A Momentum Decision Recommendation Model based on Random Forest and Game Theory Methods

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Abstract. Momentum, as an important indicator of athlete status, has been widely used in sports competitions. This paper chose tennis games to establish standard momentum measuring model, momentum forecast model, tennis game model based on mixed strategy simultaneous decision game under momentum influence. First, this paper constructed a standardized physiological and psychological measurement model for player momentum using critic weight method and coefficient of variation method, which is highly correlated with score. Second, this paper used the random forest algorithm to predict the trend of the competition and obtained the weights of the factors that affect the momentum. Lastly, this paper further introduced the concept of game theory and established a payment matrix based on mixed strategy simultaneous decision game to calculate the Nash equilibrium solution of both parties under the influence of the current momentum. According to the models, this paper can predict the trend of the athlete's status and prompt the coach or the athlete to make a more correct choice according to the status of both sides.

Keywords: Momentum, Prediction Model, Game theory.

1. Introduction

Tennis is a competitive sport that involves subtle movements, complex and varied techniques and tactics, as well as intense confrontations. It has high requirements for the physical and psychological qualities of athletes. In order for tennis players to win the championship of high-level professional tennis events, in addition to basic skills, comprehensive technical and tactical abilities, and flexible and innovative thinking, they must also have stable psychological and physical qualities. Matthew A Wood, Stephen D Mellalieu (2023) 11 [1], in contrast, argued that physiological arousal is the most critical factor in the establishment, maintenance and disruption of momentum. The current mainstream explanation for momentum is that a significant triggering event may lead to changes in various cognitive and physiological variables.

Proposing a clear, observable, comprehensive and operational definition of momentum has been conceptualized in the sports world in the form of qualitative considerations such as the conceptual model previously proposed by Jeemin Kim & Katherine A. Tamminen (2023) [2] The conceptualization of momentum, on the one hand, and the formulation of momentum as "psychomomotor" and psychological factors linked to correlational studies, on the other hand, seem to lack accuracy in analysis and do not take into account the influence of physical state and physiological performance, social and environmental factors on momentum during the game. Based on the work of Elia Morgulev and Simcha Avugos (2023) [3], among others, as well as authoritative international tennis organizations such as the International Tennis Federation (ITF) and the Association of Tennis Professionals (ATP), social and environmental factors have the same impact on both tennis players, which means momentum can be expressed as a linear combination of psychological and physiological factors affecting athletes [4].

This paper aims to handle the following questions:

(1) Develop a model that captures the flow of play as points occur and apply it to a match to analyse how much better the player perform at specific time.

(2) Develop a model to predict the swings in the match and identify the factors most relevant to the swing.

(3) Based on the game theory thinking, this paper aims to analyze the momentum flow of the two sides, and establishes the relevant payment matrix model to solve the mixed strategy Nash equilibrium. Make recommendations to athletes or coaches in real time according to the Nash equilibrium solution.

2. Data Description

2.1. Data Resources

In order to ensure the credibility and authority of the data sources, the data of this paper comes from the following open-source website

(1) Wimbledon tennis Championships Open Data network: https: //www.wimbledon.com/index.html

(2) French Open or Roland-Garros Data network: https: //www.rolandgarros.com/en-us/

(3) Australian Open Data network: Official Website of the Australian Open 2024 | AO (ausopen.com)

(4) US Open Data network: Official Site of the 2024 US Open Tennis Championships - A USTA Event

(5) Cricsheet Open Data network: https: //cricsheet.org/

2.2. Data Pre-processing

The preprocessing of the data directly affects the efficiency of data utilization and the accuracy of the model. For example, the running distance rate of players is 0 which has been shown in Figure 1,which should be deleted these out of the ordinary data directly.

