Retraction

Retracted: Model for Evaluating the Technical and Tactical Effectiveness of Tennis Matches Based on Machine Learning

Mobile Information Systems

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Liu, "Model for Evaluating the Technical and Tactical Effectiveness of Tennis Matches Based on Machine Learning," *Mobile Information Systems*, vol. 2022, Article ID 3878072, 13 pages, 2022.

Research Article

Model for Evaluating the Technical and Tactical Effectiveness of Tennis Matches Based on Machine Learning

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As the level of tennis improves, the ability and strategy to play in the game determine the responsibility for the outcome of the game. It is committed to improving the professional and strategic level of Asian tennis players and narrowing the gap with high-level European and American tennis players. The purpose of this paper is to study the application of machine learning in the study of the evaluation model of the technical and tactical effectiveness of tennis matches, and proposes the decision tree algorithm, artificial neural network, reinforcement learning algorithm, and related concepts of tennis matches. Therefore, this paper selects Federer's technical and tactical games from 2013 to 2017 as the research object. And by paying attention to the application characteristics of Federer's methods and strategies in each stage, a detailed statistical analysis of the data is carried out point by point. The exploratory outcomes show that through the AI calculation, it is found that the incredible skill and vital sufficiency of Federer's hard court game change around 0.600, and the typical worth is 0.594. Particular and vital efficiency showed a sluggish recuperation in 2017.

1. Introduction

Tennis was admired by a few European and American countries in the mid-nineteenth century. In 1877, junior tennis tournaments were held in England, marking the introduction of modern tennis. With the rise of tennis, tennis has gradually become popular around the world after entering the twentieth century. Tennis is respected by increasingly countries and develops step by step. Tennis has been perceived, recognized, and worshipped by more people. Tennis originated in France, was introduced to the world in England, and was born in the USA. As the second largest sport on the planet, tennis has become a mode of movement on the planet.

A series of events such as the four major tennis championships, the masters, and the year-end finals are gradually expanding. Driven by interest, the athlete should perform at the best level of competition and achieve better results. Therefore, it is particularly important to explore the strategies and tactics of athletes, which is also the starting point of this article. As a net-fighting sport, the strategic significance level

for individual occasions is "Level 4." Therefore, in the current focused and intense tennis competition, players should not only fight for strength, but also for intelligence. With the help of innovation, speed, perseverance, and mental capacity, athletes on both sides of the net can make the most of their strategic plans. Without the carrier of strategy, the role of other aspects cannot be reflected.

The innovation of this paper is that (1) the application of machine learning to the research on the evaluation model of the technical and tactical effectiveness of tennis matches, which is innovative and practical. (2) First, this study utilizes AI strategies to just and obviously break down the cooperation and dynamic course of members in tennis matches. It can improve the strategic proficiency of mentors and competitors participated in tennis and go with their choice-making ways of behaving more judicious, logical, and prescient. (3) It gives another hypothetical apparatus to the investigation of tennis, further improves the hypothetical arrangement of tennis strategies, and advances the philosophical establishment in the field of tennis, which is useful to the improvement of tennis hypothesis.

2. Related Work

With the gradual rise of sports, increasingly scholars have gradually studied the technical and tactical effectiveness of tennis matches and other sports techniques. Pinto F briefly reviewed the theoretical basis for the application of technical tactical behavior in ultimate full-contact training [1]. Zhang concentrated on a programmed discovery strategy for table tennis specialized and strategic pointers in light of direction expectation of remunerated fluffy brain organization [2]. Li et al. established a data mining model of tennis technical offensive tactics and association rules [3]. Papadopoulou et al. planned to make a near investigation of the specialized and strategic capabilities of the phenomenal men's ocean side volleyball crew in the 2004 Athens Olympic Games [4]. However, the shortcoming of these studies is that the models constructed are not scientific enough.

In fact, the construction of machine learning algorithm models has become a research hotspot. Many scholars have used neural network models in various researches. Zhou et al. presented the ML on big data (MLBiD) structure to direct the conversation of its chances and difficulties [5]. The reason for the Kavakiotis I study was to efficiently survey the use of AI information mining methods and devices in the field of diabetes research, utilizing an assortment of AI calculations [6]. Liu et al. gave a far-reaching examination and understanding of this quickly creating area of intelligent model investigation [7]. Zheng et al. will likely create a semiautomated system in light of machine learning [8]. However, these studies should not be extensive enough, and there is still much room for improvement.

3. Machine Learning and Its Related Algorithms

3.1. Decision Tree Algorithm. The explanation choice tree innovation is so well known that the development of choice tree requires no area information or boundary setting, so it is appropriate for exploratory information revelation. Choice trees can deal with high-layered information. The gained information addressed as a tree is natural and handily comprehended by people.

3.1.1. Overview of Decision Tree Algorithm. Contrasted with and different information investigation techniques, the choice tree has little intricacy, simple development, and quick running pace. It can deal with both multilayered information and datasets with less data; the acquired choice tree is more obvious; the exactness of grouping results is likewise higher [9].

3.1.2. Definition of Decision Tree. Choice tree is a tree structure. A characteristic tree is developed from the traits of each example in the preparation set, which is built start to finish. Choice tree is a graphical strategy, which has a place with a more natural order and relapse technique. The grouping choice tree model characterizes the occurrences in

a spellbinding manner, which is addressed as a tree structure graph. It can be seen that the decision made by this decision tree is whether the subject will meet the blind date. At each node, a feature is used to classify; first judged by age, one class is less than or equal to 30, and another class greater than 30. Then, those less than or equal to 30 are classified according to their appearance, and a complete decision tree is constructed until they cannot be divided in the end [10, 11]. Figure 1 shows a graphical representation of numbers and decision trees.

As displayed in Figure 1(b), it is a choice tree. The inner hubs of the test characteristic in the choice tree are addressed by square shapes, and the leaf hubs are addressed by circles. It is unequivocally a result of this design and portrayal that the choice tree characterization technique is exceptionally simple to change over into positive top notch grouping sentences. Different choice tree calculations produce various types of choice trees. Some choice tree calculations can deliver paired trees, while others can create nonbinary trees [12].

3.2. Artificial Neural Network

3.2.1. Artificial Neural Network Model. Neural network is a complex network composed of many connected neurons. After the adjustment of the weights between neurons, the input sample data are modeled and simulated so that it finally has the ability to solve and deal with problems [13].

