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Retraction

Retracted: Monitoring of Physical Fitness and Tactical Ability Based on Data-Driven Technology

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

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[1] X. Zhang and Y. Zhou, "Monitoring of Physical Fitness and Tactical Ability Based on Data-Driven Technology," *Mobile Information Systems*, vol. 2022, Article ID 8721752, 10 pages, 2022.

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Research Article

Monitoring of Physical Fitness and Tactical Ability Based on Data-Driven Technology

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Tennis is a competitive sport, which requires players to have good physical fitness and long-lasting endurance. Monitoring the physical training and technical and tactical abilities of tennis players is a necessary work to improve the physical fitness and competitive status of tennis players. Monitoring the physical training and technical and tactical capabilities of tennis players is necessary to improve their physical fitness and competitive status. Most of the traditional monitoring systems are incomplete, inaccurate, and inefficient, which can no longer meet the requirements of tennis training monitoring in the new era. Therefore, it is urgent to establish an efficient and more accurate tennis training monitoring system. With the rise of big data, data-driven technology has been concerned about and frequently used. It means using data as a production material, applying it in a scientific way to business operations, and giving continuous positive feedback to facilitate business optimisation. This study selected tennis sports training, physical fitness, and technical and tactical abilities as the monitoring object, and it analyzed the monitoring system combined with the grey relation algorithm and TOPSIS algorithm. The experiment showed that the monitoring system based on data-driven technology can comprehensively and accurately monitor the physical ability and technical and tactical abilities of tennis sports training, and the accuracy improves by 5.9%.

1. Introduction

The basic purpose of tennis training is to improve the physical quality of athletes by the technical and tactical requirements to adapt to the continuous development of sports needs and achieve excellent sports results. Exercise training is a long-term process, and training monitoring is one of the most important links. Unlike physical fitness, sports and tennis can be completed through training with quantitative indicators such as the number of sets, time, distance, and weight. It monitors and evaluates the training load and the effect of athletes on the training volume, training intensity, or related physiological and biochemical indicators. Therefore, the monitoring of technical and tactical training in tennis is essential. General sports can be supplemented by group number, time, distance, weight, and other monitoring. The difference between tennis is that it is monitoring and evaluating the training load and effect of athletes based on the training volume, training intensity, or related physiological and biochemical indicators. Therefore, the technical and tactical training and monitoring work of tennis events are essential. Currently, data-driven methods and technologies are also being used in sports. It relates training data for individual athletes. Through the monitoring and diagnosis of motion process, the data flow logic is connected to form a unified system to complete the application of data-driven technology in motion training monitoring.

At present, the application of data-driven methods and technologies in various fields has been studied and discussed. Li and Liu proposed a novel distributed data-driven consensus protocol, where the reference input is designed as the average of the proxy output over time. The performed numerical and practical examples demonstrate the validity of the proposed protocol [1]. Wei et al. proposed a novel data-driven zero-and neural optimal control portal for continuous-time unknown nonlinear systems with perturbations. Taking the system disturbance as the control input, a two-person zero-sum optimal control problem is established [2]. Feng et al. developed a data-driven multimodel wind forecasting method. Experiments showed that this data-driven multimodel wind forecasting method can accurately predict both deterministic and probabilistic wind directions [3]. Zhu and Hou proposed a new data-driven model adaptive control method for a class of discrete-time single-input single-output linear systems. The effectiveness and applicability of the method are further verified by experiments on the control process [4]. Eggimann et al. proposed a data-driven urban water resource management (UWM) system, which uses data-driven methods to conduct research and analysis on urban rainfall data management, urban flood risk management and prediction, and operation of drinking water and sewage pipe networks. The findings demonstrate that data-driven UWM enables the development and application of new methods to improve the efficiency of urban water resource management systems [5]. Amasyali and El-Gohary analyzed and compared many typical data-driven prediction methods according to the complexity and reliability of the measurement and control system, determined some methods suitable for application in measurement and control, and designed the framework of fault prediction system. Finally, future research on fault prediction in the fields of tracking, telemetry, and command is prospected based on existing methods [6]. Xie et al. proposed a data-driven filtered reduced-order model framework for the numerical simulation of fluid flow. Finally, new coefficients are found in the closed filter ROM to solve the numerical optimisation problem [7]. The research work on data-driven technology in these fields is relatively abundant, but its application in sports ability training and technical tactics has not been mentioned.

