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Development of sequential winning-percentage prediction model for badminton competitions: applying the expert system sequential probability ratio test

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Abstract

Background This study developed a sequential winning-percentage prediction model for badminton competitions using the expert system sequential probability ratio test (EXSPRT), aiming to calculate the difficulty of each event within a match and establish the initial prior probability.

Methods We utilized data from 100 men's singles matches (222 games) held by the Badminton World Federation (BWF) in 2018 to evaluate event difficulty across six models for each determining factor. For setting the initial prior probability calculation method, 30 men's singles matches (74 games) organized by the BWF in 2019 were randomly selected. The odds for these matches were obtained from www.oddsportal.com.

Results The efficacy of the six models was assessed based on application rates (15%, 20%, 25%, and 30%) of the collected odds, with the initial prior probability reflecting 25% of the odds chosen owing to its superior validity.

Conclusions This research yielded six sequential winning percentage prediction models capable of offering real-time predictions during matches in badminton competitions by leveraging EXSPRT. These models enhance spectator engagement and provide foundational data for developing similar prediction models for other sports. Future research should focus on developing a program to identify the most effective model among the six and implement it practically.

Keywords Badminton analytics, Sequential prediction models, Event difficulty, EXSPRT framework, Real-time sports modeling

Background

The outcome of a sporting event is readily available as soon as the event concludes. Nevertheless, before significant sporting events, including the Olympics, Asian Games, and World Cups, predictions about the winning team or player are shared with the public via the media [1–3]. The dissemination of these outcome predictions boosts public interest and excitement for the upcoming event.

Previous studies on predicting sports game outcomes have explored various approaches across different sports. In baseball, research utilizing Bill James's Pythagorean expectation for win probabilities has been conducted [4, 5], whereas in soccer, studies have applied the Poisson probability model for outcome predictions [6]. Similarly, research has also been conducted on predicting basketball game outcomes [7]. Additionally, studies on real-time sports game outcome prediction include

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research predicting events during soccer games using a Bayesian lens [8], research using clustering algorithms to develop strategies and predict soccer game outcomes [9], research predicting the distribution of basketball game scores using the gamma process [10], and research predicting game outcomes based on machine learning and IoT [11, 12]. Particularly, clustering algorithms and Bayesian lens algorithms play a crucial role in real-time data analysis. Clustering algorithms help analyze various patterns that occur during a match and provide real-time strategy recommendations for the game. Similarly, Bayesian lens algorithms effectively model real-time changing events, such as player injuries, fouls, and other in-game occurrences, enabling more accurate predictions as the game progresses. These algorithms are essential in overcoming the limitations of traditional pregame data-based models by integrating dynamic, real-time factors into the prediction process. However, most existing studies have predominantly relied on pregame data, such as game records, stadium environment, and player information, without accounting for in-game events (e.g., player injuries, fouls, ejections, and spectator numbers) [13–15]. Furthermore, these studies often focus on limited data types or specific scenarios within a sport and cannot predict outcomes when encountering previously unobserved game situations.

Then, what methods can be used to develop a real-time win probability prediction model for sports games? One potential approach is the expert system sequential probability ratio test (EXSPRT), an advanced version of the SPRT (sequential probability ratio test) model originally proposed by Welch and Frick [16, 17]. A key advantage of the EXSPRT model over its predecessor lies in its adaptability to diverse situational nuances by assigning varying difficulty levels to distinct events. Particularly in sports, where player performance fluctuates throughout the match [18, 19], the EXSPRT model can account for this variability, providing more accurate predictions. Furthermore, compared to the complex Rasch model from item response theory (IRT), the EXSPRT model is distinguished by its mathematical simplicity and practicality. Although previous applications of the EXSPRT model have been primarily documented in the educational sector, particularly for assessing item difficulty in test development [20–22], its utilization in sports research remains largely unexplored.

Moreover, sports such as volleyball, tennis, table tennis, and badminton are suitable candidates for sequential win probability prediction for individual players. Among these, badminton is distinguished by the sequential accumulation of points, with the match being won by the player who first achieves a predetermined score (21 points) [23]. Additionally, because the game excludes variables related to physical contact and continuous time, it offers a more straightforward approach to match analysis. These characteristics have enabled numerous studies to analyze badminton matches and identify factors influencing scores using data [24, 25]. Research has shown that the primary factors affecting badminton match scores include technical skills [26], such as smashes, drops, and hairpins used to score points; situational factors [27], such as the opponent's racket failing to contact the shuttlecock, contacting it unsuccessfully, or committing errors; and timing factors [28], such as the time difference between the winner and loser during the early, mid, and late stages of the match. This study evaluated the scoring difficulty of each event by analyzing technical, situational, and timing factors based on badminton match records. The results demonstrate that the EXSPRT model can sequentially predict win probabilities based on these variables.

To illustrate, consider a badminton match between Player A and Player B. The initial preliminary probabilities are based on the odds of each player winning, as provided by an official sports betting site. Once the match commences, the objective is to develop a model that adjusts the predicted odds in real time for each point scored. This should reflect the varying degrees of difficulty associated with scoring a point with a successful smash and a missed drop.

This study focused on creating a sequential winning percentage prediction model for badminton competitions using the EXSPRT model. For this, two specific research directions were identified. The first calculates the difficulty level of events in badminton competitions, considering skill, situational, and timing factors. The second aims to determine the initial prior probability value (the winning percentage attributed to a player before the match begins) to facilitate the development of the EXSPRT model, guided by the validity index.

Theoretical framework

EXSPRT model

Sequential situations refer to events that occur over time intervals [17]. Wald (1947) proposed the SPRT for determining the defect rate of light bulbs, establishing a sequential decision-making scenario. SPRT is a sequential verification method that relies on Bayesian theory to update the posterior probability ratio to determine whether a light bulb is defective [17, 29].