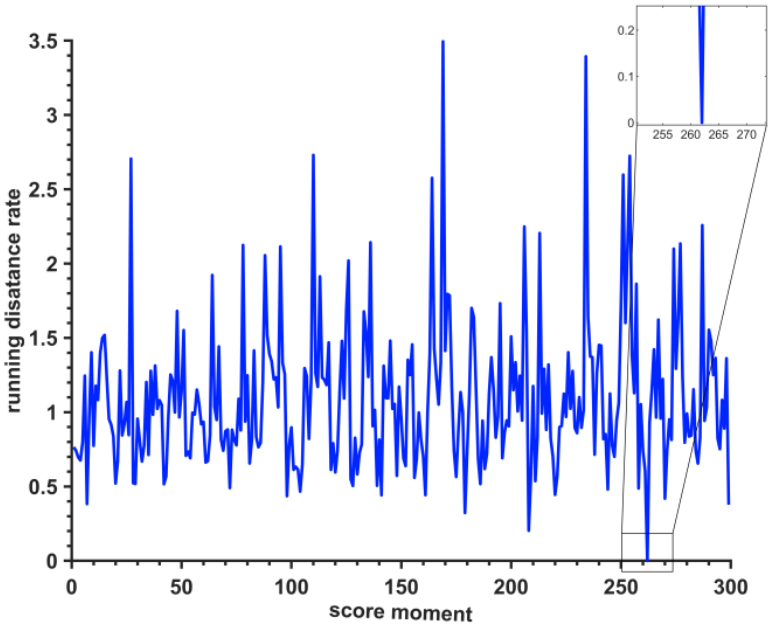


Figure 1. Abnormal running distance rate recognition

2.3. Data normalization

After data cleaning, the study can get a data matrix where x_{ij} expresses the i-th data in the j-th index:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \quad (1)$$

This paper normalize the data according to whether they describe the athlete's status as good or bad, so as to eliminate the scale while retaining the discrete characteristics of the data itself, which

better reflects the internal structure of the data. The normalized data are as follows where the max (x_j) means the maximum of any data in the j-th index, the min (x_j) means the minimum of any data in the j-th index.

For positive data, the normalized data meets the following criteria

$$x_{ij}^{'} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{2}$$

For negative data, the normalized data meets the following criteria

$$x_{ij}^{'} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{3}$$

3. Research Methods

3.1. The Fundamental of Random Forest

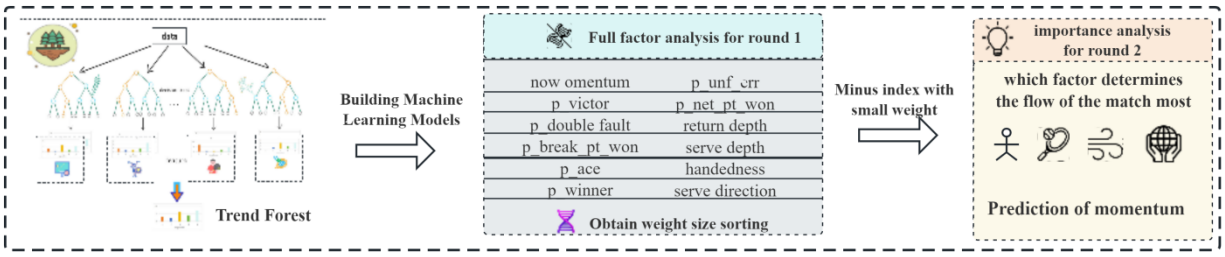


Figure 2. Random Forest Solution Flowchart

Random forest is a machine learning algorithm of cluster classification model[5] , which uses a random way to establish a forest composed of multiple unrelated decision trees. Random Forest Solution Flowchart is shown as Figure 2. Due to the use of cluster classification algorithm, the accuracy is high and it is not easy to fall into overfitting merger, and it has a certain anti-noise ability. Random forest prediction has high interpretability and can accurately predict the momentum trend during the competition. Its operation process is adaptive to big data analysis, saving computational resources

3.2. The Fundamental of Game Theory

In this paper, game theory is introduced to make momentum decisions for both athletes, and the hitting style of the two athletes is established as a probability-related mixed strategy analysis based on the rational assumptions of both sides of the game[6].The definition of Nash equilibrium is a stable state of a system involving the interaction of different participants, in which no participant can gain by a unilateral change of strategy if the strategies of the others remain unchanged. Meanwhile, the mathematical definition of nash equilibrium in hybrid strategy is: $\phi^* = (\phi_1^*...,\phi_i^*,...,\phi_n^*)$ is a mixed strategy combination of N-person strategic game $G = \{N; S_1,\ldots,S_n; u_1,\ldots,u_n\}$ .For any i=1,…,n, there is $U_i(\phi_i,\phi_{-i}^*) \le U_i(\phi_i^*,\phi_{-i}^*)$, $\forall\varphi_i \in \Phi_i$ then $\phi^* = (\phi_1^*,\ldots,\phi_i^*,\ldots,\phi_n^*)$ is the mixed strategy Nash equilibrium of this game.