Sports training can improve the physical quality of athletes, better fulfill the technical and tactical requirements, and adapt to the changing and developing needs of sports. To carry out the scientific management of athlete training, many scholars have carried out related research on it. Wu et al. proposed a monitoring method for different temporal structure-level motor training based on the fusion of motor commitment theoretical models. In the process of monitoring the motor commitment theory model, unlabeled samples can be effectively labeled according to the motor commitment theory model, which finally shows that the motor training can be effectively estimated [8]. Zhang and Wang proposed a dynamic monitoring solution for Android and used plug-in technology to create host applications with monitoring behavior. He analyzed the temporal distribution characteristics and obtained the statistical characteristics. Finally, the safety of sports training for young female athletes was accurately monitored [9]. Jiang designed a target detection and tracking algorithm. Algorithms and tracking methods take neural network algorithms and apply them to athlete training models. The research results showed that the method has a certain recognition effect and can be applied to athlete training [10]. Grymanowski et al. studied the front kick dynamics method of Muay Thai athletes. The BTSSMART DX 6000 sports complex analysis system is designed for an athlete with long-term training experience and high-level training. Analysis shows that, in most cases, aerial kicks are characterized by a higher foot velocity relative to the target kick [11]. The team of Tang et al. established an athlete's heart rate measurement model based on the support vector machine and combined it with the improved algorithm. They adopted the denoising algorithm of multichannel spectral matrix decomposition to eliminate the interference factors, and the final control experiment verified the efficiency and accuracy of the model [12]. These athlete training studies are relatively specific and have a certain reference value for the advancement of training work, but relatively novel data-driven methods and technologies have not been used.

This study uses data-driven methods and technologies, combined with the grey relational algorithm and TOPSIS algorithm, to research and analyze the current situation of tennis training, physical fitness, and technical and tactical abilities monitoring. The purpose is to change the traditional monitoring system and tactical capability monitoring technology, to make the monitoring method scientific and effective. Finally, it provides objective and accurate data for coaches and athletes in tennis training competitions to promote the development of scientific training.

2. Data Driven

2.1. Data-Driven Layer. From the depth of data processing or application level, data-driven is divided into four levels: monitoring, analysis, mining, and enabling, as shown in Figure 1. Monitoring is the shallowest level of data driven and refers to the use of data to document what actually happened. In this case, data are a realistic representation of objective things, people just simply process the data, and the data are usually presented in a raw and coarse-grained form. The value of data is like a wilderness that has not been fully exploited [13].

Analysis is the second data-driven level, with slightly higher stem monitoring. In this part, people use various analytical models and analytical methods to understand the data and gradually become familiar with many analytical tools for deep data processing. The value of the data is slowly being shown. The keywords corresponding to this section are systematization, diagnosis, and visualization, where one can analyze data with specific frames. Data diagnosis can be used, and data-finding imaging technology can be used to obtain the results of data analysis.

Mining is the third level of data driven, used as further analysis of the data. In this part, one is able to take over a lot of programs and process data with some multifunctional algorithms. Like the classical machine learning algorithm, which is the most common method in this step? At this level, the value of data can be fully mined and released. The keywords of this stage are modelling, formulating, and regularizing.

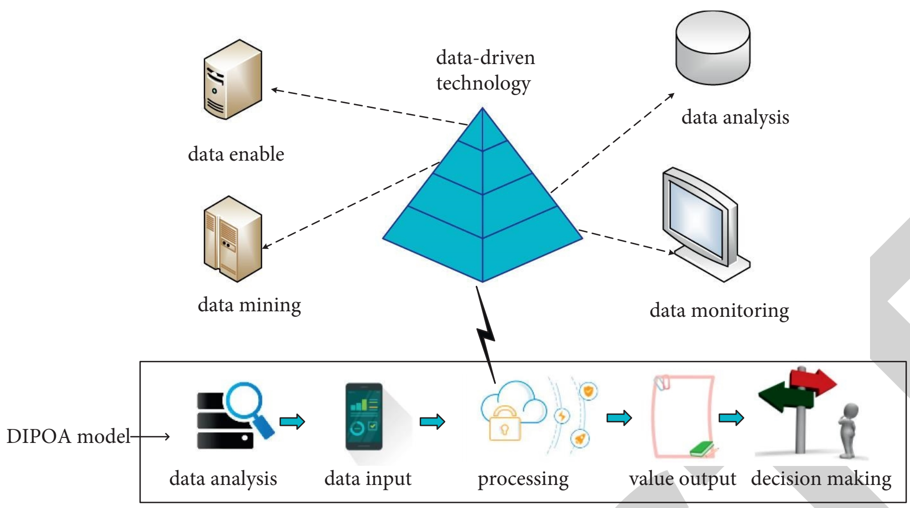

Figure 1: Data-driven hierarchy and data-driven chain.

Empowerment is the last level of data driven, with the same meaning as empowerment, meaning "have some ability." Data in this part inject vitality into the business and become an important factor of production [14].

