation model.

(7) Modeling of the Analysis of the Correlation Trend between Match Fluctuations and Player Performance (Boolean Operation Visualization Method)

Taking the correlation between the win-loss of the last ball in the match and the final win-loss of the match as the starting point, the cumulative performance is analyzed.

(8) Boolean Operation on Cumulative Performance

The win-loss situation of the last ball in each match is regarded as a key event and is associated with the final win-loss result of the match. Through Boolean operations, the cumulative performance of players throughout the match is transformed into logical values. That is, if a player wins the last ball and the match finally wins or loses the last ball and the match finally loses, it is recorded as one logical state; otherwise, it is recorded as another logical state. In this way, the correspondence between player performance and match results is simplified and clarified.

(9) Visualization and Correlation Analysis

The dichotomy is used for value-taking, and the results of the Boolean operations are represented in an intuitive way. For example, the orange line represents the player number of the winning side of the match, and the blue dotted line represents the player side with a more advantageous performance. Using data visualization tools, a special chart is drawn to graphically present the relationship between match fluctuations and player performance. In the correlation analysis, the Pearson correlation coefficient and the Spearman rank-correlation coefficient are used again to calculate the correlation between the two, constructing a model that can accurately reveal the correlation trend.

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## 3. Experimental results and analysis

### *3.1 Establishment and verification of simulation mode*

Taking into account factors such as serve advantage, time interval between wins, errors, and psychological burden in winning streak, seven features such as match point difference, number of aces, number of game-winning points, length of the match, unforced errors, player's final win/loss, and winning streak coefficient were selected as evaluation indexes, and an improved entropy weighting method to assign weights to the features was used to establish a model that can predict which player will be the best performer at a certain point of the match. A model that can predict which player will perform better at a certain moment of the game is more likely to win the game. As shown in Figures 1 and 2.

The data for this study was obtained from the 2023 Wimbledon Tennis Championships Focus Match Records, and the data was stored in the form of Excel tables containing detailed technical statistics and match progress information for multiple matches. The data for each match recorded information on multiple dimensions such as the time of the match, player performance, points scored, serve data, and distance run. The data covers a number of highlight matches such as Carlos Alcaraz vs Nicolas Jarry and Alexander Zverev vs Matteo Berrettini. By analyzing these data, it is possible to gain a deeper understanding of the key points in the game, the technical characteristics of the players and the game strategy, and to provide data support for the subsequent training and prediction of machine learning models.

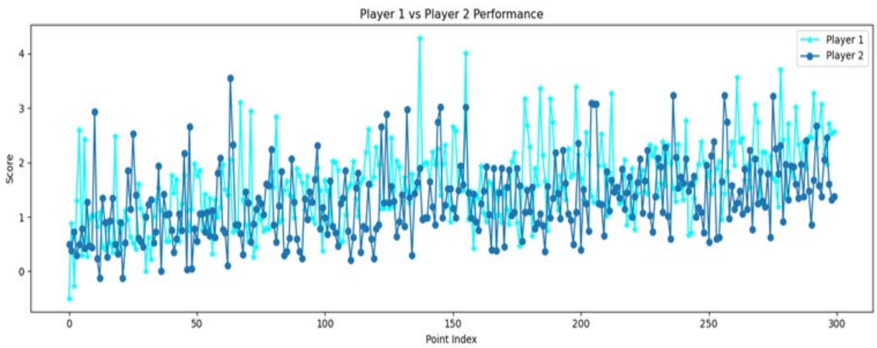


*Figure 1 Schematic diagram of factors related to the calculation of player performance scores*

The player performance evaluation of a match was carried out by this evaluation model, and according to the observations in Figures 1 and 2, the vertical axis reflects the performance scores of the players in each match, and the horizontal axis indicates the number of the match. Overall, player 1 showed a more impressive performance throughout the match and scored slightly higher than player 2.

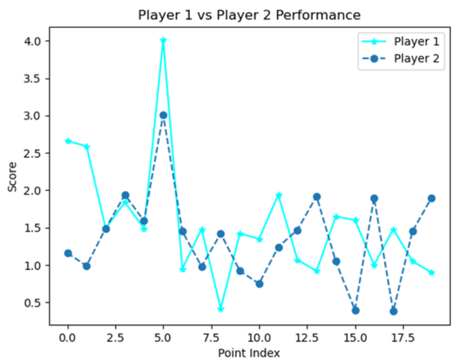


*Figure 2 Player 1 vs Player 2 Performance Score Chart (partial)*

Upon further scrutiny of Figure 2, the data segment intercepted in the middle shows the significant dominance of Player 1 during this period, with a significantly higher score than that of Player 2, highlighting the difference in performance between the two players. This may indicate that Player 1 had a more prominent level of performance at a particular stage of the game, providing the researcher with clues to analyze and explain the differences between the two players in depth. Demonstrates the superior performance of player 1 relative to player 2. The experimental results verified the validity and accuracy of the model in reflecting the overall performance of the players.

