Quantitative Research of Tennis Match Momentum Based on Factor Analysis and Granger Causality Test

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Abstract. This paper studies the phenomenon of "momentum" in the men's final of 2023 Wimbledon Tennis Championships. The potential factors influencing momentum were extracted by factor analysis, and the momentum quantification model was established. Meanwhile, Granger causality test is used to verify the causal relationship between momentum and game score. The results show that momentum has a significant impact on the score of the game, which proves that momentum is the key factor affecting the result of the game. This study provides an important tactical reference for coaches and athletes to better harness momentum and improve performance.

Keywords: Factor analysis; Momentum quantification; Granger causality test; Tennis match.

1. Introduction

In the 2023 Wimbledon Gentlemen's final, 20-year-old Carlos Alcaraz secured a notable victory against 36-year-old Novak Djokovic, marking Djokovic's first Wimbledon loss since 2013 [1]. The match featured remarkable swings, and it has won widespread discussion in society.

The greatest charm of competitive sports lies in the uncertainty during the game, as no one knows who the competition will be in favor of and who will emerge as the ultimate winner. For instance, in tennis matches, it is often observed that some players in advantageous positions capitalize on their hot streaks to gain significant advantages, easily securing a small lead. Many experts refer to this phenomenon as Momentum [2] Identification and quantification of the Momentum is of crucial importance in the competitive sports. Understanding how momentum interact with games and swings can provide substantial assistance to players and coaches to adopt effective tactical preparation and make timely adjustments, creating a revolution in the entire sports industry [3].

Considering the background information and restricted conditions identified in the problem statement, we need to solve the following problems:

(1) Determine the measurement of Momentum based on the provided and selected data, filter features, and construct indicators to quantify a player's scoring advantage over opponents within specific time during a match.

(2) Develop an evaluation model to assess a player's performance and advantage during scoring, apply the model to different matches, and establish a visualization method to depict the match flow.

(3) Analyze and validate the role of "momentum" in the game, determining whether a player's momentum significantly influences performance scores.

2. Data Pre-processing

Before data analysis, the availability of data must be guaranteed. No measures, regardless of its value, can provide accurate assessments if based on unreliable data. Upon observation on the provided data, we have sorted out the logic of different terminologies, and understand the rules of tennis showed in the figure below, on the basis of which we can carry out data pre-processing.

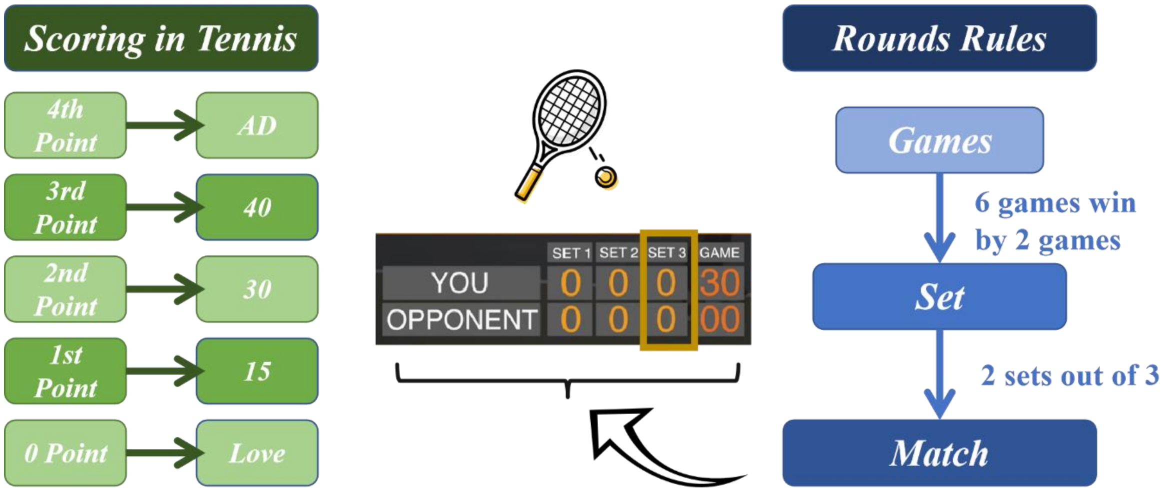

Figure 1: Round and Scoring Rules of Tennis

To ameliorate the condition of data set, there are four consecutive steps: data classification, data cleaning, information filtration, set-up of new attribute and data-measuring, as shown in the figure.

Step 1: Divided the data into qualitative and quantitative indicators and process them separately. Turn the 'AD' in p1_score into '60', change '40' into '45' based on the link attached introducing the possible reasons for the scoring system. Qualitative indicators contain winner_shot_type, serve_width, serve_depth, return_depth, server etc.

Step 2: In the stage of data cleaning, initially we check the missing value by using the "duplicated () method" in python.

There exist 752 missing items. Combined with the descriptive statistical analysis, we fill in missing values with the average number of each set and using Newton Interpolation method to make implements.

For other missing value, decision tree is applied to predict and fill the vacancy.

Step 3: Outlier processing is mainly used in the determination of correctness. For extremely outlier values, we should think about its cause to decide whether to keep or delete.