4. Results and Analysis

4.1. Standard Momentum Measuring Model

Momentum can be expressed as a linear combination of psychological and physiological factors affecting athletes.

$$\vec{M} = \theta Psy + (1-\theta)Phy \tag{4}$$

Where$\vec{M}$means the momentum,Psy means psychological factors and Phy means physiological && physical factors.

4.1.1. Psychological factors (Psy)

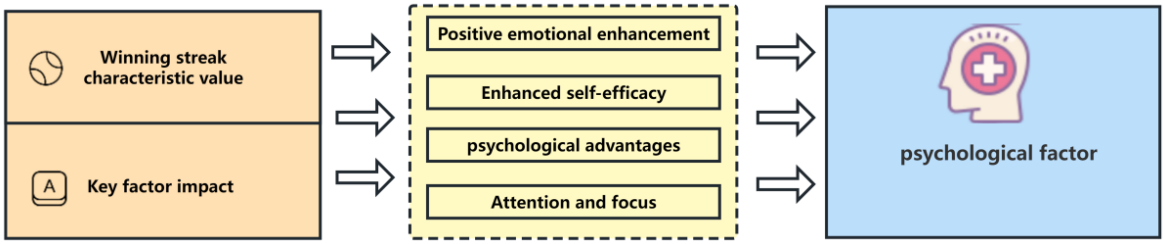


Figure 3. Psychological factors analysis

Due to the fact that in the middle of a strenuous sports competition, based on the theoretical research of Philip Furley (2023)[7] and others who proposed that “success breeds happiness”[8] as well as the significant increase in the emotional ups and downs of athletes in the critical moments, whis paper chose two indicators, Wsc and Kfi, as the main weighted components affecting the psychological factor as Figure 3.

$$\text{Psy} = \text{Kfi} * \text{Wsc} \tag{5}$$

Wsc denotes Winning streak characteristic value i.e. the psychological impact of winning in the past moments.

$$\text{Wsc} = s_1 {}^* s_2 \tag{6}$$

The Wsc here consists of the number of the current winning streaks including this moment in time, the consecutive scoring status of the athlete and the psychological impact of the reason for the scores on the winning streak factor weighted by the number of consecutive winning streaks.The winning streak factor indicates the weight of winning at different stages. Based on the model proposed by the Zhang Weiqing [9] and the theoretical model proposed by *ATHLETICS* [10] in 2022, the scoring difficulty gradient is:

$$\text{Winning on serve} < \text{Winning on confrontation} < \text{Winning in the service-receiving} \tag{7}$$

WHich means the relationship to the psychological impact, i.e., the streak factor, is the same.

Kfi denotes key factor impact i.e. the psychological impact weight of winning a key set: In the rules of tennis, the number of key sets is often encountered as Table 1:

Table 1. Factor types and Descriptions

Factor type	Description
I key factor	both players win 40 points each in a game
II key factor	both players win 6 games in a set (tie-break)
III key factor	both players win two sets in a tennis match

4.1.2. Physiological && physical factors (Phy)

According to the American Psychological Association [11] a tennis player's physical condition at a given moment can be measured by four dimensions, which are Competence in Attachment (CA), Breaking Scoring Efficiency (BSE), Serving Scoring Efficiency (SSE) and Stability (S).

$$\text{Psy} = \xi_1 \text{ CA} + \xi_2 BSE + \xi_3 SSE + \xi_4 S \tag{8}$$

After reviewing the actual on-field performance associated with each dimension and comparing it to the given dataset, the study selected nine tertiary correlates from the given dataset for analysis, as shown in the Table 2.