The most significant feature of SPRT is its ability to apply different numbers of trials depending on the ability of the subject while maintaining high reliability [30]. Traditionally, statistical analysis methods for hypothesis testing require a predetermined number of samples to be measured, after which one must choose between accepting or rejecting the null hypothesis based on the measured results. However, SPRT allows for a third option, continuing the test. If sufficient evidence is not available to support the acceptance or rejection of the null hypothesis during the testing process, the option to continue testing can be selected.

However, Wald's SPRT [17] is suitable only for evaluating a single event repeatedly and cannot be applied to situations involving two or more events. For example, Wald's SPRT can determine success or failure for a single basketball free-throw event but cannot be applied to evaluation situations that include multiple events like free throws and dribbling.

To address the limitation of SPRT's applicability to only single events, Frick [31] proposed the EXSPRT based on SPRT. SPRT cannot assign different difficulties to multiple events; however, EXSPRT can perform the same, reflecting the characteristics of various situations in the evaluation. Notably, the multifaceted Rasch model of IRT, which enables the assessment of various events, is mathematically complex and challenging to apply in practice; however, EXSPRT is mathematically straightforward, making it easier to apply in real-world settings. Consequently, the use of EXSPRT has been increasing in fields where the development of evaluation tools is necessary.

In this study, we aimed to develop a sequential win probability prediction model based on EXSPRT by calculating the scoring difficulty of each event based on technical, situational, and temporal factors using badminton match records. However, several important considerations should not be overlooked when developing a win probability prediction model based on EXSPRT.

First, the model assumes that the athlete's performance remains stable over time, which may not always align with reality because of fluctuations in performance or external factors. Second, the model assumes that the input data comprehensively reflect the dynamics of the match by incorporating various scoring events and situational factors. However, relying on a specific dataset may pose the risk that the model does not represent the overall competitive environment. Third, the EXSPRT model determines the outcome based on (α and β). In cases where there are slight differences in the players' skills, the model may make incorrect decisions. Fourth, actual matches involve various variables and unpredictable elements. If EXSPRT cannot encompass these, the accuracy of predictions may decline. Finally, this model may result in situations where the outcome cannot be determined after the match, leading to the classification of results as a "draw."

Nonetheless, the EXSPRT model is mathematically straightforward and easily applicable in practice, making it suitable for various types of sports. Moreover, researchers can adjust the previously noted error rates according to the situation, making the EXSPRT model a powerful tool for sports prediction, analysis, and decision support.

Example of sequential win probability prediction using EXSPRT

The following example demonstrates a sequential win probability prediction model for badminton matches using EXSPRT, in which the win probabilities for each player are calculated. To construct a test model utilizing the EXSPRT, the researcher must establish the initial prior probabilities for each player, including the parameters alpha, beta, theta0, and theta1 [5]. Assuming we are predicting a singles match between a Korean player and a Chinese player, we have determined which player is likely to win and which player is likely to lose. The difficulty levels for the technical factor events are listed in Table 1, and the initial prior probabilities are assumed to be 50–50, given that no prior match record between the Korean and Chinese players exists. The error rates indicating decision errors, alpha and beta, are set at 0.025 each. All difficulty levels, error rates, and initial prior probabilities were arbitrarily determined by the researcher, and the techniques used in the rally were randomly selected for demonstration.

We assume that the Korean player scored a point against the opponent with a clear shot in the first rally of the match. In this scenario, the posterior probability ratio calculated using the EXSPRT model is listed in Table 2.

The results show that multiplying the initial prior probabilities assigned to each judgment by the respective difficulty of the technical events of the game generates the posterior probability ratio. Normalizing the posterior probability ratio yields values that represent the probabilities of winning and losing. Normalization is conducted by summing the posterior probability ratios calculated for both winning and losing and then dividing each posterior probability ratio by that sum. The sum of the posterior probability ratios for winning and losing must equal 1. Because the Korean player lost a point with a clear in the first rally, the winning probability for the Korean player becomes 23.9%, whereas the losing probability is 76.1%. Therefore, the posterior probability ratio of the EXSPRT

Table 1 Difficulty levels of technical factor events (Example)

Technical Event	Winner		Loser	
	Theta0	1-Theta0	Theta0	1-Theta0
Drop	0.92	0.08	0.47	0.53
Smash	0.98	0.02	0.86	0.14
Clear	0.89	0.11	0.65	0.35

Table 2 Calculations of posterior probability ratio for clear technique events

Initial Prior Probability			Clear Difficulty		Posterior Probability Ratio		
Win	0.5	×	0.11	=	0.055 / sum	=	0.239
Lose	0.5	×	0.35	=	0.175 / sum	=	0.761
				Sum =	0.230		

is 23.9/76.1 = 0.314. Because 0.314 falls between the loser decision criterion (B/(1-a) = 0.025641) and the winner decision criterion ((1-B)/a = 39), no prediction of the outcome is made, and the match observation continues. As the match progresses, if the probability of winning or losing reaches 100%, a decision regarding the outcome will be made, and the match observation will be stopped.

Methods

Target data

This study aimed to develop a sequential winning percentage prediction model for badminton competitions by applying the EXSPRT model. Therefore, specific datasets were selected and aligned with the research topics. The first topic of the research focused on calculating the difficulty levels of events in badminton matches based on skill, situational, and timing factors. Therefore, data were randomly selected from 100 men's singles matches (21 tournaments, 43 participants, 222 games) from international competitions organized by the Badminton World Federation (BWF) in 2018. In this study, only tournaments classified as Grades 1 and 2 events, as presented in the BWF World Tour Overview [32], were selected. The analyzed matches included various rounds, specifically: 4, 8, 16, 25, 21, and 16 matches from the rounds of 64, 32, 16, quarterfinals, semifinals, and finals. This also included 10 group stage matches from the World Tour Finals qualifiers.