The basic unit of artificial neural network is called artificial neuron. The single-output neural network model is

$$X = \left[X_1, X_2, X_3, \cdots, X_n \right]^T. \tag{1}$$

Define the weight vector ε:

$$\varepsilon = \left[\varepsilon_1, \varepsilon_2, \varepsilon_3, \cdots, \varepsilon_n \right]^T. \tag{2}$$

∂ is the threshold of the neuron, and f is the activation function of the neuron. Then, the neuron output vector B is

$$B = \left(\sum_j^N X_j \varepsilon_j + \partial \right). \tag{3}$$

The neural network structure model is

$$I_i^k = \sum_j w_{ij}^k o_j^{k-1} + w_{je}^k. \tag{4}$$

One of them is

$$o_i^k = f\left(I_j^k \right). \tag{5}$$

Usually take

$$f\left(I_j^k \right) = \frac{1}{1 + \exp\left(-I_i^{k^2} \right)}. \tag{6}$$

Among them, k is the number of layers. $ok - 1/j$, Ik/j, $f(Ik/j)$ are the input, net output, and output center of the i-th neuron in the k-th layer, respectively.
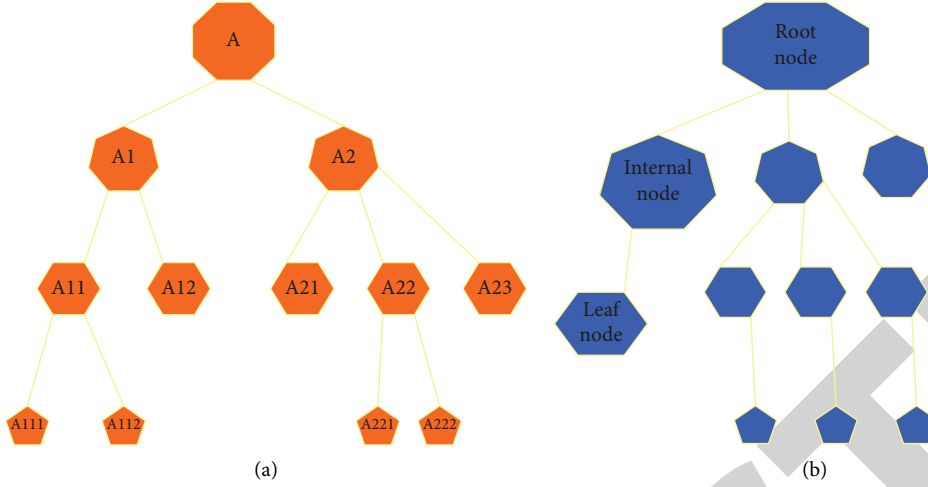
Figure 1: Graphical representation of numbers and decision trees. (a) Graphical representation of the tree. (b) Graphical representation of the decision tree.

wk/ij is the connection between the k-th neuron in the i-th layer and the $k − 1$ neuron in the j-th layer. The weight is closed.

3.2.2. Hebb Learning.
When a neuron is activated, the strength of its connections increases accordingly [14]. It can be represented by a mathematical model as

$$\Delta T_{ij}(n) = F\big(B_i(n), X_j(n)\big). \tag{7}$$

In the formula, $B_i(n), X_j(n)$ are structure of neurons of T_{ij}, as usually:

$$\Delta T_{ij}(n) = \eta B_i(n) X_j(n). \tag{8}$$

Because ΔT and $B_i(n), X_j(n)$ are related, it is also called related learning rule.

There are two kinds of networks that apply this rule: discrete Hopfield networks and continuous Hopfield networks.

3.2.3. Mathematical Statistics.
Use MATLAB 2015b to program to build energy consumption prediction model. A three-layer BP neural network model is initially planned to be established. The number of input layer nodes is the count feature value of the three-axis accelerometer sensor and the selected subject-related physical parameters.

After the model (ANN) is established, the accuracy of the model is evaluated and described by means of mean absolute error (MAE, formula (1)) and mean square error (MSE, formula (2)) based on the measurement data of each subject. Bland–Altman plots are used to test for trends comparing predicted and actual total energy consumption.

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |(xi − u)|,$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (xi − u)^2, \tag{9}$$

where xi denotes the model predicted value and u denotes the measured observed value.

3.3. Basic Theory of Reinforcement Learning

3.3.1. Principle of Reinforcement Learning Algorithm.
Reinforcement learning refers to the problem of mapping agents from a state space to an action space. Smart experiences are compared at different times based on different states, after which there is a reward, or at least a reward or discipline signal. The motivation for reinforcement learning is to increase the value of rewarding work for an ideal learning system. The supportive learning framework consists of three parts: state space, activity space, and resilience. Figure 2 shows the relationship between an agent utilizing a reinforcement learning algorithm and its current environment state D, the selected activity X, and the return to work H [15].

The set of state spaces where the agent is located is $D = \{d_0, d_1, \cdots, d_n\}$, the set of selectable actions is $X = \{x_0, x_1, \cdots, x_n\}$, and the set of reward functions obtained is $H = \{h_0, h_1, \cdots, h_n\}$. According to Figure 2, the agent and state space $d \in D$ can be obtained, and the sequence of the selected action $x \in X$ and the reward function $h \in H$ is

$$d_0 \xrightarrow{x_0} h_0, d_1 \xrightarrow{x_1} h_1, \cdots, d_n \xrightarrow{x_n} h_n. \tag{10}$$

In the support learning calculation, after the specialist sees the ecological state d_0, it will choose an activity, and subsequent to making the move x_0, the state space will change to d_1. Simultaneously, a prize capability h_0 will be produced and taken care of back to the specialist, and afterward the specialist will pick the following activity as indicated by the ongoing climate state and the size of the award capability h_0. The specialist will pick various activities as per different natural states and lastly get the most extreme aggregate award during the time spent planning from state space to activity space.
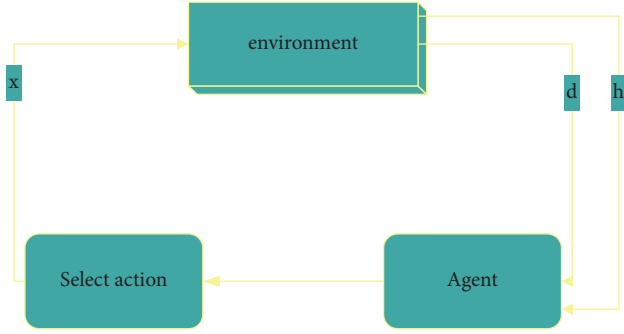
Figure 2: Structure diagram of reinforcement learning algorithm.

$$H_t = h_t + \gamma h_{t+1} + \gamma^2 h_{t+2} + \cdots = \sum_{u=0}^{\infty} \gamma^u h_{t+u}. \quad (11)$$

Among them, γ represents the discount factor of $\gamma \in (0, 1)$, and the learning purpose of the agent is to make the learning strategy $\pi:D \longrightarrow X$ and finally get a reward value with the largest sum [16].

Reinforcement learning algorithms differ from function approximation algorithms in the following ways:

(1) In reinforcement learning, the agent has a problem of action selection. By exploring the unknown environment, it selects the actions that have been learned and can produce high rewards in a certain state space.

(2) The state space of reinforcement learning is partially observable, and each execution step cannot perceive the entire state of the environment, but it can only perceive part of the environment state.

(3) The reinforcement learning algorithm has delayed rewards. When the agent gets the final reward, it will finally determine the action at which moment the reward belongs according to the different time allocations.

(4) Reinforcement learning is a permanent learning process.