Step 4: After the above steps, our data set has become more acceptable, but we look more closely at these intrinsic relationship between each technical indicator. We roughly divided these indicators for depicting different aspects of the flow of match, like serving indicators, players' intrinsic indicators, long-run performance, faults.

Step 5: Set-up new attribute. To better analyze the performance of players and depict its match flow, we establish several new attributes listed in the above notations table.

3. Factor Analysis to Evaluate Momentum

According to the data sets, data for every point from all Wimbledon 2023 men's matches after the first 2 rounds is provided, containing the technical indicators of every motion between two players. At a given time, the performance of two players is influenced by complicated interacting factors, which are difficult to quantify. Momentum comparison between two players is always oscillating, and high momentum could help players to achieve key points.

3.1. Indicator Extraction and Determination

Although data set, especially technical indicators included, provides rich information about the flow of play and scoring condition, it's still necessary to apply dimensionality reduction on features for more representative classification and assessment. However, the essence and direction of change for each indicator varies. Based on the data descriptive analysis, we finally determine 9 indicators, between which correlation differ, so as to analyze the potential influential factors of Momentum, recorded as x_i, $i = 1,2\ldots9$. Some of these indicators are provided in the data set, while others are obtained after calculation.

Table 1: Indicators Related to Players

x_i	**Indicators**
x_1	$wins_{cons}$
x_2	unf_err_{cum}
x_3	win_{cum}
x_4	ace_{cum}
x_5	$serspeed_{ave}$
x_6	ser_sco_{rate}
x_7	$distance_{cum}$
x_8	bp_{rate}
x_9	$serve\_not$

For example: $wins_{cons}$ represents for count of consecutive wins, which is obtained by the accumulation on a set basis, some of other special operating method are as follow:

$$sersco_{rate} = \frac{\sum serving\ scoring\ times\ in\ a\ match}{\sum serving\ times\ in\ a\ match} \tag{1}$$

$$erspeed_{ave} = \frac{\sum serving\ speed}{\sum serving\ times\ in\ a\ match} \tag{2}$$

$$serve_{not} = \begin{cases} 1, & if\ serves \\ -1, & if\ not \end{cases} \tag{3}$$

The correlation heatmap of 9 indicators we selected is shown in the Figure:

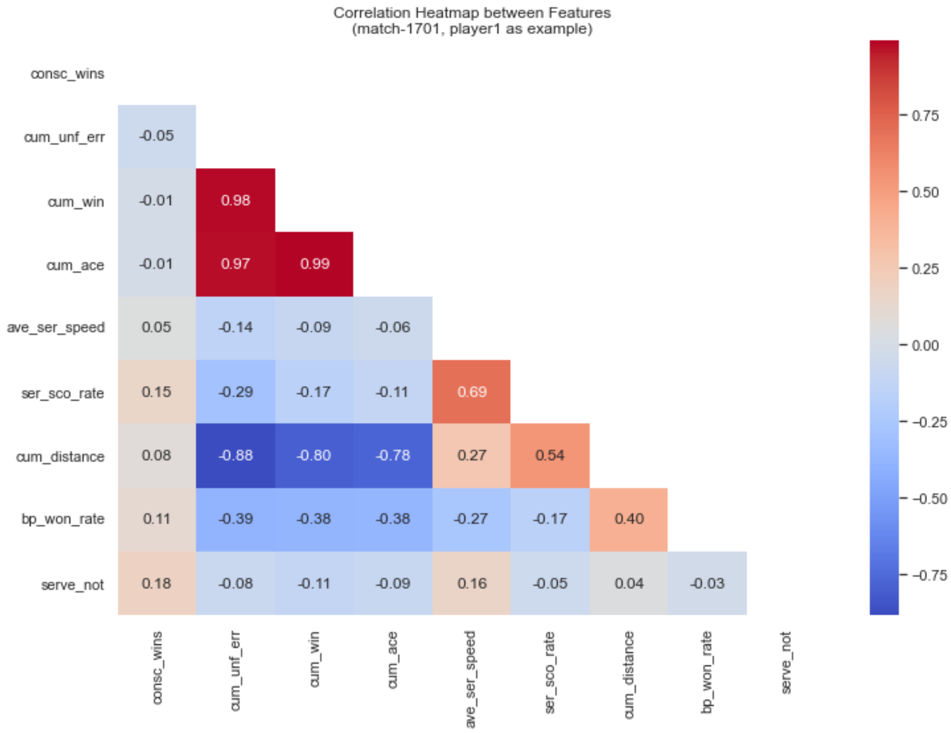

Figure 2: Heat Map of Correlation of 9 Indicators (match-1701)

3.2. Establishment of Factor Analysis Model

Factor analysis model is adopted to further evaluate the internal relationships between each indicator and its effect of Momentum. Momentum is an abstract phenomenon, describing the "strength/force" during a match/game, which is hard to measure in a rapid swinging occasion. So, digitalizing the interdependence relationships within indicators, attributing a large number of complex relationships to a small number of comprehensive factors is the basis of subsequent analysis. By analyzing the variance contribution between factors, the original system is presented as a new combination of factors.

Existence of Latent Factors: The core assumption of factor analysis is that observed variables can be explained as linear combinations of latent factors that cannot be directly measured. In our model, serving related factors, players' physical condition and mental condition are all latent factors.