Table 2. The Symbol of Factors and Description

I. Symbol	Description	II. Symbol	Description
RDR	Running Distance Ratio	CA	Consistency ability
MN	Make Nets		
US	Untouchable Shot		
BS	Breaking Successfully	BSE	breaking score efficiency
MBC	Miss the Breaking Chance		
SSSR	Service Success Score Rate	SSE	serving score efficiency
SA	Serve Ace		
UE	Unforced Error	S	stability
SSR	Service Success Rate		

x_j expresses factors related to a player's on-field performance at the score moment of j. The uantitative relationships are as follows:

$$\begin{cases} CA_j = w_1 * BDR_j + w_2 * MN_j + w_3 * US_j \\ BSE_j = w_4 * BS_j + w_5 * MBC_j \\ SSE_j = w_6 * SSSR_j + w_7 * SA_j \\ S_j = w_8 * UE_j + w_9 * SSR_j \end{cases} \tag{9}$$

After identifying these factors for evaluation, in order to objectively assign weights to the indicators and to take into account the impact of data volatility and correlation on the evaluation, this study then used the CRITIC weighting method to determine the weight share of these tertiary factors under the four dimensional weights.

$$S_j = \sqrt{\frac{\sum_{i=1}^{m}(x_{ij} - \overline{x}_j)^2}{n-1}} \tag{10}$$

Firstly, the standard deviation is calculated to indicate the fluctuation of the differences in the values within each indicator: the larger the standard deviation, the greater the difference in the values of the indicator, the more information it reflects, the stronger the evaluation strength of the indicator itself, and the more weight should be assigned to the indicator.

$$\mathrm{r_{ij}} = \frac{\sum_{j,k=1}^{n}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2}} \tag{11}$$

Secondly, the correlation coefficient is then used to indicate the conflictedness of the indicators: if the value of the correlation coefficient between the indicators is higher, it means that the conflictedness is lower, and then their weights are lower. Then, the conflicting calculation formula of this indicator as well as the amount of information contained in the indicator is obtained.

$$A_j = \sum_{i=1}^{n}(1 - r_{ij}) \tag{12}$$

$$C_j = S_j * A_j \tag{13}$$

$$w_j = \frac{c_j}{\sum_{j=1}^{n} c_j} \tag{14}$$

Thirdly the contrast intensity is multiplied with the conflictedness indicator and normalized to get the final weights w_{ij} which is shown as Figure 4.

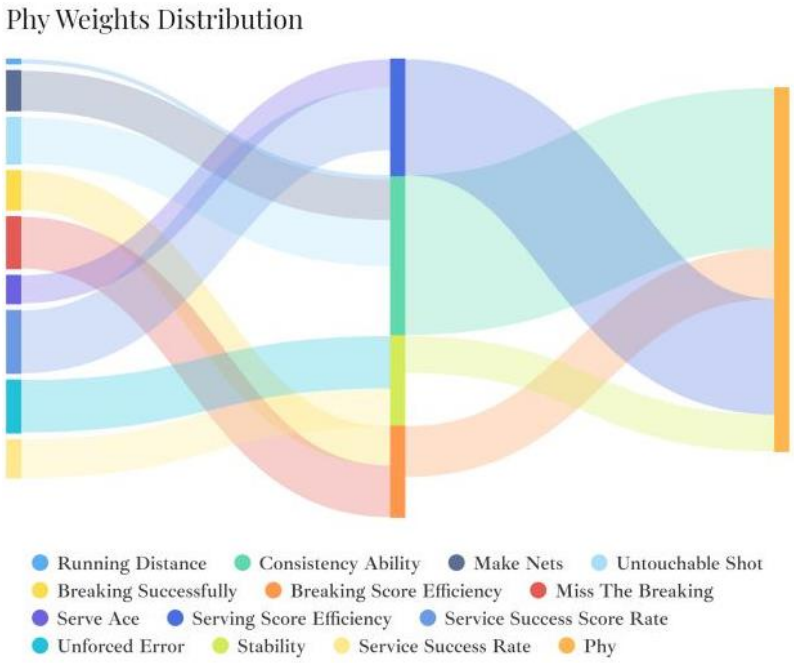


Figure 4. Phy Weights Distribution

4.1.3. Model solution

With the above model, based on the datasets, the study find the relevant weights as Table 3 below:

Table 3. Weight of Indicators

I. Symbol	Weight	II. Symbol	Weight
RDR	0.05016803	CA	0.4400812954159679
MN	0.44238448		
US	0.50744749		
BS	0.43111246	BSE	0.13997720089375654
MBC	0.56888754		
SSSR	0.57589592	SSE	0.3188695043310114
SA	0.42410408		
UE	0.57589592	S	0.10107199935926414
SSR	0.42410408		

At the same time, the trend picture is shown as Figure 5.