2.2. Data-Driven Chain. Considering data as the raw material for the production and operation of an enterprise, the "data-driven" process can be understood as the DIPOA model, that is, the data-input-process-output-action point. The data-driven chain can regard data as the raw material for the production and operation of the enterprise, and the "data-driven" process can be understood as the DIPOA model, as shown in Figure 1. It is divided into five parts: data investigation, data input, processing, output, decision-making, and action [15]. Data, as a production component, require specific steps of processing, resulting in corresponding outputs, which then generate values for the corresponding action points, and then create a "data unit" of a work chain [16]. The DIPOA model is designed with reference to the classical SIPOC model, which can explain the data-driven action process and mechanism in the form of a conduction chain.

3. Monitoring of Physical Fitness and Technical and Tactical Abilities of Tennis Sports Training under Data-Driven Technology

The training intensity of athletes is becoming greater and greater, and the requirements for technical and tactical capabilities are also getting higher and higher. Accurate and comprehensive scientific monitoring of athletes' "training progress is an essential and important link in athletes'" scientific training [17]. The so-called sports training monitoring is to ensure that the coach clearly knows which stage the athlete is in so that he can respond accordingly. Otherwise, when the coach ignores the concept of monitoring, all training is guesswork.

This study uses data-driven technology to study the monitoring of physical fitness and technical and tactical capabilities of tennis training, aiming to provide a comprehensive, scientific, and efficient monitoring system for tennis players, and the monitoring system architecture is shown in Figure 2. First of all, all physical data of the athletes will be uploaded to the cloud, and the coaches will obtain the data from the cloud and analyze it, to have a comprehensive grasp of the athletes' situation. Then, the coach will make technical and tactical arrangements according to the different conditions of the athletes. Athletes' training data, ability indicators, test data, abnormal results, and side information will be uploaded to the monitoring system in time. The data-driven approach simulates a decision by the coach based on the specific data of each athlete. Finally, the coach made a comprehensive analysis and decision on the athletes' physical and technical and tactical training for this decision, to achieve the purpose of training monitoring.

Technical and tactical training analysis is to obtain the object of tennis game training technical and tactical analyses through data-driven technology and then conduct a specific analysis of the research object's tennis technical and tactical analyses. For example, five tennis players are selected from the monitoring data, and the five data-driven research objects are named as A, B, C, D, and E, as shown in Figure 3. They are used for fixed-point and fixed-focus shooting of the monitoring scene, and the athletes are arranged to perform overhand serving techniques and hit the ball on the spot. The shooting frequency is 240 Hz, the shutter speed is 1/2000 s, the diameter of the three-dimensional calibration frame is 2.5 m, and the angle between the two cameras and the measured object is 90°. The techniques and tactics used by tennis players at each stage and the physical fitness displayed during the game can be clearly and accurately recorded by these two machines. When the game is over, the coaches and athletes will retrieve the data for analysis, to make arrangements for the next training work.

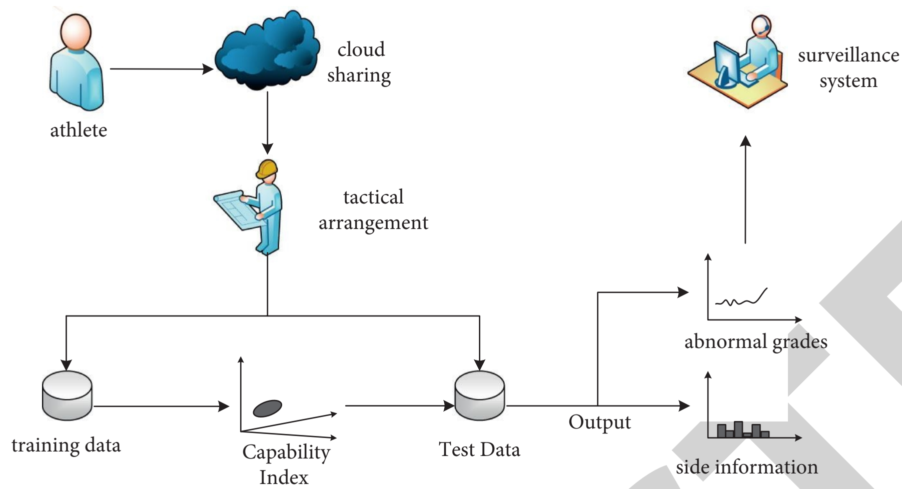

Figure 2: A tennis monitoring system based on data-driven technology.