3.3.2. Markov Decision Process. In the process of Markov decision-making, the agent perceives the environmental state d_t in a certain environment at time t and then performs corresponding actions x_t. After the action is applied to the environmental state, the environmental state will respond accordingly, giving a reward function $h_t = h(d_t, x_t)$, and then a subsequent state $d_{t+1} = \delta(d_t, x_t)$ will be generated. In the Markov decision-making process, $h(d_t, x_t)$ and $\delta(d_t, x_t)$ have nothing to do with the previous environmental state and the actions taken, and it only depends on the current environmental state and behavioral actions.

The Markov decision process can be represented by a quaternion (D, X, T, H). D denotes the set of state spaces, X the set of action spaces, T the state transition function, and H the reward function for taking an action X in the D state [17]. People generally use the converted cumulative return to obtain the optimal strategy of the Markov decision process,

which is defined in the initial statd_t, and the converted cumulative return of executing the corresponding strategy π is 77$W^{\pi}(d_t)$, as shown in formula (13).

$$W^{\pi}(d_t) = h_t + \gamma h_{t+1} + \gamma^2 h_{t+2} + \cdots = \sum_{u=0}^{\infty} \gamma^u h_{t+u}. \quad (12)$$

Among all converted cumulative returns, we denote the largest cumulative return by 55, as shown in formula (14).

$$\pi^*(d) = \mathrm{argmax} W^{\pi}(d). \quad (13)$$

3.3.3. Q-Learning Algorithm. The Q-learning algorithm was originally a widely used reinforcement learning algorithm based on the changing Markov decision process [18]. The Q-learning algorithm does not need to establish an accurate model in advance, nor does it need to have detailed expert knowledge and training data. It only needs to put the agent in a completely unknown environment, explore the environment through continuous trial and error, and use reward or punishment signals to feedback the impact of actions on the environment, to continuously improve their own behavior and adaptability to the environment. Different actions taken in different environments can be represented by an evaluation function $Q(d, x)$, where d represents a state in different environments, and x represents a corresponding action taken in this state, and a cumulative reward value will eventually be obtained. This cumulative return value is represented by $Q(d, x)$, as shown in formula (15). The combined award esteem is equivalent to the prompt prize worth in the wake of performing activity x in state d in addition to the ideal postponed reward worth of the resulting state space to activity space planning.

$$Q(d_t, x_t) = h(d_t, x_t) + \gamma \max Q(d_{t+1}, x_{t+1}). \quad (14)$$

In formula (17), $h(d_t, x_t)$ represents the immediate reward value obtained by performing the x action in the d state. Since the initial condition is unknown, $\max Q(d_{t+1}, x_{t+1})$ is uncertain. In the initial learning stage of the agent, formula (17) cannot be established, so people must meet the conditions for the convergence of the Q-learning algorithm, so an error function is needed to represent the convergence of this algorithm. The error function is formula (16):

$$\Delta Q(d_t, x_t) = h(d_t, x_t) + \gamma \max_x Q(d_{t+1}, x_{t+1}) - Q(d_t, x_t). \quad (15)$$

The Q function can be updated by formula (16), as in formula (17):

$$\overline{Q}(d_t, x_t) = h(d_t, x_t) + \eta_t \left[h(d_t, x_t) + \gamma \max_x Q(d_{t+1}, x_{t+1}) - Q(d_t, x_t) \right]. \quad (16)$$

Among them, $\eta_t = 1/1 + \mathrm{visit}_t(d, x)$ and $visit_t(d, x)$ represent the total number of times the state-action sequence pair (d, x) is visited. d_t is the state of the agent at time t, x_t is the action performed at time t, γ is the discount factor,

and $h(d_t, x_t)$ is the reward after performing action x_t. d_{t+1} is the new state reached at time $t+1$ after the agent performs action x_t, and x_{t+1} represents the action performed in state d_{t+1}. The agent will perform different actions at different times according to different environmental states, thereby continuously updating the Q value.

To make the Q-learning algorithm easier to understand and use, the relationship between the state space $d = \{d_0, d_1, \cdots, d_n\}$, the action space $x = \{x_0, x_1, \cdots, x_n\}$, and their corresponding Q values is shown in the form of a table. The corresponding action x taken in each state d corresponds to an evaluation value Q to reflect the quality of the selected action, as shown in Table 1.

The Q-learning algorithm is convergent under the following conditions.

(1) The state of the environment is a deterministic Markov decision process.

(2) It needs to constantly visit all state-action sequence pairs.

(3) The immediate reward value is bounded; that is, for all state space d and action space X, there exists a constant c, making $|h(d, x)| < c$.

3.3.4. Exploration Strategy.
After the learning calculation joins, the specialist needs to make the comparing moves as per the Q worth of various activities in the present status. To all the more likely apply the Q-learning calculation, it is important to utilize a sensible investigation methodology to tackle the clashing issue of investigation and usage in Q-learning. The specialist can utilize the Boltzmann investigation system to choose the relating activities. The probability of the agent taking action x using the Boltzmann exploration policy in state d is shown in the following formula:

$$G(x_u \mid d) = \frac{e^{Q(d,x_u)}/N}{\sum_v e^{Q(d,x_u)}/N}. \tag{17}$$

In formula (17), N addresses a steady more prominent than nothing. In the beginning phase of learning, the worth of N is somewhat enormous, and the specialist picks activities whose Q esteem is not exceptionally huge during the investigation cycle. As the quantity of learning builds, the N esteem proceeds to diminish, and the specialist starts to pick activities with higher Q values. This likewise shows that in the beginning phase of learning, the specialist will in general investigate while picking activities and will in general involve it in the later phase of realizing, which takes care of the issue of inconsistency among investigation and usage in the Q-learning calculation.

3.4. Summary of Tennis Tactics

3.4.1. Research on Winning Factors, Winning Laws, and Tactical Relationships.
In conflict with an opponent, the shared limitations of both players are finally acknowledged

TABLE 1: Q table.

Action state	d_1	d_2	...	d_u	...	d_n
x_1	Q_{11}	Q_{21}	...			...
x_2	Q_{12}	...				
...	...		...			
x_v				Q_{uv}		
...					...	
x_m	...					Q_{mn}

through the five physical components of hitting: speed, power, landing, spin, and arc (Table 2). Competitor's serious level and capacity will eventually be displayed in the game from the reality qualities of raising a ruckus around town. Subsequently, there are unique winning elements, for example, "speedy, turn, exact, merciless, and change" proposed by the table tennis industry and "savage, change, heartless, and get" proposed by the badminton business.

Tennis-winning formula is the inferential processing of the fundamental associations of opponent interactions. It implies objective rules that mentors and competitors should abide by to overcome opponents and try to achieve excellent results within the constraints of opposition rules (Figure 3).

3.4.2. Area Division of Site Lines.
According to the "Research on the Characteristics of Hard Court Skills and Tactics of World Women Professional Tennis Players" [19], the tennis court is divided horizontally and vertically. And according to the stance of the batter facing the field, the field area can be divided into two areas: horizontal (left area, middle area, right area) and vertical (front field, middle field, back field). The horizontal division area includes left area, middle road, and right area. The horizontal division is divided into four equal areas according to their respective half-court areas, with the left area accounting for one-quarter, the middle area accounting for one-half, and the right area accounting for one-fourth (Figure 4(a)).