The second topic of the research aimed to establish the initial prior probability for each player (player winning rate before the match). To achieve this, 30 men's singles matches (8 tournaments, 16 participants, 74 games) were selected from the BWF 2019 events. The tournament grades were identical to those selected for the first research objective, and the analyzed matches included the following: two group stage matches from the World Tour Finals qualifiers and 1, 3, 6, 11, and 7 matches from the rounds of 32, 16, quarterfinals, semifinals, and finals. The odds used to set the initial prior probability for participating players were obtained from [33], an international betting site that provides odds for various sporting events.

To facilitate the analysis, the selected matches were obtained using videos provided by the BWF YouTube channel (https://www.youtube.com/@bwftv/). All matches were selected using a random sampling method and matches that were halted owing to player withdrawal or injury were explicitly excluded. In terms of sample representativeness, the aim was to include as many high-level matches as possible and to encompass a wide range of events. This study was approved by the Korea National Sports University ethics committee (approval number: 1263–202,003-HR-008–01). The data used in this study are detailed in Table 3 and Supplementary.

Research models

The first research topic entailed developing six sequential winning percentage prediction models, drawing on events within badminton matches by examining scoring skills, situational, and timing factors. These models were divided into two main categories: three based on individual factors, scoring skills, situations, and timing, and the other three that integrated these factors. Specifically, the models included Model 1, which incorporated 10 events related to scoring-skill factors [34, 35]; Model 2 focused on four events aligned with scoring situational factors [28, 36]; Model 3 included five events associated with scoring-timing factors [28, 37]; Model 4 integrated 40 events that combined scoring-skill and situational factors; Model 5 combined 20 events related to scoring-situation and timing factors; and Model 6 encompassed 50 events that merged scoring-skill and timing factors. The

Table 3 Target data by research topic

Research topic	Number of matches	Number of games	Number of players	Total score
Research topic 1 Calculation of difficulty by event	100	222	43	7871
Research topic 2 Selection of initial prior probability	30	74	16	2654

definitions of events used in the aforementioned models are listed in Table 4, and the events for each model are presented in Table 4. Figure 1 shows the algorithmic process by which the posterior winning probabilities were derived from the initial prior probabilities.

Quantification of match events

The I-Minton badminton match analysis program (program registration number: C-2018–005553), developed by the Sports Analysis Center at Korea National Sports University, was employed to quantify match events (Fig. 2). This program was developed based on the research by Yeon-Ja Kim published in 2011 [28], and the match situations were recorded based on the methods presented in the study. The data recorded through the match analysis program were compiled using Excel 2013. Three recorders with over 10 years of experience as former badminton players were trained to use the I-Minton program for approximately two weeks before the recordings commenced. To minimize recording errors, the intraclass correlation coefficient for interobserver reliability was checked after the two-week training period and was confirmed to be above 0.80. This ensured that actual match data analysis could begin. Three months were allocated for the video data quantification process. To ensure accuracy and minimize discrepancies during data recording, the recorders meticulously reviewed and discussed ambiguous segments to reach a consensus on the scoring skills and situational factors involved.

Data processing method

This study aimed to create a sequential winning percentage prediction model for badminton competitions utilizing the EXSPRT model. Six sequential winning percentage prediction models were constructed to fulfill this objective by determining the difficulty levels and initial prior probabilities, considering skill, situational, and timing factors during badminton matches. Microsoft Excel was employed to develop the sequential probability prediction model for badminton matches. The methodology

Table 4 Factors and events by initial sequential winning percentage prediction models

Model	Factor	Possible events during a match
Model 1	Skill	Drop, clear, smash, drive, smash cut, smash receive, hairpin, push, under clear
Model 2	Situation	Racket no touch (where the shuttlecock does not touch the opponent's racket and scores), racket touch (where the shuttlecock touches the opponent's racket and scores), opponent's mistake (where the opponent commits an error and scores), other situations (rally situation scored because of other situations including badminton regulations or environmental factors)
Model 3	Timing	0–5 points, 6–10 points, 11–15 points, 16–20 points, after 21 points
Model 4	Skill-situation combinations	Drop-opponent's mistake, drop-racket touch, drop-racket no touch, drop-other situation, clear-opponent's mistake, clear-racket touch, clear-racket no touch, clear-other situation, smash-opponent's mistake, smash-racket touch, smash-racket no touch, smash-other situation, drive-opponent's mistake, drive-racket touch, drive-racket no touch, drive-other situation, smash cut-opponent's mistake, smash cut-racket touch, smash cut-racket no touch, smash cut-other situation, smash receive-opponent's mistake, smash receive-racket touch, smash receive-racket no touch, smash receive-other situation, hairpin-opponent's mistake, hairpin-racket touch, hairpin-racket no touch, hairpin-other situation, push-opponent's mistake, push-racket touch, push-racket no touch, push-other situation, under clear-opponent's mistake, under clear-racket touch, under clear-racket no touch, under clear-other situation, service-opponent's mistake, service-racket touch, service-racket no touch, service-other situations
Model 5	Situation-timing combinations	Racket no touch-0–5 points, racket no touch-6–10 points, racket no touch-11–15 points, racket no touch-16–20 points, racket no touch-after 21 points, racket touch-0–5 points, racket touch-6–10 points, racket touch-11–15 points, racket touch-16–20 points, racket touch-after 21 points, opponent's mistake-0–5 points, opponent's mistake-6–10 points, opponent's mistake-11–15 points, opponent's mistake-16–20 points, opponent's mistake-after 21 points, opponent's mistake-after 21 points, other situation-0–5 points, other situation-0–5 points, opponent's mistake-6–10 points, opponent's mistake-11–15 points, opponent's mistake-16–20 points, opponent's mistake-after 21 points, other situation-0–5 points, other situation-6–10 points, other situation-11–15 points, other situation-16–20 points, other situation-after 21 points
Model 6	Skill-timing combinations	Drop-0–5 points, drop-6–10 points, drop-11–15 points, drop-16–20 points, drop-after 21 points, clear-0–5 points, clear-6–10 points, clear-11–15 points, clear–16–20 points, clear-after 21 points, smash-0–5 points, smash-6–10 points, smash-11–15 points, smash-16–20 points, smash-after 21 points, drive-0–5 points, drive-6–10 points, drive-11–15 points, drive-16–20 points, drive-after 21 points, smash cut-0–5 points, smash cut-6–10 points, smash cut-11–15 points, smash cut-16–20 points, smash cut-after 21 points, smash receive-0–5 points, smash receive-6–10 points, smash receive-11–15 points, smash receive-16–20 points, smash receive-after 21 points, hairpin-0–5 points, hairpin-6–10 points, hairpin-11–15 points, hairpin-16–20 points, hairpin-after 21 points, push-0–5 points, push-6–10 points, push-11–15 points, push-16–20 points, push-after 21 points, under clear-0–5 points, under clear-6–10 points, under clear-11–15 points, under clear-16–20 points, under clear-after 21 points, service-0–5 points, service-6–10 points, service-11–15 points, service-16–20 points, service-after 21 points