Common Factors and Unique Factors: Common factors are factors shared by multiple variables, explaining the common variability among them. Unique factors are specific to each variable, explaining the unique variability of each variable.

These latent factors represent underlying commonality or structure that can explain the covariance among observed variables. Relationships between observed variables and latent factors is shown below:

$$\begin{gathered} x_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + e_1 \\ x_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + e_2 \\ \\ x_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}F_m + e_m \end{gathered} \tag{4}$$

$X = \left(x_1, x_2, \dots, x_p\right)^T$ is random vectors. In our model, it represents the indicators we selected, and the value of p is 9, it satisfies $E(X) = 0, Cov(X) = \Sigma$. Here Σ is the covariance matrix of observed variables.

$F = (F_1, F_2, \dots, F_m)^T (m < p)$ is the matrix containing latent factors, it is unmeasurable. In our model, F_i is the i_{th} latent factor that may influence on Momentum. it satisfies $E(F) = 0, Cov(F) = 1$, and each F_i is independent.

$\varepsilon = \left(e_1, e_2, \dots, e_p\right)^T$ is the matrix containing unique factors.

Its matrix form is: $X = AF + \varepsilon$. $A = \left(a_{ij}\right)_{p*m}$ is the factor loading matrix. This formula represents that observed variables can be decomposed into a linear combination of latent factors and unique factors.

$$\begin{gathered} F_1 = \omega_{11}x_1 + \omega_{12}x_2 + \cdots + \omega_{1p}x_p \\ F_2 = \omega_{21}x_1 + \omega_{22}x_{2_2} + \cdots + \omega_{2p}x_p \\ \\ F_m = \omega_{m1}x_1 + \omega_{m2}x_2 + \cdots + \omega_{mp}x_p \end{gathered} \tag{5}$$

Factor Extraction: One of the objectives of factor analysis of a tennis match is to mathematically extract latent factors that explain the relationships among observed indicators. The extracted factors should maximize the explanation of the observed indicators ' variance. $VAR = AA^T$ is a diagonal matrix, where the diagonal elements represent the variance of each common factor.

Factor Rotation: To better interpret the meaning of factors, rotation is often applied to the extracted factors. Factor rotation aims to make each variable have higher loadings on one or a few factors, making it easier to interpret the practical meaning of these factors.

Determining the Number of Factors: This is typically done by considering the explained total variance or using statistical criteria such as the Kaiser criterion, parallel analysis.

Factor Loadings: Factor loadings represent the strength of the relationship between each variable and the latent factor. Larger factor loadings indicate a stronger relationship between the variable and the factor, providing insight into the interpretation of the factors.

3.3. Feature Extraction based on PCA and Solutions to FA

We conduct the KMO test and Bartlett's sphericity test for the feasibility of factor analysis, which is the fundamental of factor analysis.

Table 2: KMO test and Bartlett's sphericity test

Value of KMO		0.666
Bartlett's sphericity test	approximate chi-square	3955.162
	df	36
	P	0.000***

The results of the KMO test indicate a KMO value of 0.666. Additionally, the results of Bartlett's sphericity test show a significant p-value of 0.000***, suggesting a significant level of correlation among variables. The rejection of the null hypothesis indicates that there is correlation between 9 variables, making factor analysis effective, although the fit may not be optimal.

According to the principal component analysis (PCA) method, factors were extracted based on the criterion that the eigenvalues of factors should be greater than 1. A total of 3 common factors were extracted. As shown in Table 4, the cumulative contribution rate of these 3 common factors reaches 78.439%, summarizing approximately 80% of the information from the original variables. Therefore, it can be considered that these 3 common factors explain a significant portion of the variables.

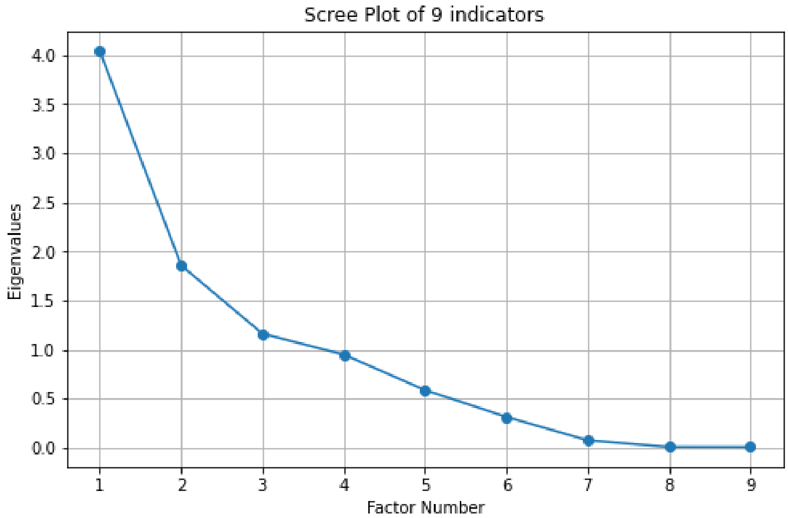

Figure 3: Scree Plot of 9 Indicators

Table 3: Overview of Factor Eigenvalues and Contribution Rates(match-1701)