The vertical division area includes three areas: front-court, midfield, and backcourt. The horizontal division is divided according to the length of the respective half-court area (as shown in Figure 4(b)): frontcourt—the front court is determined by the distance between 4 meters behind the net. Backcourt: The backcourt is determined by the distance 3 meters forward from the bottom line. Midfield: The distance between the frontcourt and the backcourt is determined as the midfielder [20].

According to the horizontal and vertical field division, the players of both sides can extend nine small areas in turn, which are the left area of the front court (1), the middle road of the front court (2), the right area of the front court (3), the right area of the midfield (4), midfield middle road (5), midfield left area (6), backfield left area (7), backfield middle road (8), and backfield right area (9). Use the digital code form to represent the corresponding area (Figure 5).

According to the position of the receiving player, the serving point (taking the receiving area in one area as an example) can be divided into three areas: the inner corner,

TABLE 2: Winning factors of table tennis, volleyball, and badminton.

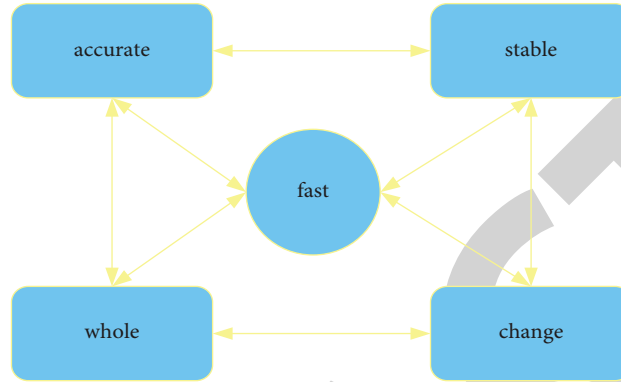| Project	Winning factors				
Table tennis	Fast	Accurate	Ruthless	Change	Turn
Volleyball	Whole	High	Fast	Change	Live
Badminton	Fast	Ruthless	Whole	Accurate	
Commonality	Fast	Change	Whole	Accurate	Ruthless

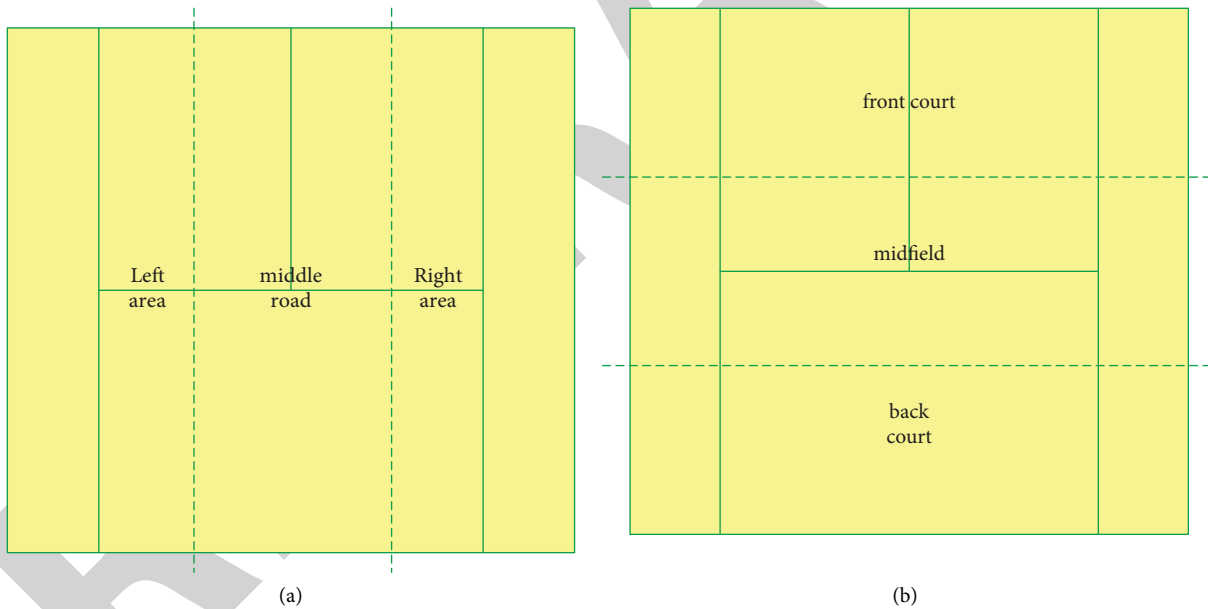FIGURE 3: Interrelationship of tennis-winning factors.

FIGURE 4: Schematic diagram of the horizontal/vertical division of the batter's stance. (a) Schematic diagram of the horizontal division of the batter's stance. (b) Schematic diagram of the vertical division of the batter's stance.

the middle, and the outer corner. The serving area is divided into four equal areas: the outer corners account for one-fourth, the middle one-half, and the inside corners one-fourth. According to the selection of multiple serving points by the serving player, the three areas of the inner corner, the middle road, and the outer corner are divided into three areas, and six small areas are extended. The order is the shallow inner corner (1), the shallow middle road (2), the shallow outer corner (3), the outer corner (4), the middle

road (5), and the inner corner (6); the corresponding areas are expressed in the form of digital codes (Figure 6).