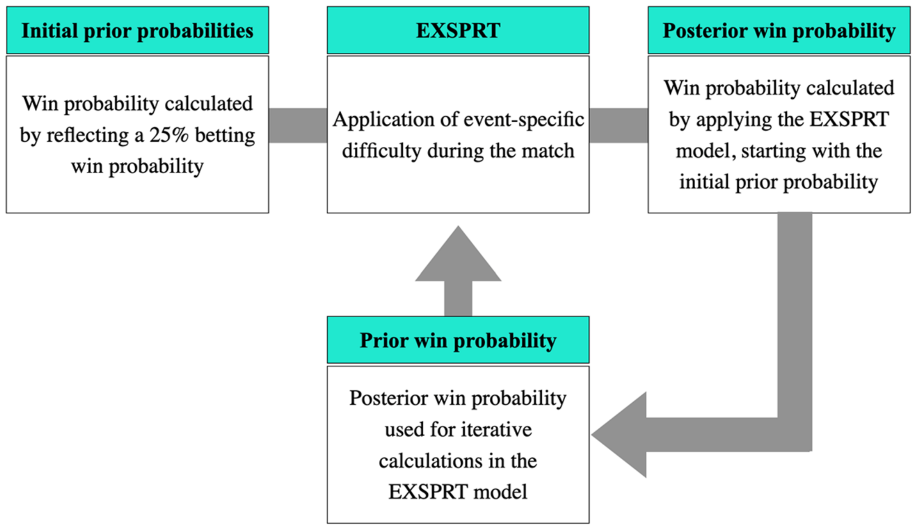

Fig. 1 EXSPRT model validation process

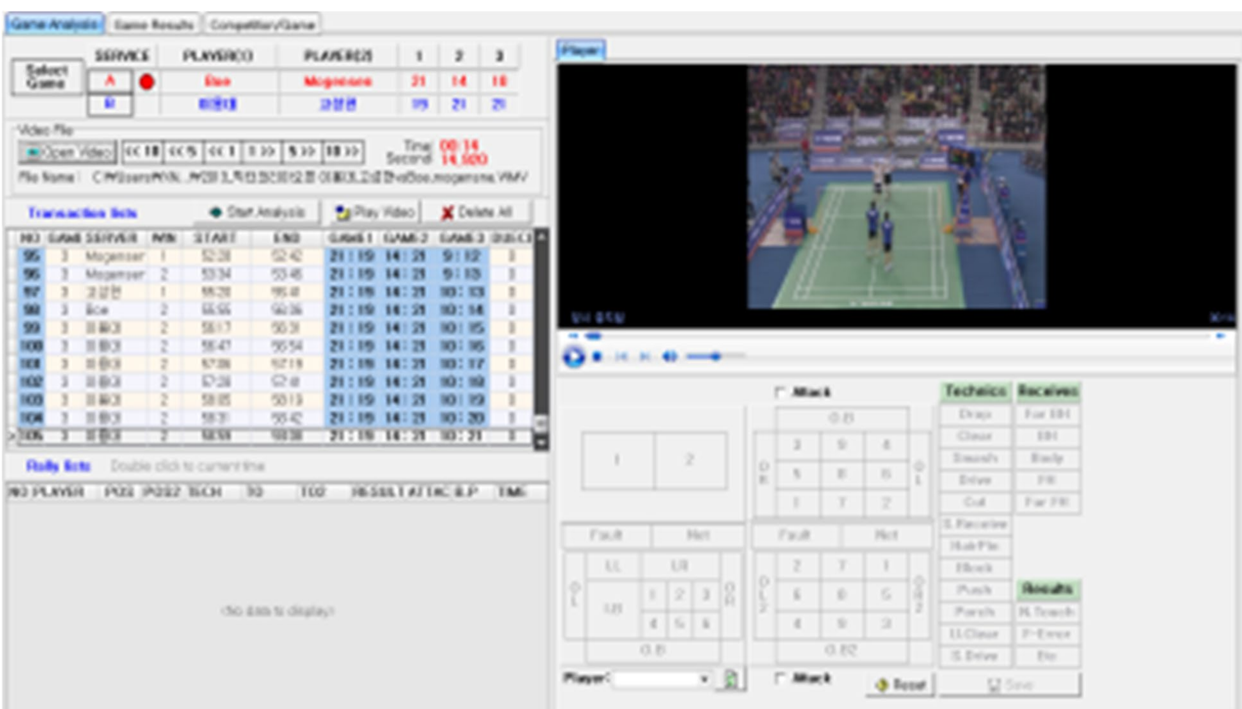

Fig. 2 Example of video analysis using the badminton analysis program "I-Minton"

for processing the specific data is detailed in the following subsections.