Indicators	Variance Explained Before Rotatio			Variance Explained After Rotation		
	Eigenvalues	Variance Explained (%)	Cumulative Variance Explained (%)	Eigenvalues	Variance Explained (%)	Cumulative Variance Explained (%)
1	4.04	44.89	44.89	394.153	43.795	43.795
2	1.858	20.643	65.533	192.292	21.366	65.161
3	1.162	12.907	78.439	119.511	13.279	78.439
4	0.949	10.549	88.988			
5	0.587	6.517	95.505			
6	0.314	3.494	98.999			
7	0.076	0.839	99.839			
8	0.008	0.086	99.925			
9	0.007	0.075	100			

The factor loading matrix heatmap allows for the analysis of the importance of latent variables in each principal component. The closer the value is to 1, the greater the contribution of that indicator to the factor.

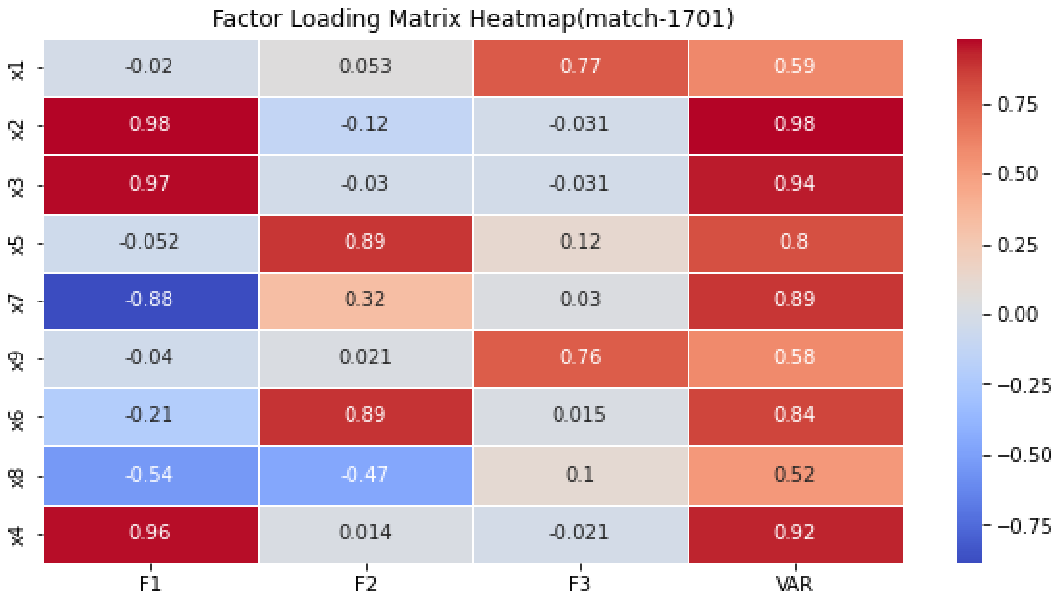

Figure 4: Factor Loading Matrix Heatmap

Through the analysis of the rotated factor loading matrix, it is observed that in the first factor, variables such as cumulative unforced errors, cumulative untouchable winning shots, and cumulative aces exhibit significant loadings. Therefore, it is defined as the "hitting factor." In the second factor, variables such as average serving speed, service scoring rate, and breakpoint success rate show significant loadings, hence defined as the "serving factor." In the third factor, variables related to consecutive wins or losses and serving actions exhibit substantial loadings, and it is thus defined as the "process factor." [4].

The factor scoring coefficient matrix calculated using the regression estimation method is as follows:

Table 4: Component Scoring Matrix Table

Indicators	Latent Factor		
	F1- Hitting Factor	F2- Serving Factor	F3- Process Factor
x1	0.029	-0.013	0.647
x2	0.249	-0.013	0.021
x3	0.25	0.036	0.016
x4	0.251	0.058	0.022
x5	0.037	0.465	0.051
x6	-0.008	0.466	-0.043
x7	-0.213	0.126	-0.028
x8	-0.161	-0.283	0.091
x9	0.022	-0.031	0.646

From the table above, we can calculate the total F score, which is the linear combination of hitting, serving and process factors.

$$F_1 = 0.029x_1 + 0.249x_2 + 0.25x_3 + 0.037x_5 - 0.213x_7 + 0.022x_{10} - 0.008x_6 - 0.161x_8 + 0.251x_4$$

$$F_2 = -0.013x_1 - 0.013x_2 + 0.036x_3 + 0.465x_5 - 0.126x_7 + 0.031x_{10} + 0.466x_6 - 0.283x_8 + 0.058x_4$$

$$F_3 = 0.647x_1 + 0.021x_2 + 0.016x_3 + 0.051x_5 - 0.028x_7 + 0.646x_{10} - 0.043x_6 + 0.091x_8 + 0.022x_4$$

Therefore, the factor analysis model can be represented as:

$$F = \left(\frac{0.438}{0.784}\right) \times F_1 + \left(\frac{0.214}{0.784}\right) \times F_2 + \left(\frac{0.133}{0.784}\right) \times F_3 \tag{6}$$