The return line is divided in "Research on the hitting line of the world's outstanding male tennis players in hard court competition.". According to the stalemate stage, this paper is divided into straight line, middle road, diagonal line, middle road to left, middle to right, and hitting line. The following sequence is the return flight route of the straight line (BE, CF, AD), the middle road (CE, AE), the diagonal line (CD,
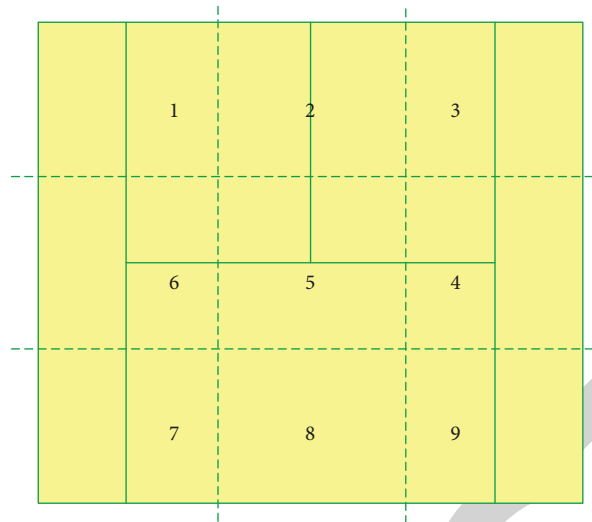
FIGURE 5: Schematic diagram of the digital codes for the nine areas in the half-court.
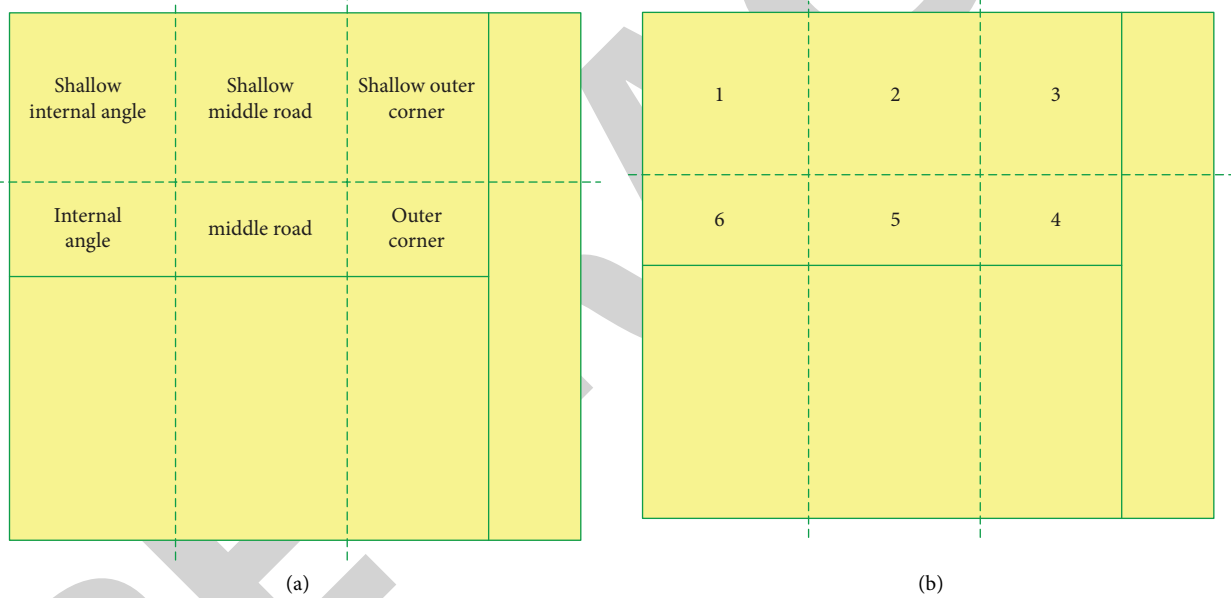

(a)

(b)

FIGURE 6: Schematic diagram of the division of the server landing area/digital code. (a) Schematic diagram of the division of the server landing area. (b) Schematic diagram of the digital code for the division of the server landing area.

AF), the middle road to the left road (BF), and the middle road to the right road (BD) [21](Figure 7).

4. Experiments on the Evaluation Model of Tennis Game Technical and Tactical Effectiveness Based on Machine Learning

4.1. Constructing the Evaluation Index System of Tennis Technical and Tactical Effectiveness. Figure 8 summarizes the typical usage rates and normal scoring rates for the specialized and strategic use of each racket for 92 of the world's elite men's tennis players in the basic unit competition of hard-court confrontation. Since the typical usage rate of each racket after the 15th racket is less than 1.00%, the total

normal usage rate is only 4.62%, and the sample size is small. Therefore, this paper only investigates the application quality and application impact of the specialized and strategic use of the initial 15 rackets, thus providing the premise for the development of the specialized and strategic documentation framework [22].

From the typical utilization rate in Figure 8, it very well may be seen that the best men's tennis players on the planet have three phases in the utilization of each racket procedure and strategies in hard court contests. The primary stage incorporates the first and second beats, the usage rate is the most noteworthy and shows a sharp vertical pattern, arriving at the top, and in the second beat, the use rate is 14.47% and 19.53% separately. The subsequent stage is 3~6 beats, and the use rate shows a sharp descending pattern, from the most
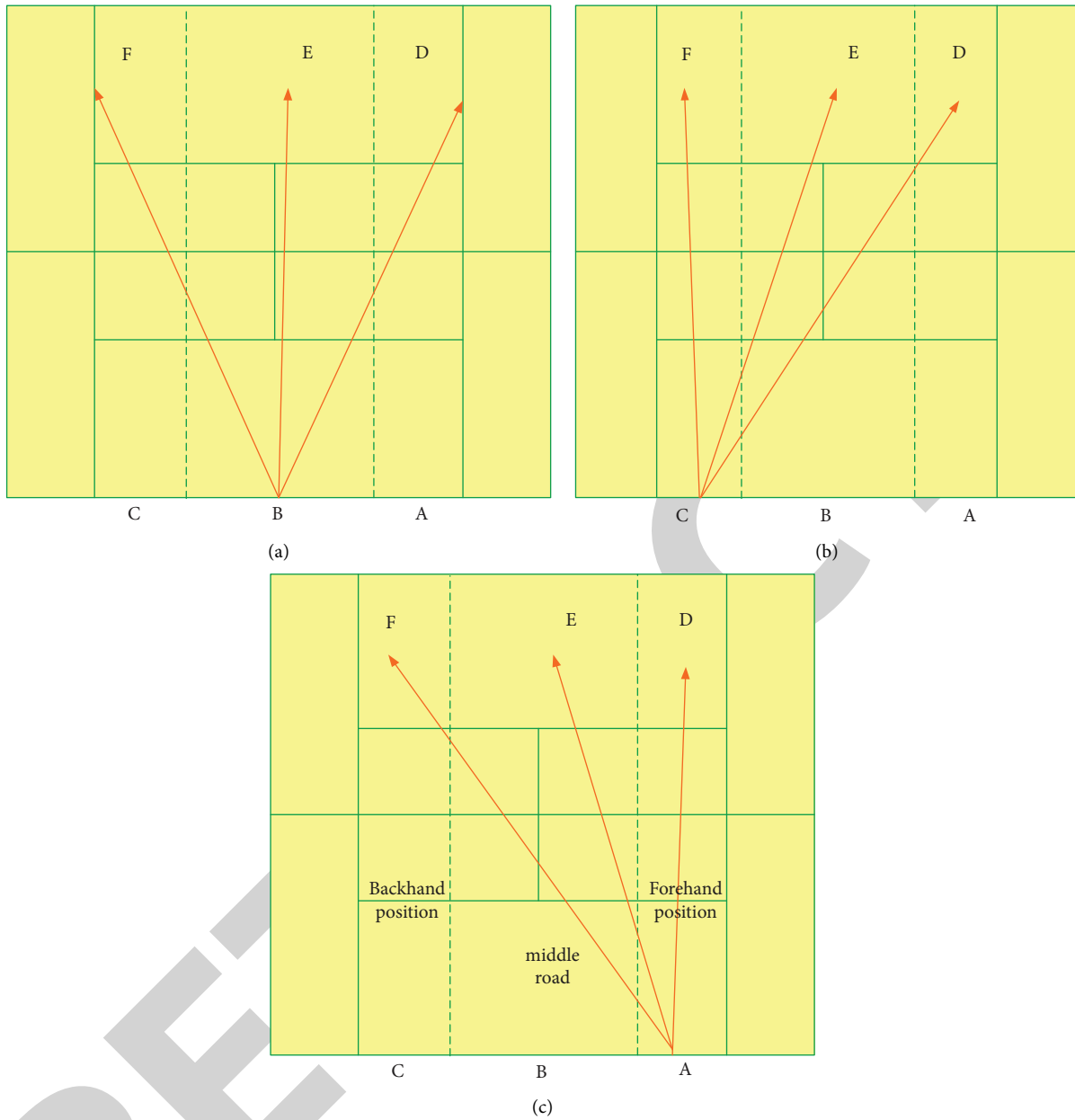
(a)