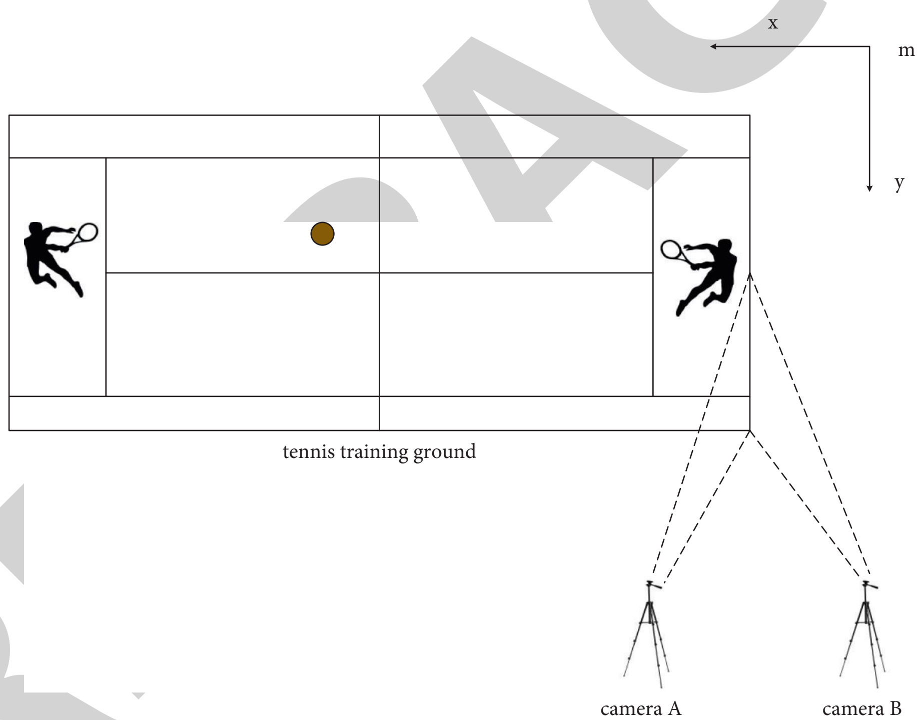

Figure 3: Monitoring and analysis of tennis training techniques and tactics.

The training of tennis sports technical and tactical abilities cannot be separated from the professional grip method [18]. As shown in Figure 4, there are seven basic tennis grip styles. Including eastern forehand, western, semiwestern, superwestern, continental, eastern backhand, and two-handed grip, each has its advantages and disadvantages. During the monitoring process, it can be found that the five tennis players have different handles. The handle style of each tester was changed during the serve. A and B are oriental, while C, D, and E use handles between western and oriental styles. The five players changed their handling from play to serve, changing from front to back, but each subject had a different switch degree, which also shows the adaptability of the athletes during the training competition.

4. Tennis Training and Technical and Tactical States Monitoring Calculation Method

The central idea of tennis skills and tactics is the word “steady” in the first place, be patient, and hit the ball steadily. Do not abuse a style of play you are not yet familiar with because it pays more than you pay for it. Generally, the hitting point is within 60 cm from the sideline. The two most

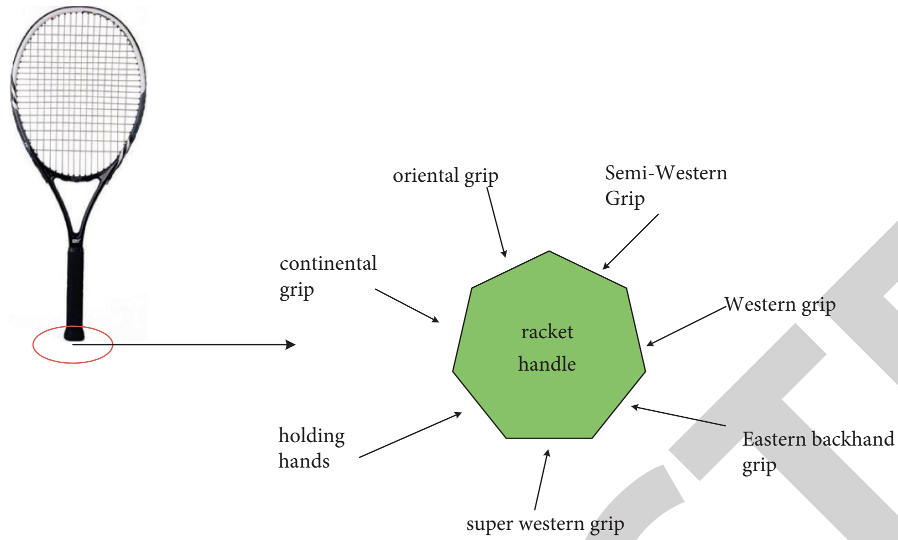

Figure 4: Tennis grip.

Table 1: Tennis game tactics and codes.