Table 5: Factor Weight Analysis

Factor	Rotated Variance Explained (%)	Rotated Cumulative Variance Explained (%)	Weight (%)
F1- Hitting Factor	0.438	43.795	55.833
F2- Serving Factor	0.214	65.161	27.238
F3- Process Factor	0.133	78.439	16.929

Based on the calculated F values and the information provided in the question that "the serving side is more likely to gain an advantage," we further adjusted the weights of different factors using the AHP method. By incorporating the AHP-adjusted weights, we constructed a relatively reasonable expression to quantify the Momentum. This expression considers the impact of various factors comprehensively and provides individual scores for each player in every match.

$$M = 0.559F_1 + 0.273F_2 + 0.170F_3 \tag{7}$$

To quantify the contrast in momentum between two players, we further illustrate these differences by taking the point-wise score differences $\Delta Score$. Since the scores are discrete values ranging from 0 to 60 (except for the tiebreaker ranging from 0-7×15), we normalize the differentials by dividing them uniformly by 60 to narrow their range of variation.

$$\Delta M = M_1 - M_2 \tag{8}$$

$$\Delta Score = (Score_1 - Score_2)/60 \tag{9}$$

Through visualization, we can observe a lag between ΔM and $\Delta Score$. Therefore, we identify the optimal lag value and perform a time series alignment. The result indicates that M has an optimal lag of 1, and the correlation coefficient for the aligned time series is 17.061, which signifies that there is a high relationship between the aligned ΔM and $\Delta Score$.

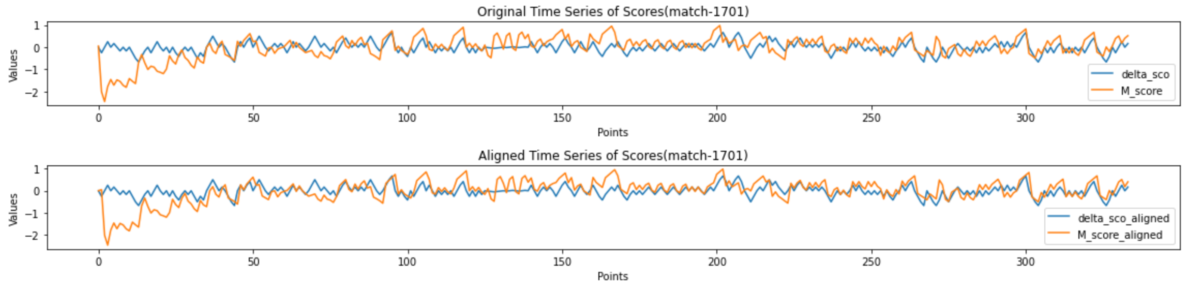

Figure 5: Time Series of Scores

In addition, we have further enhanced the accuracy of future predictions by employing exponential smoothing to eliminate noise in the data shown as the red line.