(b)

(c)

FIGURE 7: Schematic diagram of the return line area.

elevated usage pace of 12.01% to 7.15%. The third stage is 7 beats and the ensuing beats (alluded to as the seventh beat), and the use rate shows a delayed descending pattern, from 5.38% to 1.00%. From the typical scoring rate in Figure 8, it tends to be seen that the scoring pace of each shot additionally presents the attributes of three phases: the main stage is the first and second shots, and the scoring rate drops pointedly. Fell to 33.06% from 90.35% initially. The subsequent stage is 3~6 rounds, the scoring rate shows a wave-like change in the principal rising and afterward falling, and the scoring pace of the serving game (3, 5 beats) is fundamentally higher than that of the getting game (4, 6 beats). The third stage is after the seventh beat, and the change pattern of the scoring rate is delicate and vacillates

consistently above 40.00%. There is little distinction in the scoring rate between each shot in the serving game (7, 9, . . .) and each shot in the getting game (8, 10, . . .).

4.2. Empirical Application of Technical and Tactical Effectiveness Evaluation Model. Examination of tennis players' specialized and strategic records can reflect specific contributors to this issue in the game. To reflect the overall nature of the competition, we wish to thoroughly assess the adequacy of each major and strategy document, as shown in Table 3. It has information on the impact of Federer's applications and strategy in hard court games from 2013 to 2017.
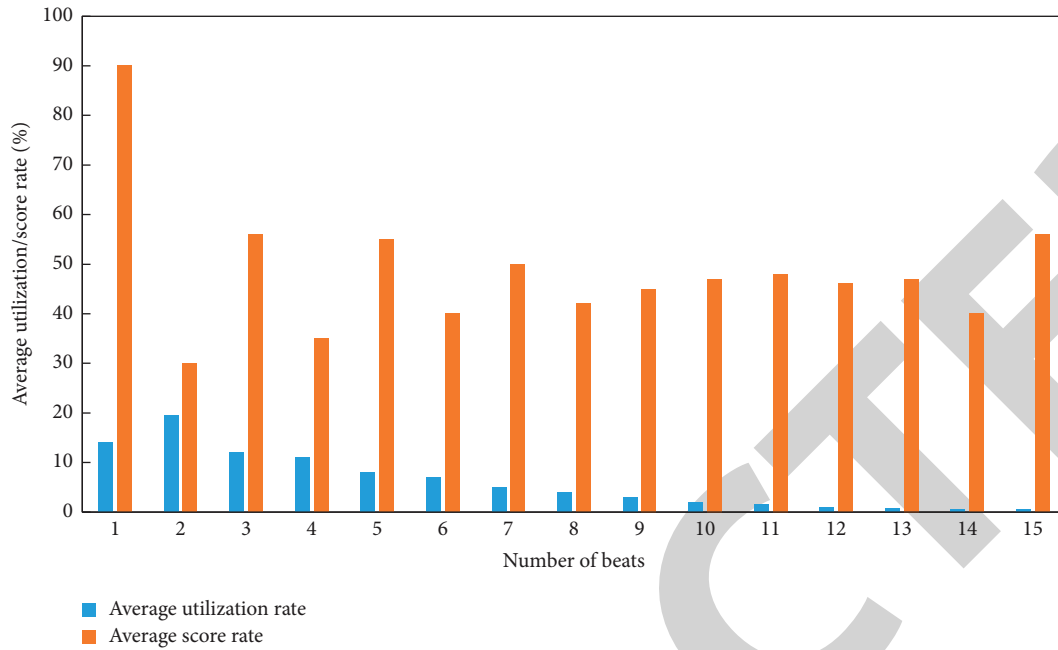
Figure 8: Schematic diagram of the average usage rate and average scoring rate of the world's top men's tennis players.

Table 3: List of effects of Federer's game techniques and tactics.

| Match	S_1	S_2	S_3	S_4	S_5
2017 Australian Open final	0.9377	0.5413	0.4511	0.3311	0.3751
2017 Australian Open semifinals	0.9377	0.5723	0.4067	0.3058	0.3216
2016 Australian Open semifinals	0.9654	0.4523	0.3102	0.1864	0.2943
2015 year-end finals	0.8891	0.6363	0.3146	0.1057	0.3479
2015 year-end finals and semifinals	0.8321	0.6571	0.7512	0.3101	0.5021
2015 US Open finals	0.8801	0.5253	0.3575	0.3407	0.4533
2015 US Open semifinals	0.9297	0.7025	0.4167	0.3311	0.6666
2014 year-end finals and semifinals	0.9742	0.5687	0.3078	0.3311	0.3687
2014 US Open semifinals	0.9652	0.4653	0.3311	0.2396	0.3311
2014 Australian Open semifinals	0.9611	0.4910	0.4801	0.2534	0.2754
2013 year-end finals and semifinals	0.9375	0.5426	0.4517	0.3311	0.3751
2013 Australian Open semifinals	0.9543	0.6356	0.2727	0.210	0.3001

The reference packet and associated sequence are determined from the first information {1.000 00702, 7, 0.750, 0, 0.391, 3, 0.666, 7, 0.583, 3}. Since the components of the selected token are not bound together, the upper part of the evaluation pointer should be normalized. These five specialized strategic pointers are interest markers. See Figure 9 and Table 4 for the weighted gray correlation degree of each index.

4.3. Comprehensive Evaluation of Federer's Technical and Tactical Effectiveness. Federer achieved the highest and best professional and strategic adequacy assessment in the semifinal against Wawrinka at the 2015 US Open with a score of 0.8429. In 2014, the US Open to Cilic had the worst semifinal, with only 0.489 in specialization and strategic productivity. Over the next five years, Federer's professional and strategic efficiency changed around 0.600, from a normal value of 0.594. Further observation of Figure 10

shows that from 2013 to 2017, Federer's technical and tactical effectiveness showed three stages of characteristics in three hard games.

The first stage: From the 2013 Australian Open semifinals to the 2014 US Open semifinals, Federer's jacket quality showed a slow decline, and the 2014 US Open semifinals fell to the absolute bottom. At this stage, specialization and strategic productivity did not play out as well as Federer himself had feared. Declining physical fitness and injury difficulties with age are the underlying purposes behind Federer's unfortunate specialization and strategic efficiency during this period. At this stage, with Nadal, Federer's DSLR and Cilic are usually weak, and Federer's professional and strategic advantage has also diminished with age, with 1 in every 4 matches at the edge.