Data preprocessing steps

Prior to model development, data preprocessing steps were implemented to ensure the quality and reliability of the dataset. The first step involved data cleaning, where incomplete or erroneous data entries were identified and modified. Next, a data transformation process was applied to standardize the variables, including scoring events, into a consistent format for analysis. This transformation involved converting raw scores into a normalized scale, enabling a better performance comparison across different matches. These preprocessing steps significantly impacted the model's performance by enhancing the accuracy of the predictions and minimizing potential biases stemming from raw data inconsistencies.

Development of a sequential winning percentage prediction model for badminton competitions using the EXSPRT

This research leveraged the EXSPRT model introduced by Frick [29, 38] to devise a sequential winning percentage prediction model for badminton competitions. The EXSPRT model enables the decision-maker to either accept the null hypothesis (labeling the subject as a noncompleter), reject the null hypothesis (classifying the subject as a completer), or opt for a third alternative, continuing the test, based on the calculated posterior probability (PR). PR is determined using Eq. 1. The model also accounts for judgment errors, denoted by the values of α and β, where α represents the likelihood of falsely identifying a winner as a loser (type 1 error) and β indicates the chance of mistakenly labeling a loser as a winner (type 2 error). Typically, these judgment error rates are set to 0.05 for both α and β to maintain standard accuracy, although a more stringent criterion may adjust these rates to 0.01.

This study established four distinct judgment error rates: $\alpha=\beta<0.30$, $\alpha=\beta<0.10$, $\alpha=\beta<0.05$, and $\alpha=\beta<0.01$, with α and β being equal as indicated. Specifically, $\alpha=\beta<0.30$ indicates a judgment error rate of 30%, with "leading" displayed for a win; $\alpha=\beta<0.10$ signifies a 10% error rate, with "dominant" appearing for a win; $\alpha=\beta<0.05$ represents a 5% error rate, with "likely to win" shown for a win; and $\alpha=\beta<0.01$ indicates a 1% error rate, with "certain to win" presented for a win. The judgment results vary based on the error rate, and the term "close" is uniformly used when a judgment cannot be made. These judgment error rates are summarized in Table 5.

$$\mathrm{PR} = \frac{\mathrm{P_{om}} \times \mathrm{Theta0}^{\mathrm{r}} \times (1 - \mathrm{Theta0})^{\omega}}{\mathrm{P_{om}} \times \mathrm{Theta1}^{\mathrm{r}} \times (1 - \mathrm{Theta1})^{\omega}} \tag{1}$$

PR: Posterior probability

P_{om}: Prior probability when the subject is a completer

P_{on}: Prior probability when the subject is a noncompleter

Theta0: Probability of succeeding in an event when the subject is a completer

Theta1: Probability of succeeding in an event when the subject is a noncompleter

r: Number of successes

w: Number of failures

Event difficulty calculation using the EXSPRT equation

The EXSPRT model difficulty equation proposed by Frick in 1991 [31] was utilized to calculate the event difficulty for each of the six sequential probability prediction models. To ascertain the difficulty levels, events corresponding to each significant factor in the game situation were quantified, and Eq. 2 was applied to these quantified events.

Equation 2:

$$\mathrm{P(C_i \mid W) = (r_{iw} + 1)/(r_{iw} + w_{iw} + 2)}$$

$$\mathrm{P(\sim C_i \mid W) = 1 - P(C_i \mid W)}$$

$P(C_i \mid W)$ = Probability of the winner scoring a point with a given event

$P(C_i \mid W)$ = Probability of the winner losing a point with a given event

r_{iw} = Number of points scored with an event (e.g., smash) by the winning group

w_{iw} = Number of points lost with an event (e.g., smash) by the winning group

$$\mathrm{P(C_i \mid L) = (r_{il} + 1)/(r_{il} + w_{il} + 2)}$$

$$\mathrm{P(\sim C_i \mid L) = 1 - P(C_i \mid L)}$$

$P(C_i \mid L)$ = Probability of the loser scoring a point with a given event

$P(\sim C_i \mid L)$ = Probability of the loser losing a point with a given event

r_{il} = Number of points scored with an event (e.g., smash) by the losing group

w_{il} = Number of points lost with an event (e.g., smash) by the losing group

Setting the initial prior probability to develop a sequential winning percentage prediction model for badminton competitions

The initial prior probability for each player in the sequential winning percentage prediction model was established

Table 5 Judgment error rates

Judgment Error rate	Win/loss/match Continuation judgment values		Display words for win/loss/ match continuation Judgment			
	Win judgment	Loss judgment	Match continuation	Win judgment	Loss judgment	Match continuation
$a=B<0.30$	> 2.33	< 0.43	0.43 ~ 2.33	A leading	B leading	Close
$a=B<0.10$	> 9.00	< 0.11	0.11 ~ 9.00	Dominant	Inferior	Close
$a=B<0.05$	> 19.00	< 0.05	0.05 ~ 19.00	Likely to win	Likely to lose	Close
$a=B<0.01$	> 99.00	< 0.01	0.01 ~ 99.00	Certain to win	Certain to lose	Close

through a three-step process aimed at addressing the limitations of directly using betting odds as prior probabilities. Although betting odds are widely used to predict match outcomes, they often fail to reflect the dynamic nature of player performance during a match. For instance, an analysis of 308 men's singles badminton matches from nine BWF tournaments in 2019 showed that betting odds correctly predicted the winner in only 61.5% of cases, underscoring their limited ability to account for real-time variations in player performance.

Given these limitations, relying solely on raw betting odds as prior probabilities was deemed insufficient for generating accurate predictions. To address this, the study introduced an adjustment process by applying varying application rates (15%, 20%, 25%, and 30%) to refine the prior probabilities. These application rates were chosen based on their influence on predictive accuracy, ensuring that the model accounted not only for betting odds but also for player-specific factors and match conditions.