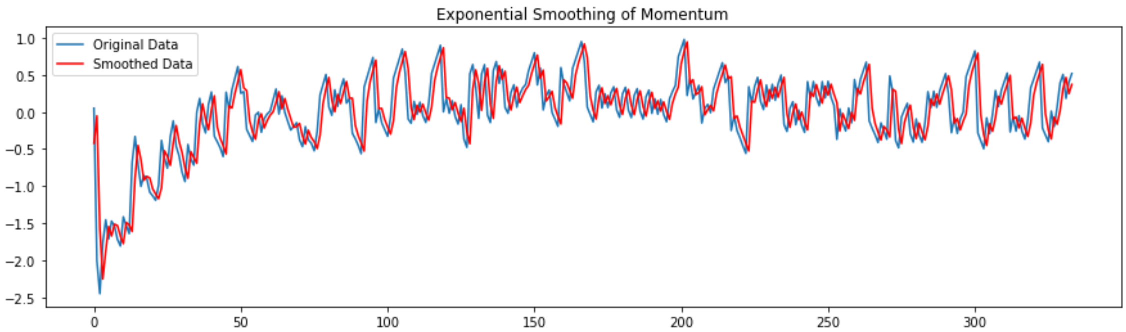

Figure 6: Exponential Smoothing of Momentum

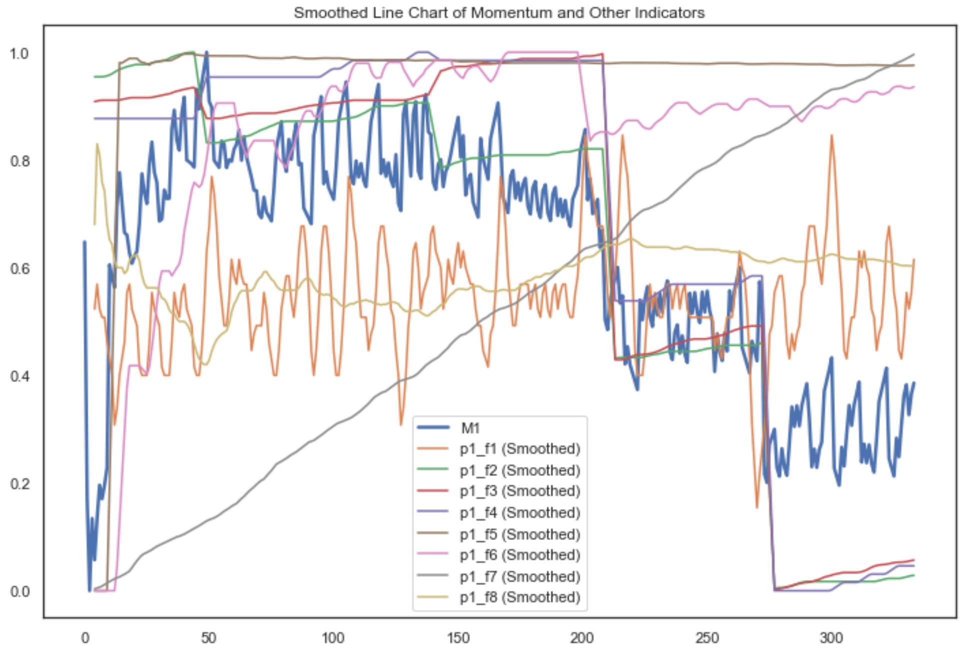

Figure 7: Line Chart of Momentum and Other Indicators

Next, we plotted time series line charts between the M score and nine other indicators. From the graph, the blue line represents the momentum score, determined by other indicators and is a linear combination of latent factors composed of these indicators. Different indicators exhibit distinct characteristics such as trend indicators, seasonal indicators, and volatility indicators, while the overall score results from the combined effects of the other curves. From this perspective, understanding the impact and correlation of these indicators on the overall momentum score aids in predicting future trends in momentum.

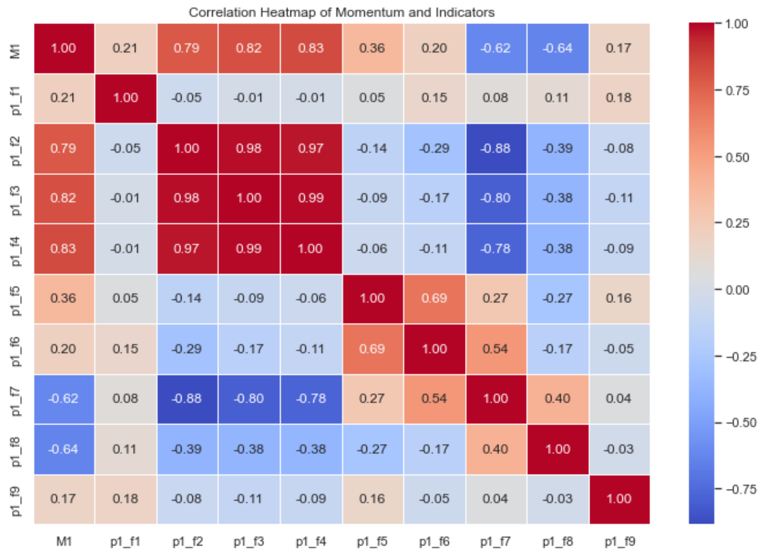

Figure 8: Correlation Heatmap of Momentum and Indicators

4. Correlation Analysis between Momentum and Scores

4.1. Data Description

Based on the data of nine existing factors calculate their mean and variance and use Monte Carlo simulation to generate random data. Use factor analysis to calculate their momentum scores. In the figure below, the SMS represents Simulated Momentum Scores, and the RMS means Real Momentum Scores.

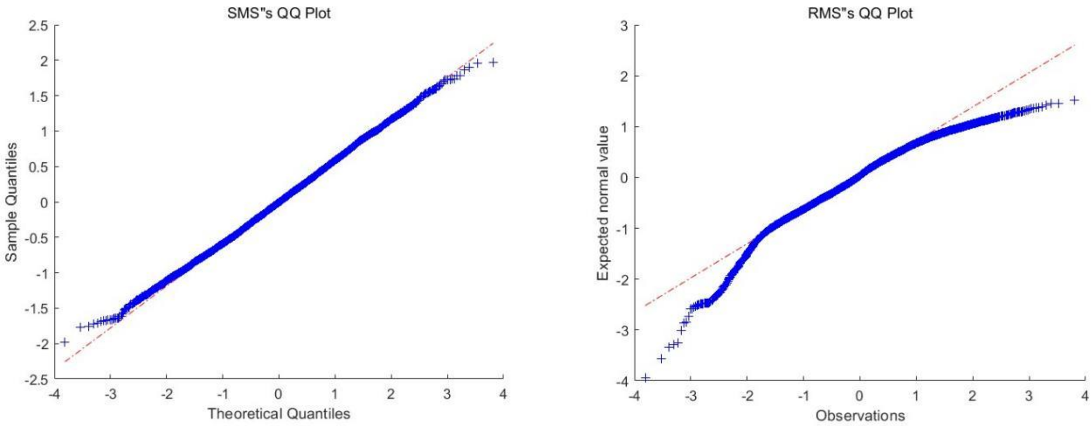

Figure 9: QQ Plot of the Normality Test

According to the Q-Q plot of the normality test, it can be observed that the momentum scores calculated based on simulated data generally follow a normal distribution, while the momentum scores calculated based on real game data generally do not follow a normal distribution. In order to further refute the viewpoint that momentum does not exist, that is, the outcome of the game is random, we further use paired Wilcoxon signed-rank test to observe whether it can significantly demonstrate the difference in momentum data obtained from random simulated game situations and real game situations, thereby demonstrating the existence of momentum in real game situations.