Rounds	Hit the ball	Score observation point and code	Ignore observation points and code	Totally code
Serve	Serve	The other party's hair loss (A+)	This part of the company (A−)	A
	Third shot	The other party's fourth shot error (B+)	The third shoot error (B−)	B
	Hold I	The sixth shot of the other party (C+)	The fifth shot of this party and later mistakes (C−)	C
Get up	Get up	The third shot of the other party (M+)	This party is getting lost (M−)	M
	Fourth shoot	The other party's fifth shot error (N+)	The fourth shooting mistake (N−)	N
	Hold II	The seventh shot of the other party and after the mistake (O+)	The sixth shot of this party and after the future (O−)	O

important exercises in technical and tactical training are serving and receiving. The operation definitions are listed in Table 1.

Tennis techniques and tactics can generally be divided into two stages, namely, the first four shots and the last four shots, and the scoring rate accounts for about 50%, respectively. The first four beats have the greatest changes, including rotation, landing point, rhythm, speed, etc. [19]. Therefore, the test in this paper consists of the scoring and losing rates of each beat in the first four beats of each round, and the scoring and losing rates of the last beat after the fourth beat (1)–(11):

$$SR_1\,(\text{First shoot score rate}) = \frac{A^+}{A+B+C}, \tag{1}$$

$$SR_2\,(\text{The second shoot score rate}) = \frac{M^+}{M+N+O}, \tag{2}$$

$$SR_3\,(\text{Third shoot score rate}) = \frac{B^+}{B+C}, \tag{3}$$

$$SR_4\,(\text{Fourth shot score rate}) = \frac{N^+}{N+O}, \tag{4}$$

$$SR_{S>4}\,(\text{Points to I}) = \frac{C^+}{C}, \tag{5}$$

$$SR_{r>4}\,(\text{Compared with II score rate}) = \frac{O^+}{O}, \tag{6}$$

$$LR_2\,(\text{Second pad loss rate}) = \frac{M^-}{M+N+O}, \tag{7}$$

$$LR_3\,(\text{Third shooting rate}) = \frac{B^-}{B+C}, \tag{8}$$

$$LR_4\,(\text{Fourth beat loss rate}) = \frac{N^-}{N+O}, \tag{9}$$

$$SR_{S>4}\,(\text{Focusing rate}) = \frac{C^-}{C}, \tag{10}$$

$$SR_{r>4}\,(\text{Composing II lost mesh}) = \frac{O^-}{O}. \tag{11}$$

The analysis of the technical and tactical states of tennis players mainly adopts two algorithms, grey relational and TOPSIS, which are evaluated from the technical state development process and the comprehensive state, respectively.

4.1. Grey Association Algorithm. An important concept in grey system theory is relevance analysis (GRA). It describes the relative changes between factors in the process of system development, that is, the relativity of indicators such as change size, direction, and speed. If the relative changes of the two in the system development process are basically the same, the correlation between the two is considered large; otherwise, the correlation between the two is small.

The difference between the correlation analysis of the grey system theory and the correlation analysis of statistics is as follows: Correlation analysis of the grey system theory is based on the grey process of the grey system, while the correlation analysis of statistics is based on the random process of the probability theory; second, correlation analysis of the grey system theory is the comparison of time series between factors, while correlation analysis of statistics is the comparison of arrays between factors.

4.2. Grey Association Algorithm. An important concept of grey relational algorithm is relational degree analysis, which describes the relative changes between system development processes, for example, direction and speed indicators; if the system process changes are consistent, then the relationship between the two will be large; otherwise, the relationship will be small.

The method for analyzing the technical and tactical states of tennis players based on correlation is as follows:

(1) Athlete technical state sequence with an observation index is obtained as follows:

$$\left\{M_1^{(0)}(t)\right\}, \left\{M_2^{(0)}(t)\right\}, \ldots, \left\{M_a^{(0)}(t)\right\}, t = 1, 2, \ldots b. \quad (12)$$

In the above formula, b is the number of tests and a represents the number of test indicators.

(2) Another ideal sequence of technical and tactical states is established, and the correlation degree is a measure of the correlation between the technical and tactical observation sequences and the ideal technical and tactical sequences [20]. Then, the formula is obtained as follows:

$$\left\{M_0^{(0)}(t)\right\}, t = 1, 2, \ldots b. \quad (13)$$

(3) *Normalization of Raw Observation Data.* In the test indicators, the score rate can be considered as the benefit data, so the formula for normalization is as follows:

$$N_{ij} = \frac{M_{ij}}{\max M_{ij}}. \quad (14)$$

The loss rate can be considered as cost data, and its normalization formula is as follows:

$$N_{ij} = \frac{\min M_{ij}}{M_{ij}}. \quad (15)$$

(4) *Calculation of Correlation Coefficient.* The technical ideal sequence is denoted as $\{X0(t)\}$, and the technical observation sequence is denoted as $\{Xi(t)\}$. Then, at time $t = k$, the correlation coefficient $C_{0i}(k)$ of the ideal value sequence $\{X0(k)\}$ and the observed value sequence $\{Xi(k)\}$ can be simplified as follows:

$$C_{0i}(k) = \frac{\rho\Delta_{\max}}{\Delta_{0i}(k) + \rho\Delta_{\max}}. \quad (16)$$