To validate this approach, the adjusted probabilities were tested across six sequential winning percentage prediction models, with each model being validated using the four application rates. The process for determining the initial prior probability involved three steps. First, the refund rate for each player was calculated based on the odds assigned for each match, as provided by Odds Portal site [33]. Second, the betting win probability for each player was derived using the refund rate and the odds. Third, the betting win probability, adjusted by a rate other than 100%, was used to set the initial prior probability. Specifically, the constant for each player according to different application rates (42.5%, 40%, 37.5%, and 35%) was determined by halving the remaining percentages (85%, 80%, 75%, and 70%) after excluding the rates applied for betting wins. Each of the initial six sequential winning percentage prediction models was validated across the four betting win probability application rates. Furthermore, based on the validation outcomes, an equation for setting the initial prior probability for each player was developed. The equation for calculating the initial prior probability at each stage is as follows:

Equation 3:

Step 1 $$\text{Refeund rate} = \frac{\text{Winning odds} \times \text{Losing odds}}{\text{Winning odds} + \text{Losing odds}}$$

Step 2 $$Bettingwinprobability = \frac{Refundrate}{odds}$$

Step 3 $$Initialpriorprobability = (Bettingwinprobabilty \times Applicationrete\%) + (Player - specificconstant)$$

Selecting initial prior probability for developing a sequential winning percentage prediction model for badminton competitions

The initial prior probability for the sequential winning percentage prediction model for badminton competitions was determined based on validating each player's initial prior probability. As badminton is a sport with clear win/loss outcomes, a binary classification table is commonly employed to assess a model's validity. However, in certain instances, the sequential probability prediction model developed for this study could not ascertain a win or loss at the match's conclusion. Consequently, instances wherein the outcome could not be determined were classified as draw predictions. To accommodate this and validate the model, a 3×3 classification table was used to verify the classification accuracy. The validity indices derived from the 3×3 classification table included accuracy (ACC), error rate (EER), geometric mean (GM), F-1 score (F-1), and the Matthews correlation coefficient (MCC), all of which are widely recognized as algorithm evaluation metrics.

Results

This study aimed to devise a sequential winning percentage prediction model for badminton competitions utilizing the EXSPRT methodology. To achieve this, two primary research topics were delineated. First, the study aimed to compute the difficulty level of six models grounded in events transpiring within badminton competitions, considering skill, situational, and timing factors. Second, the focus was on establishing the initial prior probability value based on the validity index.

Calculating difficulty by event for badminton competitions

The events associated with each of the six models were quantified to determine the event-specific difficulty for the sequential winning percentage prediction model. Subsequently, the EXSPRT model difficulty equation, as proposed by Frick [31], was applied to these quantified events.

Calculating event difficulty based on scoring skill (Model 1), situational (Model 2), and timing (Model 3)

Events related to these factors were quantified to assess the event-specific difficulty within the sequential winning percentage prediction model, which reflects the impact of scoring skill, situational context, and timing on winning or losing points. Following this quantification, the EXSPRT model difficulty equation proposed by Frick [38] was applied. The outcomes of this difficulty calculation for events associated with scoring skill (Model 1), situation (Model 2), and timing (Model 3) are listed in Table 6.

In this context, theta0 represents the probability of the winner scoring a point through event X, and 1-theta0 signifies the chance of the winner losing a point through event X. Conversely, theta1 indicates the probability of

Table 6 Event difficulty in the sequential winning percentage prediction model

Model	No	Scoring skill	Winner		Loser	
			theta0	1-theta0	theta1	1-theta1
1	1	Drop	0.48	0.52	0.25	0.75
	2	Clear	0.32	0.68	0.17	0.83
	3	Smash	0.75	0.25	0.61	0.39
	4	Drive	0.58	0.42	0.35	0.65
	5	Smash cut	0.27	0.73	0.15	0.85
	6	Smash receive	0.51	0.49	0.23	0.77
	7	Hairpin	0.40	0.60	0.19	0.81
	8	Push	0.86	0.14	0.75	0.25
	9	Under clear	0.29	0.71	0.19	0.81
	10	Service	0.02	0.98	0.03	0.97
2	1	Opponent’s mistake	0.59	0.41	0.41	0.59
	2	Racket touch	0.59	0.41	0.41	0.59
	3	Racket no touch	0.61	0.39	0.39	0.61
	4	Other situations	0.57	0.43	0.43	0.57
3	1	0–5 points	0.68	0.32	0.32	0.68
	2	6–10 points	0.82	0.18	0.18	0.82
	3	11–15 points	0.89	0.11	0.11	0.89
	4	16–20 points	0.95	0.05	0.05	0.95
	5	After 21 points	1.00	0.00	0.00	1.00
4	1	Drop-Opponent’s mistake	0.59	0.41	0.41	0.59
	2	Drop-Racket touch	0.56	0.44	0.44	0.56
	3	Drop-Racket no touch	0.68	0.32	0.32	0.68
	4	Drop-Other situations	0.60	0.40	0.40	0.60
	5	Clear-Opponent’s mistake	0.59	0.41	0.41	0.59
	6	Clear-Racket touch	0.60	0.40	0.40	0.60
	7	Clear-Racket no touch	0.60	0.40	0.40	0.60
	8	Clear-Other situations	0.60	0.40	0.40	0.60
	9	Smash-Opponent’s mistake	0.56	0.44	0.44	0.56
	10	Smash-Racket touch	0.61	0.39	0.39	0.61
	11	Smash-Racket no touch	0.61	0.39	0.39	0.61
	12	Smash-Other situations	0.53	0.47	0.47	0.53
	13	Drive-Opponent’s mistake	0.64	0.36	0.36	0.64
	14	Drive-Racket touch	0.55	0.45	0.45	0.55
	15	Drive-Racket no touch	0.62	0.38	0.38	0.62
	16	Drive-Other situations	0.55	0.45	0.45	0.55
	17	Smash cut-Opponent’s mistake	0.55	0.45	0.45	0.55
	18	Smash cut-Racket touch	0.63	0.37	0.37	0.63
	19	Smash cut-Racket no touch	0.63	0.37	0.37	0.63
	20	Smash cut-Other situations	0.63	0.37	0.37	0.63
	21	Smash receive-Opponent’s mistake	0.63	0.37	0.37	0.63
	22	Smash receive-Racket touch	0.67	0.33	0.33	0.67
	23	Smash receive-Racket no touch	0.67	0.33	0.33	0.67
	24	Smash receive-Other situations	0.67	0.33	0.33	0.67
	25	Hairpin-Opponent’s mistake	0.63	0.37	0.37	0.63
	26	Hairpin-Racket touch	0.62	0.38	0.38	0.62
	27	Hairpin-Racket no touch	0.62	0.38	0.38	0.62