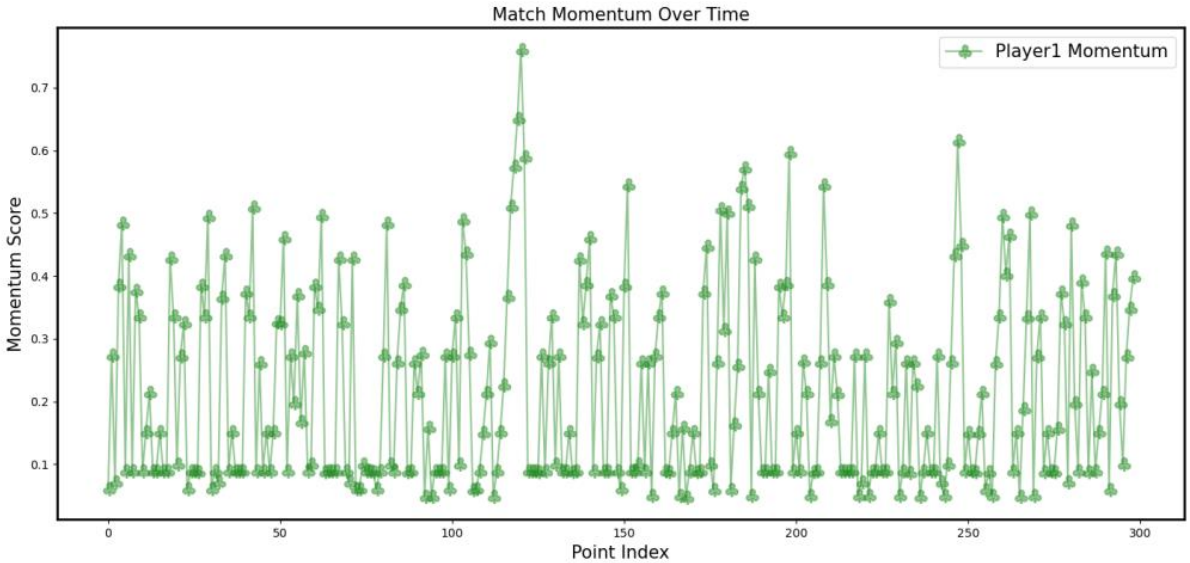


Figure 5. Match Momentum Flow

It can be observed the momentum distribution of Carlos Alcaraz and Nicolas Jarry based on the dataset trend curve as shown in Figure 6. It is evident that the momentum peaks of Carlos Alcaraz correspond to the momentum valleys of Nicolas Jarry. The momentum feedback reflects which player is performing better at a given time in the match, as well as how much better they are performing. The peak of momentum indicates that the athlete performed well at that moment, while the trough of momentum indicates that the athlete performed poorly at that moment.