The second stage: From the semifinals of the 2014 finals to the semifinals of the Australian Open in 2016, Federer's quality showed a dynamic state of first rising and then falling. At this stage, the opponents are Djokovic (3
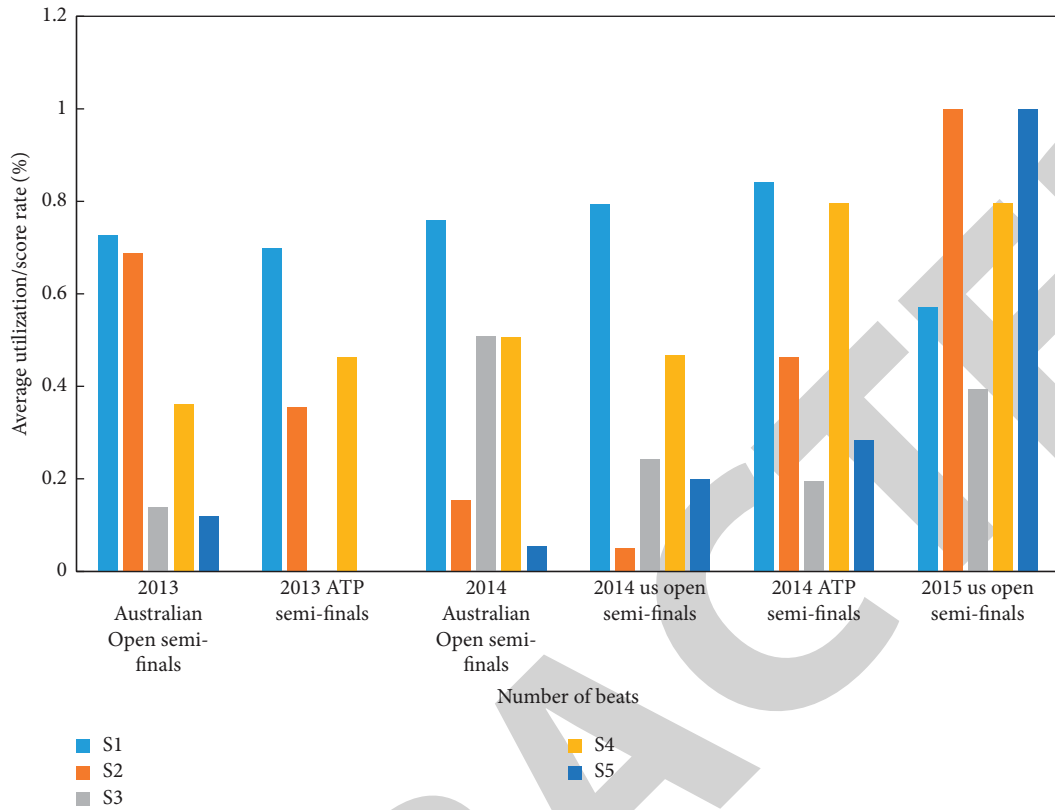
(a)
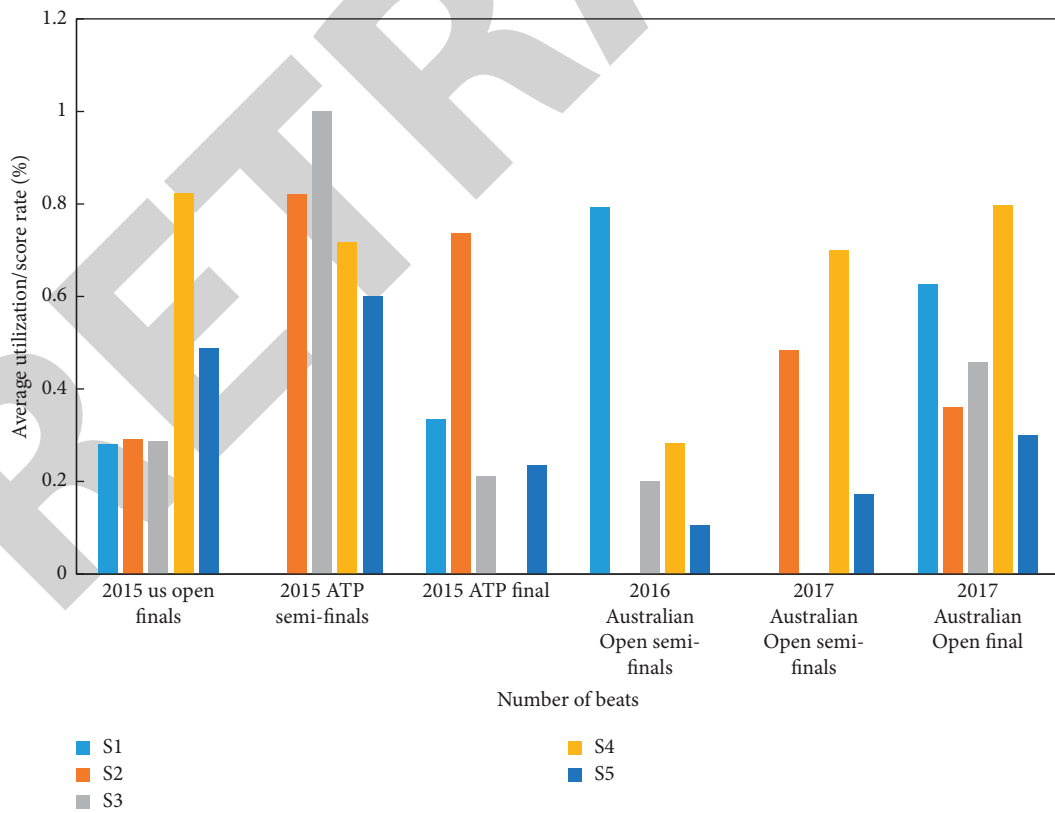
(b)

Figure 9: List of normalized data.

Table 4: Weights of each evaluation index.