Table 6 (continued)

Model	No	Scoring skill	Winner		Loser	
			theta0	1-theta0	theta1	1-theta1
	28	Hairpin-Other situations	0.66	0.34	0.34	0.66
	29	Push-Opponent's mistake	0.63	0.37	0.37	0.63
	30	Push-Racket touch	0.53	0.47	0.47	0.53
	31	Push-Racket no touch	0.58	0.42	0.42	0.58
	32	Push-Other situations	0.53	0.47	0.47	0.53
	33	Under clear-Opponent's mistake	0.58	0.42	0.42	0.58
	34	Under clear-Racket touch	0.62	0.38	0.38	0.62
	35	Under clear-Racket no touch	0.62	0.38	0.38	0.62
	36	Under clear-Other situations	0.52	0.48	0.48	0.52
	37	Service-Opponent's mistake	0.46	0.54	0.54	0.46
	38	Service-Racket touch	0.50	0.50	0.50	0.50
	39	Service-Racket no touch	0.50	0.50	0.50	0.50
	40	Service-Other situations	0.50	0.50	0.50	0.50
5	1	Opponent's mistake-0–5	0.67	0.33	0.33	0.67
	2	Opponent's mistake-6–10	0.82	0.18	0.18	0.82
	3	Opponent's mistake-11–15	0.89	0.11	0.11	0.89
	4	Opponent's mistake-16–20	0.96	0.04	0.04	0.96
	5	Opponent's mistake-21-	0.99	0.01	0.01	0.99
	6	Racket touch-0–5	0.72	0.28	0.28	0.72
	7	Racket touch-6–10	0.80	0.20	0.20	0.80
	8	Racket touch-11–15	0.89	0.11	0.11	0.89
	9	Racket touch-16–20	0.96	0.04	0.04	0.96
	10	Racket touch-21-	0.96	0.04	0.04	0.96
	11	Racket no touch-0–5	0.72	0.28	0.28	0.72
	12	Racket no touch-6–10	0.81	0.19	0.19	0.81
	13	Racket no touch-11–15	0.88	0.12	0.12	0.88
	14	Racket no touch-16–20	0.95	0.05	0.05	0.95
	15	Racket no touch-21-	0.99	0.01	0.01	0.99
	16	Other situations-0–5	0.62	0.38	0.38	0.62
	17	Other situations-6–10	0.87	0.13	0.13	0.87
	18	Other situations-11–15	0.95	0.05	0.05	0.95
	19	Other situations-16–20	0.94	0.06	0.06	0.94
	20	Other situations-21-	0.94	0.06	0.06	0.94
6	1	Drop-0–5	0.69	0.31	0.31	0.69
	2	Drop-6–10	0.76	0.24	0.24	0.76
	3	Drop-11–15	0.92	0.08	0.08	0.92
	4	Drop-16–20	0.97	0.03	0.03	0.97
	5	Drop-After 21 points	0.95	0.05	0.05	0.95
	6	Clear-0–5	0.62	0.38	0.38	0.62
	7	Clear-6–10	0.80	0.20	0.20	0.80
	8	Clear-11–15	0.88	0.12	0.12	0.88
	9	Clear-16–20	0.98	0.02	0.02	0.98
	10	Clear-After 21 points	0.92	0.08	0.08	0.92
	11	Smash-0–5	0.68	0.32	0.32	0.68
	12	Smash-6–10	0.79	0.21	0.21	0.79
	13	Smash-11–15	0.87	0.13	0.13	0.87

Table 6 (continued)

Model	No	Scoring skill	Winner		Loser	
			theta0	**1-theta0**	**theta1**	**1-theta1**
	14	Smash-16–20	0.95	0.05	0.05	0.95
	15	Smash-After 21 points	0.99	0.01	0.01	0.99
	16	Drive-0–5	0.61	0.39	0.39	0.61
	17	Drive-6–10	0.90	0.10	0.10	0.90
	18	Drive-11–15	0.91	0.09	0.09	0.91
	19	Drive-16–20	0.96	0.04	0.04	0.96
	20	Drive-After 21 points	0.94	0.06	0.06	0.94
	21	Smash cut-0–5	0.70	0.30	0.30	0.70
	22	Smash cut-6–10	0.83	0.17	0.17	0.83
	23	Smash cut-11–15	0.89	0.11	0.11	0.89
	24	Smash cut-16–20	0.97	0.03	0.03	0.97
	25	Smash cut-After 21 points	0.95	0.05	0.05	0.95
	26	Smash receive-0–5	0.90	0.10	0.10	0.90
	27	Smash receive-6–10	0.71	0.29	0.29	0.71
	28	Smash receive-11–15	0.75	0.25	0.25	0.75
	29	Smash receive-16–20	0.95	0.05	0.05	0.95
	30	Smash receive-After 21 points	0.83	0.17	0.17	0.83
	31	Hairpin-0–5	0.72	0.28	0.28	0.72
	32	Hairpin-6–10	0.90	0.10	0.10	0.90
	33	Hairpin-11–15	0.91	0.09	0.09	0.91
	34	Hairpin-16–20	0.94	0.06	0.06	0.94
	35	Hairpin-After 21 points	0.97	0.03	0.03	0.97
	36	Push-0–5	0.70	0.30	0.30	0.70
	37	Push-6–10	0.81	0.19	0.19	0.81
	38	Push-11–15	0.84	0.16	0.16	0.84
	39	Push-16–20	0.93	0.07	0.07	0.93
	40	Push-After 21 points	0.96	0.04	0.04	0.96
	41	Under clear-0–5	0.65	0.35	0.35	0.65
	42	Under clear-6–10	0.82	0.18	0.18	0.82
	43	Under clear-11–15	0.94	0.06	0.06	0.94
	44	Under clear-16–20	0.94	0.06	0.06	0.94
	45	Under clear-After 21 points	0.96	0.04	0.04	0.96
	46	Service-0–5	0.86	0.14	0.14	0.86
	47	Service-6–10	0.67	0.33	0.33	0.67
	48	Service-11–15	0.90	0.10	0.10	0.90
	49	Service-16–20	0.88	0.13	0.13	0.88
	50	Service-After 21 points	0.50	0.50	0.50	0.50