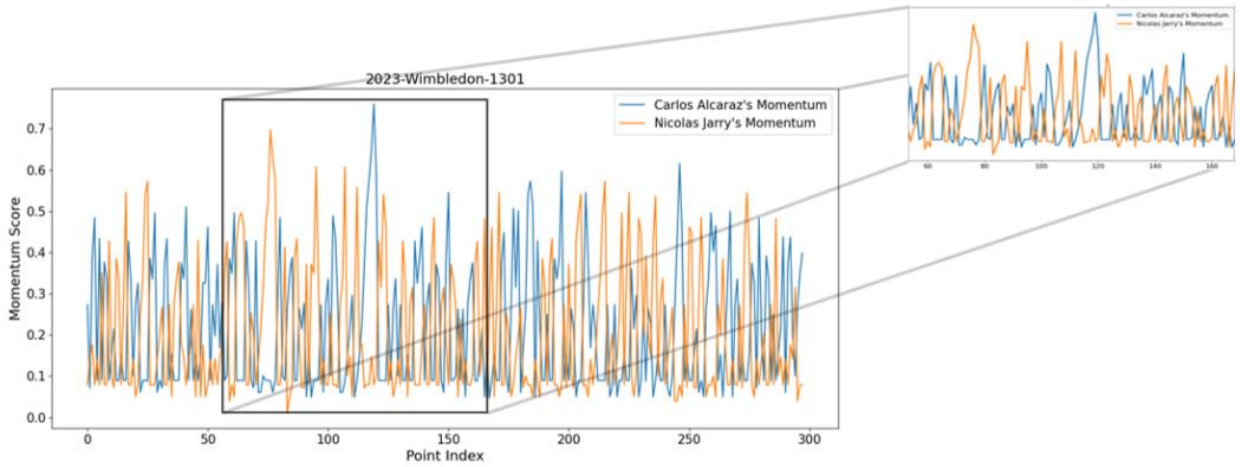


Figure 6. Momentum Flow Chart

4.2. Factor Contribution Analysis

4.2.1. Pre-training

Taking all the indicators into account and conducting a pre-training on the random forest,it can be found that except for eight indicators such as now_momentum, p_victor, p_double_fault, etc., the importance of most of the remaining indicators is even less than 0.000854691. In contrast, the importance of these eight indicators is much larger than 0.000854691, indicating that these eight indicators have the greatest influence on the future change of momentum.In order to study the impact of personalized technical characteristics of players on momentum [12], the paper selected a series of technical indicators shown as Table 4 to add to the model construction system. Note that each athlete has certain differences in their corresponding technical indicators, and the model will ultimately obtain coefficients corresponding to these technical indicators that are unique to the athlete, making the kinetic energy prediction model more in line with the athlete's own technical characteristics.

Table 4. Factors and Descriptions

Factor		Description
RD		return depth
SD		serve depth
H		handedness: forehand or backhand
Serve direction (SD)	B	serve to the body
	BW	serve to the body / lean to wide
	C	serve to the center
	W	serve to wide
	BC	serve to body/ lean to center

4.2.2. Formal training

Due to the known moderate number of data in the datasets, the training and testing sets were first divided using the 8:2 principle. Because the training of random forests involves adjusting multiple hyperparameters such as the number of trees in the forest, the maximum depth of the trees, and the minimum number of samples required to split internal nodes. In order to obtain the most suitable hyperparameters, the paper extracted 20% of the data from the training set as a cross-validation set.

The model ultimately performed on the test set with a Mean Square Error (MSE) of 0.0087078313744232.

4.2.3. Importance analysis

Here the paper select athlete Novak Djokovic (data source) to conduct specific technical analysis on him. The weight of the impact of new factors on momentum is shown in the Table 5 below:

Table 5. Factors with their importance

Initial Factor	Importance	Added Factor		Importance
now_momentum	0.468187	H		0.046002
p_victor	0.153647	RD		0.031978
p_double_fault	0.112739	SD		0.026827
p_break_pt_won	0.104848	Serve direction (SD)	B	0.005893
p_ace	0.025874		BW	0.003743
p_winner	0.007521		C	0.002445
p_unf_err	0.005109		W	0.001261
p_net_pt_won	0.003354		BC	0.000572

From the data above, it can be seen that Djokovic's four technical indicators have a certain impact on his momentum. The weght relationship is:

$$\mathbf{H > RD > SD > B > BW > C > W > BC} \tag{15}$$

According to the general statistical significance of data, due to the fact that athletes generally do not handle backhand balls as well as forehand, hitting the ball to the opponent's backhand area is often easier to score. However, through analysis, it is found that Djokovic is better at scoring by hitting the ball to the opponent's forehand area, which has become a key indicator for him.

When the serving speed and returning speed are relatively fast, it plays a role in improving the player's momentum. Note that all 5 serving directions are positive indicators, as serving itself has an advantage and is more likely to increase momentum.

However, different serving directions do not have a significant impact on his momentum. Although different directions may bring certain differences, the weight ratio is slightly lower, and the impact on the athlete is not as significant.