In the above formula, $\Delta_{0i}(k)$ represents the absolute difference between the complete technical path and the path observed in k. $\Delta_{\max}$ represents the maximum amount of absolute variance per time across all comparisons. ρ is a decimal factor, $\rho \in (0,1)$, and in this study, $\rho = 0.5$.

(5) *Calculation of Technical Observation Sequence Correlation.* The correlation degree is the average value of the correlation coefficient between the technical ideal sequence and the technical observation sequence at each moment. In this article, it is also called "technical and tactical state coefficient," which is as follows:

$$R_{0i} = \frac{1}{W}\sum_{k=1}^{w} C_{0i}(k). \quad (17)$$

In the above formula, R_{0i} is the correlation between the technical ideal sequence 0 and the technical observation sequence i, and w is the number of observation sequences.

(6) *Analyzing the Development Process of the Athlete's Technical State through the Technical State Coefficient Curve.* The technical state coefficients of the b technical observation sequences and the technical ideal sequence are formed into a curve in time order, which can analyze the development and change of the technical state of the athletes in a training period.

4.3. TOPSIS Algorithm. The TOPSIS algorithm is used to evaluate the overall technical status of the research objects. The basic idea of the algorithm is to determine the best and worst schemes among the finite schemes for the normalized original data matrix. Then, the distances between each evaluation object and the optimal plan and the worst plan are calculated, respectively, and the relative closeness of each evaluation object and the optimal plan is obtained, which is used as the basis for the quality of the evaluation object. The overall calculation method of the technical and tactical statuses of tennis players based on TOPSIS is as follows:

(1) *Construction of an Overall Assessment Matrix of Athletes' Technical and Tactical Status.* There are b athletes and test indicator, and the average value of each athlete's q data is taken to construct an overall evaluation matrix $M = (M_{ij})_{b\times a}$ of the athlete's technical and tactical states.

(2) *Normalization of Original Observation Data*. Since the scoring rate of each item is a high-intensity indicator, and the score loss rate is an indicator of low quality, formulas (18) and (19) are used for improvement:

$$N_{ij} = \frac{M_{ij}}{\sum_{i=1}^{b} M_{ij}^2}, \tag{18}$$

$$N_{ij} = \frac{\frac{1}{M_{ij}}}{\sum_{i=1}^{b} \left(\frac{1}{M_{ij}}\right)^2}. \tag{19}$$

(3) *Determination of the Best and Worst Technical State Vectors*. The matrix $N = (N_{ij})_{b \times a}$ is obtained after normalization, and the maximum and minimum values of each column constituted the best and worst technical state vectors, respectively, are as follows: $N^+ = (N_{\max 1}, N_{\max 2}, \ldots, N_{\max n})$ and $N^- = (N_{\min 1}, N_{\min 2}, \ldots, N_{\min n})$.

(4) *Calculation of the Distance between the Athlete's Technical State and the Best and Worst Vectors*. The distance between the technical state of the ith athlete and the best and worst vectors, respectively, is shown in the following formulas:

$$S_i^+ = \sum_{j=1}^{a} \left(N_{\max j} - N_{ij}\right)^2 \tag{20}$$

$$S_i^- = \sum_{j=1}^{a} \left(N_{\min j} - N_{ij}\right)^2. \tag{21}$$

(5) *Overall Assessment of the Athlete's Technical and Tactical States*. When evaluating the technical state of an athlete as a whole, it is necessary to calculate the closeness E_i of the ith athlete's technical state to the best and worst vectors. When the value of E_i is larger, the athlete's technical and tactical states are better:

$$E_i = \frac{S_i^-}{S_i^+ + S_i^-}. \tag{22}$$

5. Data-Driven Monitoring Results of Physical Fitness and Technical and Tactical Abilities in Tennis Training

The algorithms mostly used in sports training and technical and tactical capability monitoring are usually mathematical simulation, diagnosis methods, data mining, and data-driven methods used in this study. The mathematical simulation diagnosis method is to make reasoning and judgment based on the knowledge and experience provided by