4.2. Wilcoxon Signed- Rank Test

In order to refute the view that momentum is not an objective existence, Monte Carlo simulation is used to generate random match technique statistics and match results, and factor analysis is used to generate random match momentum scores. Finally, using paired Wilcoxon signed-rank test, the real momentum score and the randomly simulated momentum score results are analyzed, and a significantly unrelated result is obtained between the two.

The paired sample Wilcoxon signed-rank test is a non-parametric statistical method used to compare whether the median of two related paired samples is equal. Its principle is based on comparing the ranks of the sample data [5]. The process of the paired sample Wilcoxon signed-rank test can be divided into the following steps:

Establish hypotheses: Formulate the null hypothesis and the alternative hypothesis. The null hypothesis typically states that the population medians of the two related paired samples are equal, while the alternative hypothesis states that the population medians of the two samples are not equal.

Calculate differences: Calculate the differences for each pair of paired sample data to obtain a sequence of differences.

Sign assignment: Assign a sign to each difference to indicate its positive or negative value.

Absolute rank calculation: Rank the absolute values of the differences to obtain the ranks of the absolute values. Rank calculation:R_i。

Calculate rank sum statistic: Calculate the sum of ranks for positive differences, denoted as W^+, and for negative differences, denoted as W^-.

$$W^+ = \sum_{i=1}^{n} R_i \cdot I(sgn(x_i - y_i)) = +1 \tag{10}$$

$$W^- = \sum_{i=1}^{n} R_i \cdot I(sgn(x_i - y_i)) = -1 \tag{11}$$

In this expression denoting the indicator function, W^+ and W^- represent the sum of ranks for positive and negative signs, respectively. $sgn(x_i - y_i)$ where x_i and y_i represent the two observed values in the paired samples, and sgn denotes the sign function, indicating the positive or negative sign of the difference.

Select the smaller rank sum: Select the smaller value between W^+ and W^- as the test statistic W.

Find critical value or calculate p-value: Based on the sample size and significance level, find the critical value for the paired sample Wilcoxon signed-rank test, or calculate the test's p-value.

Make a decision: Compare the test statistic with the critical value or compare the p-value with the significance level, to decide whether to reject the null hypothesis.

If the test statistic W is less than the critical value, or if the p-value is less than the significance level, the null hypothesis can be rejected, indicating a significant difference in the population medians of the two related paired samples. This indicates that momentum objectively exists, and the outcome of the matches is not random. Conversely, if the conditions are not met, it indicates that momentum is not objectively present.

4.3. Verification of Momentum - Not a Random Phenomenon

Due to a sample size greater than 5000, which belongs to large sample data, the Kolmogorov Smirnov test was used for paired difference normality testing. The specific steps include:

First, establishing hypotheses: Set the null hypothesis (sample from specified distribution) and the alternative hypothesis (sample not from specified distribution).

Second, calculate statistics: Calculate KS statistics, usually represented as D. The calculation formula is:

$$D = max(|F(x) - \mathrm{Phi}(x)|) \tag{12}$$

$F(x)$ represents the empirical distribution function of the sample, $\mathrm{Phi}(x)$ is the cumulative distribution function of the standard normal distribution, and (x) is the sample data point.

Then, calculate the P-value based on the K-S statistic and sample size n[6-8].

Finally, comparing the P-value and significance level determines whether to reject the null hypothesis.

Table 6. Normality test for paired differences

Variable Name	Sample Size	Mean	Standard Deviation	S-W Test	K-S Test
SMS	7114	0.001	0.578	-------	-------
RMS	7114	0	0.656	-------	-------
SMS paired with RMS.	7114	0.001	0.867	0.993(0.000***)	0.023(0.001***)

Note: ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.

The SMS represents Simulated Momentum Scores, and the RMS means Real Momentum Scores.

The significance level of the p-value is 0.001***, indicating significance at the 1% level. The null hypothesis is rejected, indicating that the data does not follow a normal distribution, and thus the paired sample Wilcoxon signed-rank test can be performed [9,10].

Table 7. Paired Sample Wilcoxon Signed-Rank Test

Paired Variables	Median ± standard deviation			z	df	P
	Paired 1	Paired 2	Paired difference (Paired 1- Paired 2)			
SMS paired with RMS	-0.008±0.578	0.036±0.656	-0.043±0.867	2.137	7113	0.033**

Note: ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.

The result of the paired sample Wilcoxon signed-rank test shows that the significance level of the p-value is 0.033**, indicating significance at the 5% level. The null hypothesis is rejected, suggesting that there is a significant difference between the simulated momentum scores and the actual momentum scores. This indicates that momentum is objectively present, and that the outcome of the match is not random.