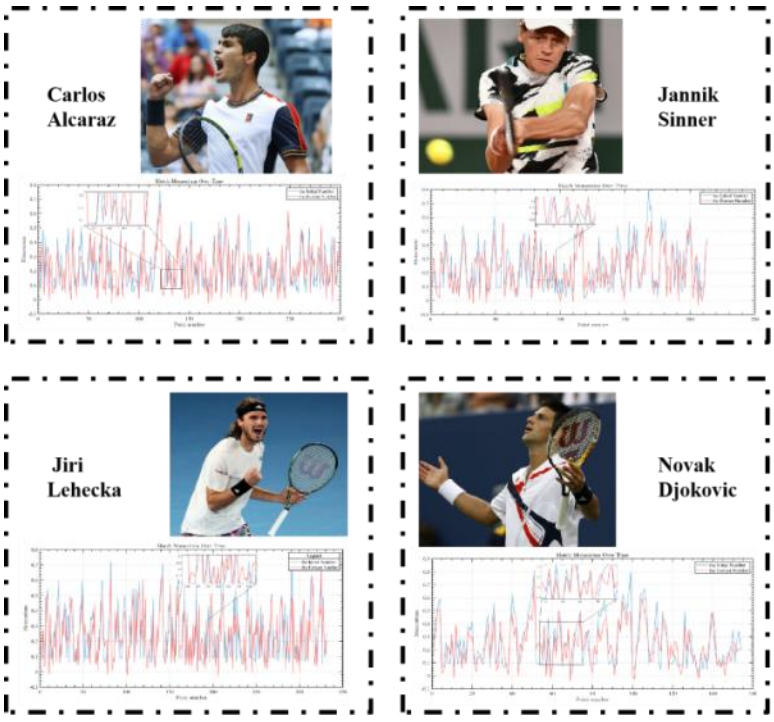


Figure 7. Comparison between initial and predicted momentum value

Through weight analysis and fitting, the study obtained the initial and predicted momentum values for four professional tennis players in four matches, and depicted the swing picture, as shown in the following Figure 7. It can be clearly observed that the predicted momentum direction corresponds to the initial momentum values, indicating that the established prediction model can well illustrate the changes in future momentum.

4.3. Nash equilibrium solution for Momentum Decision Model

In order to provide effective rationalization suggestions for tennis players in new competitions or when facing new opponents, we introduce game theory methods based on the optimization momentum model with added personalized factors to analyze the game between tennis players, so as to provide effective suggestions when players encounter different opponents. After researching literature and comparing contributions, we selected factors related to serving techniques as actions to adjust personal strategies. Considering the crucial role of receiving and serving in the trend of tennis matches, we conduct a game analysis on the strategy choices of both sides during the receiving and serving stage, and propose suggestions for selecting receiving and serving strategies for different opponents. Therefore, based on rational assumptions about both players, a mixed strategy analysis related to probability is adopted to construct the game. Set the server and receiver as A and B, respectively. The game in which the players in these two games participate is $G = \{S_1, ..., S_{n;} u_1, ..., u_n\}$

A has 10 strategies $S_1 = \{(B/BC/BW/C/W, CTL/NCTL)\}$,The first coordinate of each strategy combination represents the direction of the serve, and the second coordinate represents the depth of the serve. Probability distribution $p_A = (p_{1A}, ..., p_{9A}, p_{10A})$,where $0 \le p_{iA} \le 1$, $\sum_{i=1}^{10} p_{iA} = 1$,expresses probability of player A choosing strategy. $p_{1A} = p(B, CTL)$,expresses probability of player A choosing strategy (B, CTL) .

B has four strategies $S_2 = \{(F/B, D/ND)\}$,The first coordinate of each strategy combination represents whether to return the ball with forehand or backhand, and the second coordinate represents the depth of the return. Probability distribution $p_B = (p_{1B}, ..., p_{3B}, p_{4B})$,where $0 \le p_{iB} \le 1$ $\sum_{i=1}^{4} p_{iB} = 1$, expresses probability of player B choosing strategy. $p_{1B} = p(F, D)$, expresses probability of player A choosing strategy (F, D) . Payoff Matrix and Parameters is shown as Table 6.