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### *3.2 Correlation analysis of experimental results*

Based on the question of "correlation between player performance and match results", we used data correlation analysis methods, including the calculation of Pearson's correlation coefficient and Spearman's rank correlation coefficient [(with correlation coefficients of 0.9773 and 0.5032, respectively)], in order to quantify the relationship between the results of the matches and fluctuations in the players' performances. The research findings are presented in Figure 3, Figure 4, and Table 1.

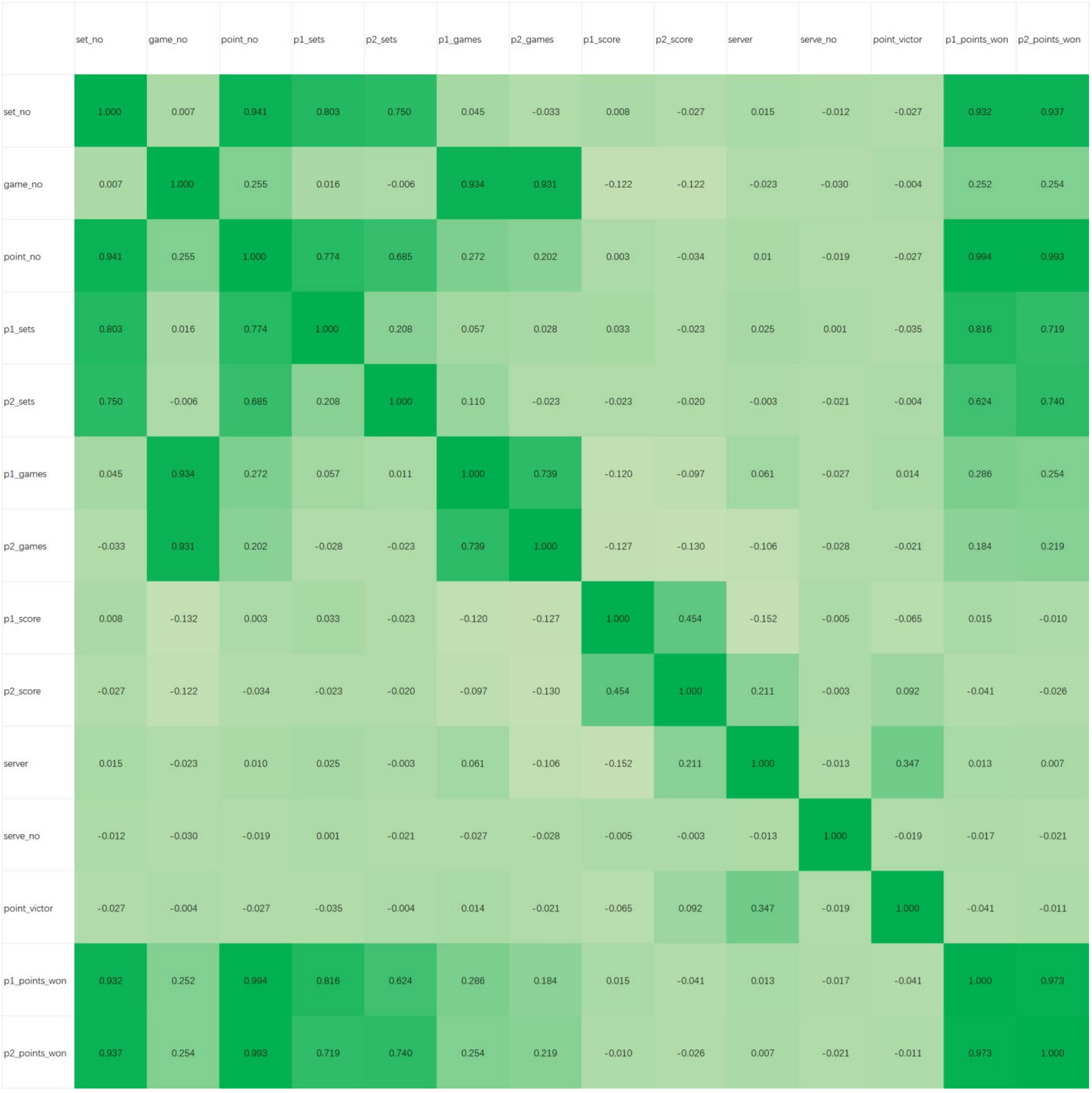


*Figure 3 Data correlation analysis*

Figure 3 details the correlation analysis results of other key data, providing coaches and researchers with a more comprehensive view of the data and helping them gain insights into the intrinsic connection between player performance and match-fluctuation-related data.