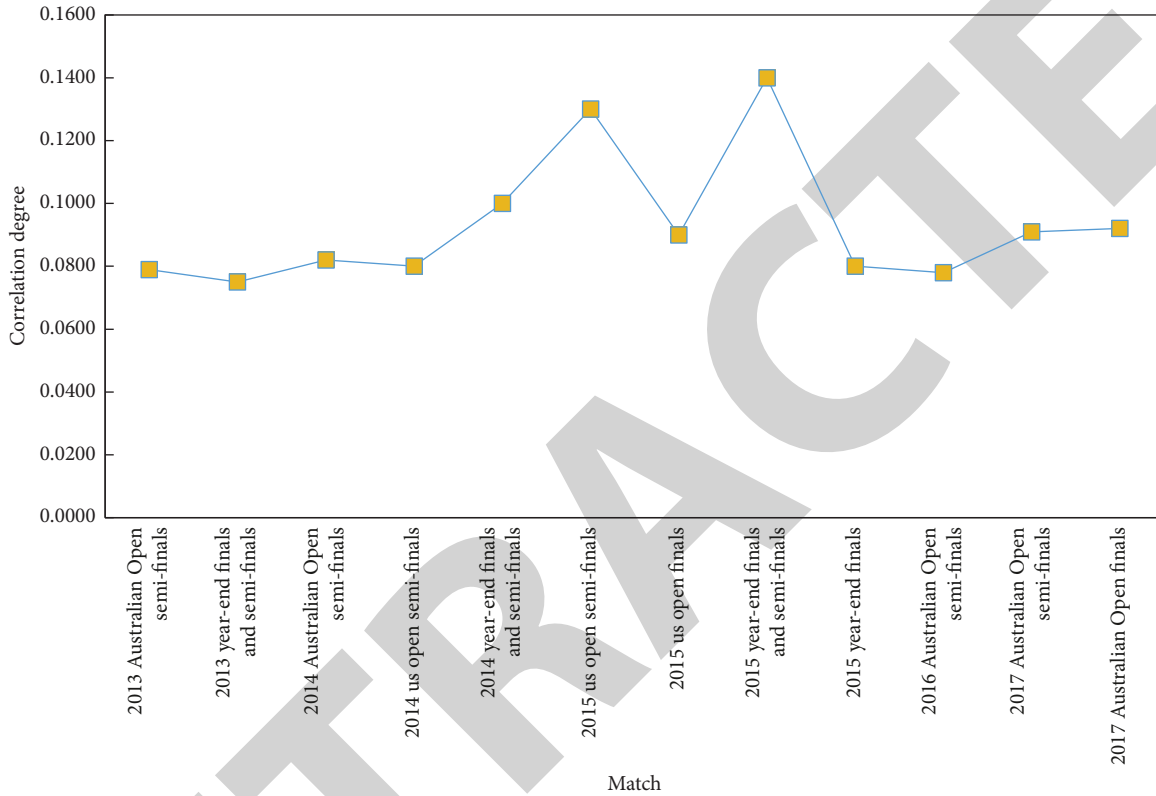| Variable	S_1	S_2	S_3	S_4	S_5
E_u	0.9478	0.8927	0.8904	0.9561	0.8913
ω_u	0.0975	0.2069	0.2116	0.0874	0.2111
Difference	Y	Y	Y	Y	Y

Figure 10: Schematic diagram of the technical and tactical effectiveness evaluation trend of Federer vs Nadal.

unfortunate) and Wawrinka (3 successful). According to Federer's own situation, at this stage, Federer changed to a large racket (90~97), which helped the speed increase, DSLR innovation also improved, and defense and ball-handling sturdiness improved (accuracy decreased). He played a prominent role with Wawrinka, dominated 3 out of 3 games, and basically addressed Wawrinka's shortcomings. Although Djokovic is at its peak, Federer's professional strategic improvement does not actually bring it any danger, with 3 games and 3 losses.

Stage 3: Entering the 2017 season, Federer's level of specialization and strategy is gradually improving, and he beat Nadal in the Australian Open. In the last Australian Open in '17, Federer won the next two grueling atp1000 s (Indian Wells and Miami Masters) and Wimbledon, finishing 19 champions. There are three explanations behind the increased professionalism and strategic adequacy at this stage. (1) In the past two years, Federer has continuously improved his innovation and further improved his professionalism and strategic ability. His play style has become

more cautious and effective, with a more solid achievement rate and attacking power. Specifically, he improved his attacking ability and fearlessness to win over his opponents. (2) A calmer attitude: Federer's quieter and calmer mental state has been honed in "lack of champions" for quite some time. The difference in mentality will positively lead to higher achievement for Federer. (3) Logic Contest: Since the 2016 season, Federer's unique game system actually guarantees physical recovery and improves the efficiency of the game.

To sum it up, from around 2013, Federer has played in three hard court matches, and the specialization and strategic productivity have been characterized by three phases. However, all in all, the 2014 US Open semifinals were the "point of limit." In the process of Federer's continuous promotion and improvement of his own innovation capability, his professionalism and strategic effectiveness rebounded step by step. A change of mind and logical-wise competitive decisions are the only way for him to run and leap forward in the tennis world.

5. Discussion

Recently, tennis has gained popularity. Many residents participated in tennis matches, setting off a boom in tennis. On the basis of real currency globalization, material, and social diversification, how to further develop the confrontation ability of tennis players and promote the improvement of the level of tennis has become a major event affecting the development of China's tennis industry.

Tennis improvements are getting bigger and bigger, as are the prerequisites for the setting and variety of scenarios. Then, there are hard courts, clay courts, and grass courts. A wide variety of environments have specific prerequisites for the actual fitness of the athlete and the choice of the athlete's hitting ability and strategy. The characteristics of the hard court are that the outer layer is set at a medium level, with high hardness, and the ball jumps in general, but the ball rebounds quickly. Most good specialist players admit that hard courts have more "dangerous power" and dominate opponents.

Red clay fields can also be called "soft fields." The characteristics of clay courts are that it is not difficult for the ball to make more significant contact with the court, and the speed of the ball is slower. Players will have a more pronounced glide pattern when running, especially during crisis pauses and starts, which requires more physical fitness, running, and mobility from the player and lasts longer on clay than on different surfaces. As the most experienced field, the grass court is characterized by small friction between the ball and the field, and the rebound speed of the ball is accelerated, which has higher requirements on the players' reaction time and reaction ability. Of the four Grand Slam tournaments, the Australian Open and the US Open are hard courts, the French Open is a clay court, and Wimbledon is a courtyard court.

6. Conclusions

According to the phased characteristics of the methods and strategies used by the world's top male tennis players in the hard court matches, the paper puts forward the evaluation document arrangement of the program and strategy feasibility in the hard court tennis men's singles matches, which is the auxiliary strategy connection, auxiliary strategy connection, and auxiliary strategy connection. And they are the serving tactical link, the serving tactical linking link, and the stalemate tactical link, which reflect the serving ability of the serving game. The tactical link of receiving and serving, the linking tactical link of receiving and grabbing, and the tactical link of stalemate II reflect the ability to break serve in the receiving and serving game.

This article uses Federer's 12 hard court matches from 2013 to 2017 as an example. Federer's specialization and strategic viability are assessed from a time grouping perspective using an instant-weighted dark connection model. It stands to reason that between 2013 and 2017, Federer's specialization and strategic adequacy of the world's top players featured three phases. Specialization and strategic viability showed a slow decline pattern from 2013 to 2014. From 2015 to 2016, specialization and strategic adequacy

showed a wave-like change pattern. In 2017, specialization and strategic adequacy showed a progressive vertical pattern. Federer's return to form in 2017 reflects the science and wisdom of his preparation and game at this stage. There are numerous documents on the quality assessment of tennis matches. In this way, we should choose lists that are deeply agency and calmly reflect what is going on to fully reflect the nature of the match. The direct weighted darkly relationship degree model can quantitatively reflect the strengths and weaknesses of competitors' specialization and strategic viability in different periods, and has practical value in evaluating tennis methods and strategies.

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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