Table 6. Payoff Matrix

Player	*B*				
A	*P/Strategy*	p_{1B} *(F,D)*	p_{2B} *(B,D)*	p_{3B} *(F,ND)*	p_{4B} *(B,ND)*
	p_{1A} *(B,CTL)*	u_{11}	u_{12}	u_{13}	u_{14}
	p_{2A} *(BC,CTL)*	u_{21}	u_{22}	u_{23}	u_{24}
	p_{3A} *(BW,CTL)*	u_{31}	u_{32}	u_{33}	u_{34}
	p_{4A} *(C,CTL)*	u_{41}	u_{42}	u_{43}	u_{44}
	p_{5A} *(W,CTL)*	u_{51}	u_{52}	u_{53}	u_{54}
	p_{6A} *(B,NCTL)*	u_{61}	u_{62}	u_{63}	u_{64}
	p_{7A} *(BC,NCTL)*	u_{71}	u_{72}	u_{73}	u_{74}
	p_{8A} *(BW,NCTL)*	u_{81}	u_{82}	u_{83}	u_{84}
	p_{9A} *(C,NCTL)*	u_{91}	u_{92}	u_{93}	u_{94}
	p_{10A} *(W,NCTL)*	u_{101}	u_{102}	u_{103}	u_{104}

u_{ij} is a two-dimensional vector, $u_{ij} = (u_{ijA}, u_{ijB})$ expresses the pay of A is u_{ijA}, the pay of B is u_{ijB} when A chooses strategy i, B chooses strategy j. Taking into account the fluctuations in momentum and the characteristics of different players, we propose an algorithm for calculating payments (im means importance):

$$im(s_{iK}) = \prod_{j=1}^{m} im(s_{ijK}) \tag{16}$$

K represents participants, i represents K's i-th combination strategy, and j represents the i-th indicator in the combination strategy. $p_{i,j}^{A} = \frac{im(s_{iA})}{im(s_{jB})}$ means the probability of A winning when A chooses strategy i and B chooses strategy j.

$p_{momentum}^{A}$ represents the probability of A winning under the current momentum.

$$u_{ijA} = 1 * p_{i,j}^{A} * p_{momentum}^{A} \tag{17}$$

Where 1 means A wins the point. Through the model above, any pay in the payoff matrix can be calculated.

4.4. Solving Nash Equilibrium for Hybrid Strategies

Expected payment with player$_k$ $U_K(p_K)$:

$$U_K(p_K) = \sum_{i=1}^{10} \sum_{j=1}^{4} u_{ijK} * p_{iA} * p_{jB} \tag{18}$$

$$\begin{cases} \frac{\partial U_A}{\partial p_{iA}} = 0, i = 1,...,10 \\ \frac{\partial U_B}{\partial p_{jB}} = 0, j = 1,...,4 \\ \sum_{i=1}^{10} p_{iA} = 1 \\ \sum_{i=1}^{4} p_{iB} = 1 \end{cases} \tag{19}$$

The study suggest that player A (B) develop their own strategy based on the Nash solution, as K's expected payment can ultimately lead to the Nash solution. Due to the unique characteristics of different athletes (K represents participants), they will change with the opponent, resulting in different payment matrices. Therefore, when facing different opponents, a new Nash solution should be calculated based on the new payment matrix, and one should adjust their serving and receiving strategies according to the new Nash solution.

5. Conclusion

This paper establishes a momentum evaluation model using critical and coefficient of variation methods, which evaluates the magnitude of momentum from both physical and psychological perspectives. It includes 9 third level physiological factors and 3 psychological factors, with a multidimensional and rich evaluation that more accurately reflects the player's momentum at the current scoring moment from different aspects.

The paper used the random forest algorithm to predict the trend of the competition and obtained the weights of the factors that affect the momentum. Meanwhile,this paper added more personalized

information to the momentum prediction model, such as serving direction, serving depth, etc., to further measure individual action recommendations. Taking Novak Djokovic as an example, his serve direction and technical indicators, as well as the changes that will greatly affect the momentum, account for nearly 5%. For Djokovic, the model provides suggestions that serving to the opponent's forehand range will promote its momentum growth.

The paper also establish a payment matrix based on mixed strategy simultaneous decision game to calculate the Nash equilibrium solution of both parties under the influence of the current momentum. And use Nash equilibrium as a strategic combination to guide coaches and players in making choices.

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