*Table 1 Cumulative Momentum Differentials*

| Cumulative Momentum Differentials | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1301 | 1302 | 1303 | 1304 | 1305 | 1306 | 1307 | 1308 | 1309 | 1310 |
| 74.7 | -92.5 | -83.5 | -1.3 | 17.8 | 166.2 | 134.8 | -77.1 | 2.3 | 62.4 |

Table 1 presents the core findings of this study, which focuses on player performance as the primary research subject. Utilizing a cumulative process analysis based on real-time data, we aim to investigate the dynamic performance of players during a match and evaluate their performance differentials ($\Delta P$). By quantifying both positive and negative performance metrics, as well as the cumulative point accumulation throughout the match, we establish a comprehensive framework for assessing player performance. This table explicitly delineates the positive and negative performance values alongside the aggregated point totals, offering a detailed representation of the player's in-match contributions. Through this analytical approach, we are able to identify the strengths and weaknesses of the player, thereby providing a robust foundation for a deeper understanding of their overall performance dynamics.

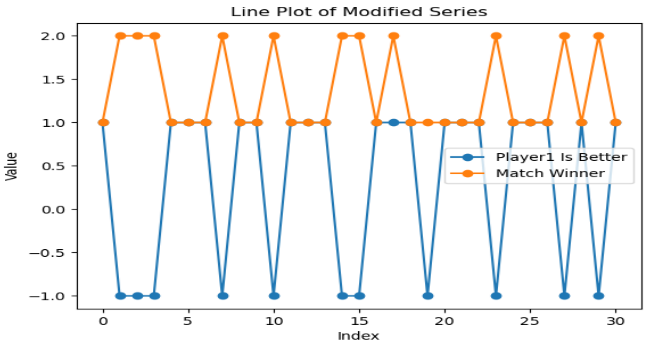


*Figure 4 Relationship between match fluctuation and player performance*

Figure 4 shows the relationship between match volatility and player performance, where the orange dash indicates the number of players on the winning side of the match, and the blue dash indicates which side had more dominant players. By analyzing the data of the last goal of each game, the direct correlation between the win or loss of that goal and the win or loss of the game is used as an entry point to perform a Boolean operation on the cumulative performances, and the dichotomous values are used to indicate which side has more dominant player performances.

For correlation analysis, the Pearson correlation coefficient and the Spearman rank correlation coefficient were used, and the results were -0.7231 and -0.7067, respectively, indicating a strong correlation between match fluctuations and player performance. This also directly reflects that in tennis the player's match momentum is the key to determine the victory of the match.

## 4. Conclusions

This research focuses on the momentum analysis in tennis matches. Based on the data of events such as the 2023 Wimbledon Men's Singles Final, it deeply explores the quantification of players' match performances and the relationship between momentum and match results. The study constructs a comprehensive evaluation model. By using the improved Entropy Weight Method and combining key indicators such as the time interval between wins and the serving advantage to assign weights to features, it effectively quantifies players' performances at different stages of the match. Through visualization, the performance differences among players are clearly presented, verifying the accuracy and effectiveness of the model. At the same time, through the analysis of Pearson and Spearman correlation coefficients, it is clear that there is a high correlation between players' performances and match results. Moreover, by studying the momentum accumulation process, a comprehensive perspective is provided for evaluating players' overall levels. Looking forward, further expansion of the research will take place in two key aspects: model application and correlation analysis. In the aspect of model application, efforts will be made to broaden the scope of the model's application across various tennis events. This is to confirm its effectiveness in different match settings. Meanwhile, by integrating players' training data, a solid foundation for personalized training can be established. When it comes to correlation analysis, in-depth exploration will be carried out on potential factors influencing the relationship between players' performances and match outcomes. These factors include the match stage, the type of opponents, the external environment, and more. With the aid of advanced technologies, a more precise prediction model will be constructed. This model is expected to provide more forward - looking guidance for coaches and players, and play a positive role in improving the levels of tennis training and competition.

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