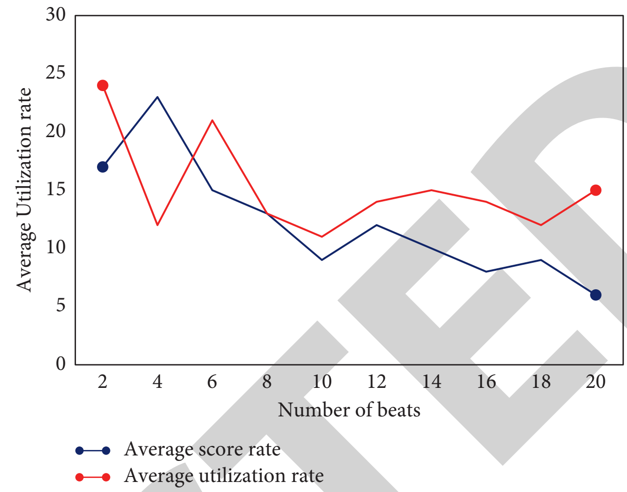

FIGURE 5: Utilization average and scoring average to beat in hard court matches.

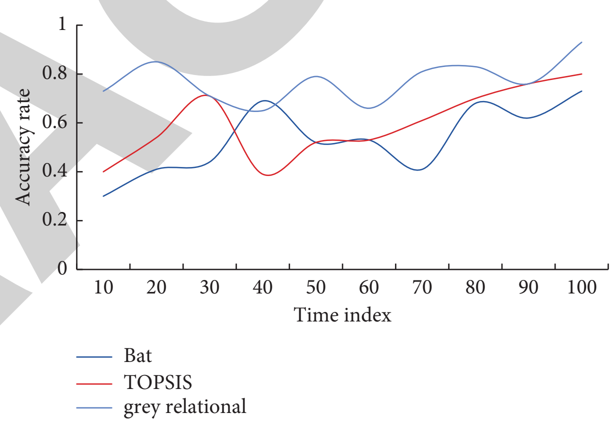

FIGURE 6: Accuracy comparison.

one or more experts in a certain field. It simulates the decision-making process of human experts to solve complex problems that require human experts to handle. Data mining refers to the process of searching for information hidden in a large amount of data through algorithms. This study selected a tennis player in a certain game training as the experimental object. During the whole course of the game, the first half of the game has been in the offensive and defensive phase, and there is no big difference in service speed and service strength. The experimental activity mainly analyzes the physical ability and technical and tactical ability of the athletes in the second half. To fully understand the techniques and tactics used by athletes and the training process, it is necessary to conduct statistical analysis on the technical and tactical indicators and acquisition process data of athletes, which is shown in Figure 5. In the process of training and competition, the difference between the average utilization rate and the average scoring rate of techniques and tactics in each section is an important embodiment of the difference in the application characteristics and scoring effect of techniques and tactics.

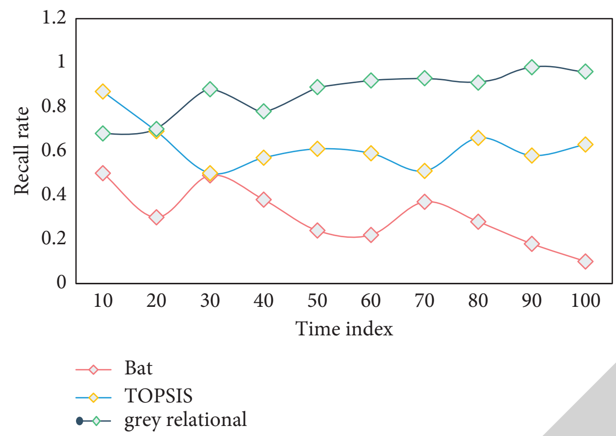

Figure 7: Recall comparison.

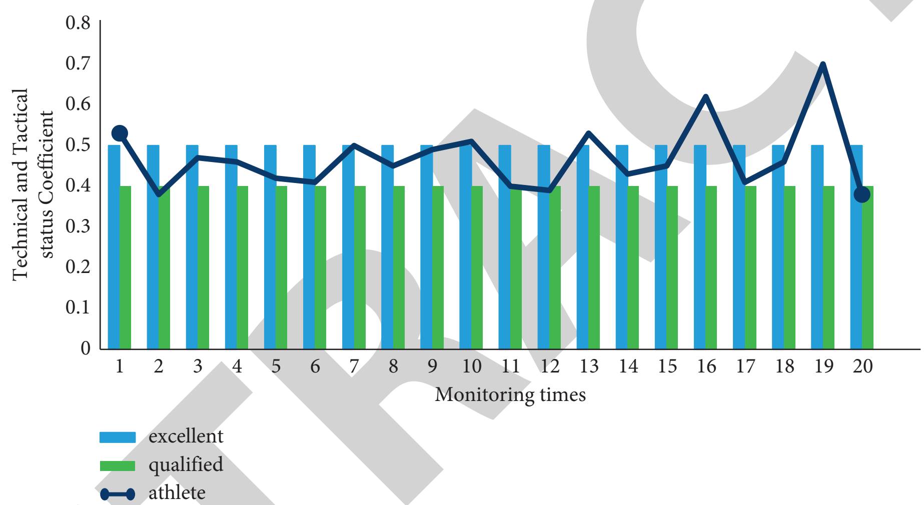

Figure 8: Athlete's physical fitness and technical and tactical state curve.