4.4. Further Proof- Causality between Momentum and Scores

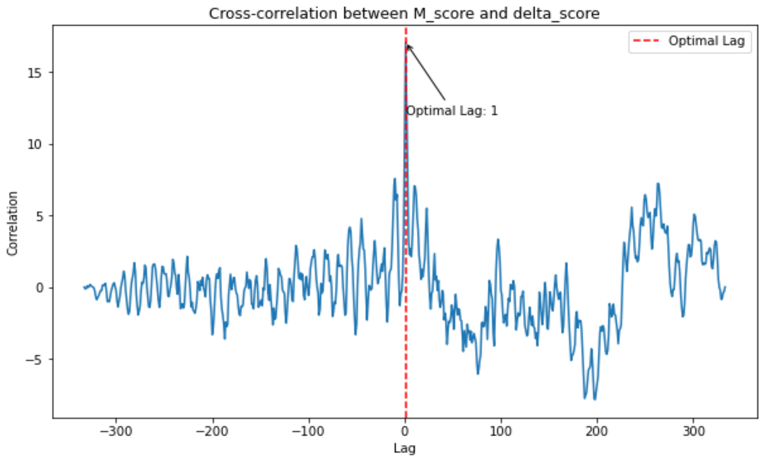

Figure 10. Cross-Correlation between Momentum and Score

Based on the visualization of momentum difference and match score difference, we can easily observe that the two series exhibit similar trends and fluctuations but with a certain time lag. Therefore, we believe there is a lag between the two sequences. Consequently, we shift the score difference forward by a certain number of time steps. Using Python, we determine the optimal lag, within a specified range, where the two series have the maximum correlation.

As a result, we further speculate that there is a stronger causal relationship between the momentum difference and the score difference. Granger causality analysis indicates that there is a high probability of causality between the two sequences, suggesting that changes in momentum may lead to alterations in match scores. This aligns with our postulate and understanding.

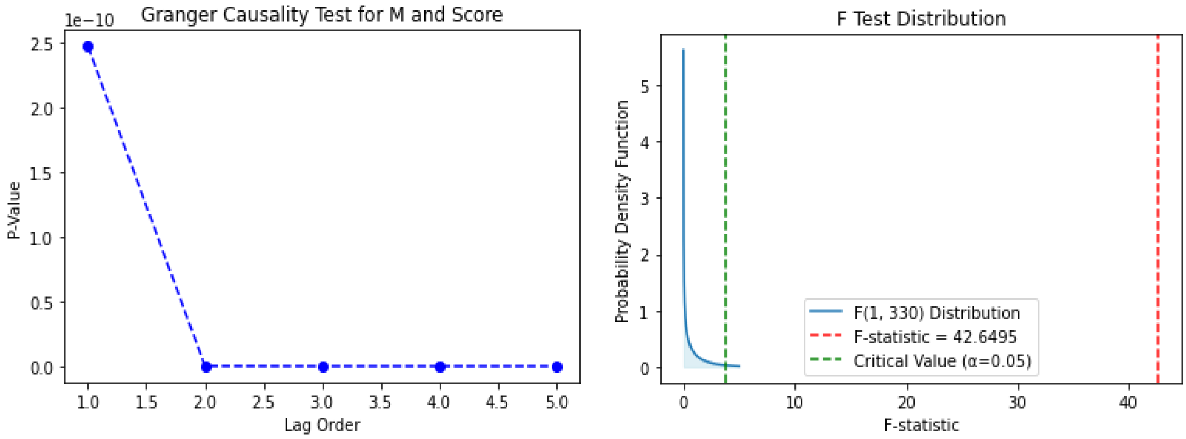

Figure 11. Granger Causality Test for M and Score and F-Test Distribution

In the Granger causality analysis, various statistical tests were conducted:

SSR based F test: Utilizing the F-statistic derived from the regression model, the obtained F-value of 42.6495 with a p-value of 0.0000 implies a significant relationship. The null hypothesis can be rejected at the commonly chosen significance level of 0.05, indicating the existence of a Granger causal relationship.

SSR based chi2 test: Applying the chi-square statistic through the chi-square test, the calculated chi-square value of 43.0372, coupled with a p-value of 0.0000, also supports a Granger causal relationship, mirroring the findings from the F-statistic.

Likelihood ratio test: Based on the likelihood ratio test, the chi-square value of 40.4747 and a p-value of 0.0000 reinforce the evidence for a Granger causal relationship, aligning with the results from the F-statistic and chi-square test.

F-statistic test: The F-statistic derived from the regression parameters mirrors the SSR based F test, confirming the consistent pattern of significance with an F-value of 42.6495 and a p-value of 0.0000.

In summary, all statistical measures consistently exhibit p-values significantly below 0.05. This collective evidence supports the rejection of the null hypothesis, indicating the presence of a Granger causal relationship. Thus, past values of the first time series offer valuable insights into the current values of the second time series, affirming the influence of the former on the latter.

5. Conclusions

In this paper, factor analysis and Granger causality test are used to study the phenomenon of "momentum" in the men's final of 2023 Wimbledon Tennis Championships. By factor analysis, the potential factors affecting momentum are extracted, momentum quantification model is established, and Granger causality test is used to verify the causal relationship between momentum and game score. The results show that momentum has a significant impact on the score of the game, which proves that momentum is the key factor affecting the result of the game. As a result, coaches and athletes can improve performance by observing and using momentum to develop sound tactics. This study provides an important theoretical basis for tennis and has practical significance for players and coaches to formulate tactics.

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