In the field of sports training, there are usually three kinds of algorithms used in the research of physical fitness and technical tactics: the bat algorithm, two calculation methods of grey correlation, and TOPSIS cited in this study.

The advantage of grey relational algorithm is that it is accurate, efficient, and comprehensive. In the training process of tennis games, it can divide the data of each stage according to the order of serving, which can compare the physical fitness and technical and tactical ability of different players in the same stage or the same player in different stages. On the other hand, it is also helpful to evaluate the players' on-the-spot performance in competition training. The obtained accuracy and recall are shown in Figures 6 and 7.

Under the monitoring system based on data-driven technology, the technical monitoring data of an athlete's physical fitness and technical and tactical training are extracted, as shown in Figure 8. The percentile method is used to evaluate the coefficient of technical and tactical status. The standard is as follows: when $P80 > X \geq P50$, it is excellent; when $P50 > X \geq P20$, it is qualified; when $X < P20$, it is unqualified. The blue column in the figure indicates that the technical state coefficient is excellent, the green column indicates that the technical state coefficient is qualified, and the broken line indicates the technical state of the athletes in different time periods. It can be clearly seen from the picture that the athlete's technical and tactical states have not been high at the beginning of training. By the seventh time, the state has improved significantly. In the final stage of training, his technical and tactical states improved relatively high, and the number of excellent levels reached three times. However, from the overall trend, the athlete's technical and tactical states have great fluctuations. These data are relatively comprehensive and accurate and are conducive to evaluating the competitive state of athletes.

The "stalemate stage" is a key stage for monitoring the ability and technical and tactical level of tennis players throughout the game. At this stage, the two sides of the competition are highly competitive for a long time, and their strength relationship is not very different. At present, relatively common technologies are used in the field of monitoring, including satellite monitoring, monitoring

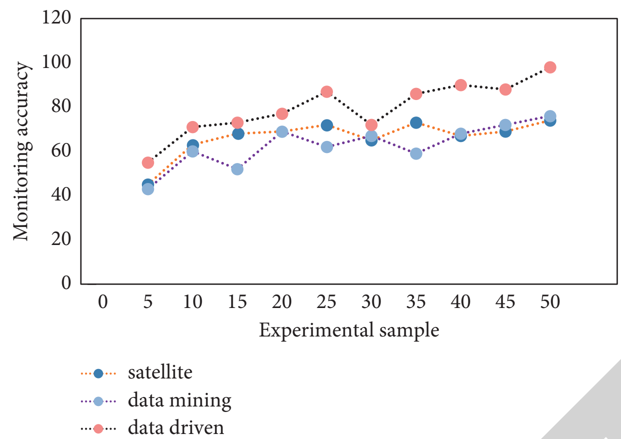

FIGURE 9: Accuracy of tennis training monitoring under different systems.

based on data mining technology, and data-driven technology studied in this study. Practical experiments are conducted under the monitoring system established in this study to compare the accuracy of three different systems in monitoring the physical fitness and tactics of tennis sports training. The results are shown in Figure 9. It is concluded that the proposed data-driven monitoring system has the highest monitoring accuracy in the physical training and technical and tactical level, which is 5.9% higher than the other systems. It further confirms the practicability and feasibility of the monitoring system.

6. Conclusion

This study selects the physical fitness and technical and tactical abilities as the monitoring object, the basic data-driven technology, combining the grey relation algorithm and TOPSIS algorithm. The experiment showed that the basic stem data-driven monitoring system can fully and accurately monitor the player's tennis, physical training, and technical and tactical abilities. The monitoring method is scientific and effective, which can predict the sports state of athletes to a certain extent and provide accurate training data for coaches and athletes. These data allow athletes to have a comprehensive grasp of their physical fitness and technical and tactical skills, thus preparing for the next physical and technical and tactical training. The monitoring of physical fitness and technical and tactical ability of tennis sports training based on data-driven technology promotes the development of scientific training and provides some general ideas and suggestions for the tennis sports monitoring technology, which has certain practical value.

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 authors declare that they have no conflicts of interest.

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