the loser scoring through event X, and 1-theta1 shows the likelihood of the loser losing a point through event X. A significant discrepancy between theta0 and theta1 in the difficulty calculations suggests a significant skill difference between winners and losers for that event. Furthermore, if a player continues to score with a technique that has high discriminative power, this means that the time required to predict the winner is reduced.

In Model 1, the skill event with the highest discriminative power for scoring situations is the "smash-receive," where the probabilities of the winner and loser scoring with a smash-receive are 0.51 and 0.23, respectively. Conversely, the event with the lowest discriminative power is the "service," where the probabilities of the winner and loser scoring with a service are 0.02 and 0.03, respectively.

In Model 2, the situation event with the highest discriminative power for scoring is the "racket no touch," where the probabilities of the winner and loser scoring owing to the opponent's mistake are 0.61 and 0.39, respectively. Conversely, the event with the lowest discriminative power is the "other situations," where the probabilities of the winner and loser scoring owing to other situations are 0.57 and 0.43, respectively.

In Model 3, we can observe that the discriminative power increases as the game point approaches 21. The event with the highest discriminative power for scoring at different game points is "after 21 points," where the probabilities of the winner and loser being two or more points ahead after 21 points are 1.00 and 0.00, respectively. The event with the lowest discriminative power for scoring at different game points is "0–5 points," where the probabilities of the winner and loser being two or more points ahead between 0–5 points are 0.68 and 0.32, respectively.

Overall, technical factors (Model 1) demonstrated lower predictive accuracy during the early stages of the game (e.g., "Service") but highlighted the potential strategic importance of specific techniques such as "Push." In contrast, timing factors (Model 3) showed higher predictive accuracy in the later stages of the game, suggesting that focusing on timing factors is particularly effective for developing strategies in the final phases of a match. Furthermore, situational factors (Model 2) proved effective in predicting the opponent's mistakes, making them a valuable tool for real-time analysis that considers in-game variability.

Calculating event difficulty with skill-situational (Model 4), situational-timing (Model 5), and timing-skill (Model 6) factors

Table 6 presents the event-specific difficulty of the sequential winning percentage prediction model, incorporating combinations of badminton scoring skill-situational, situational-timing, and timing-skill factors. After quantifying events that combine these factors, the EXSPRT model's difficulty equation was applied. When calculating the scoring difficulty in a skill-situational event, the most discriminatory event was the "drop-racket no touch," with the probabilities of 0.68 and 0.32 for the winner and loser to score with drop-racket no touch, respectively. In contrast, the event with the lowest discriminative power is the combination of "service" and the scoring situation. This indicates a situation where points are scored through a service. In assessing the scoring difficulty with situation-timing factor events, the most discriminatory events were the "opponent's mistake-after 21 points" and "racket-no-touch-after 21 points." Regarding the scoring difficulty of skill-timing factor events, the most discriminatory event was the "smash-after 21 points," which exhibited the probabilities of 0.99 and 0.01 for the winner and loser to score with a smash-after 21 points, respectively.

When comparing the models, the skill-situational combined model (Model 4) demonstrated superior performance during mid-game events, such as "drop-racket no touch," where the difference in scoring probabilities between the winner and loser reached 0.36 (0.68 vs. 0.32). This indicates that combining skill-based and situational factors can provide stronger insights into predicting outcomes, particularly in the middle stages of a match. Conversely, the situational-timing combined model (Model 5) excelled during late-game events, exemplified by "racket-no-touch-after 21 points," where the scoring probability difference between the winner and loser was as high as 0.98 (theta0 = 0.99, theta1 = 0.01). These findings suggest that situational factors play a more critical role in the early stages of a match, whereas timing factors become increasingly important as the game progresses.

Additionally, the skill-timing combined model (Model 6) demonstrated consistent performance across all stages of the match, with particularly strong predictive power in late-game scenarios. For instance, in the "smash-after 21 points" event, the difference in scoring probabilities between the winner and loser was also 0.98 (theta0 = 0.99, theta1 = 0.01), emphasizing the decisive importance of technical execution during critical moments. This underscores the model's effectiveness in leveraging both technical and timing factors, making it a valuable tool for strategies focused on the late stages of a match. In summary, these results highlight the distinct strengths of each combined model, suggesting that their application should be tailored to the specific context and phase of the match.

Selecting initial prior probability for developing a sequential winning percentage prediction model for badminton competitions

To set the initial prior probability for developing a sequential winning percentage prediction model for badminton competitions, the application rates for betting win probabilities were determined to be 15%, 20%, 25%, and 30%. The model underwent validation by applying these four winning probabilities across each of the six sequential winning percentage prediction models. The outcomes of this validation process for each model and the validation rankings based on the betting win probability application rates are detailed in the following subsection.

Betting win probability by sequential winning percentage prediction model validity result according to application rate

Table 7 lists the outcomes of validating the sequential winning percentage prediction models by applying varying rates of betting win probability. Specifically, for the model that incorporated the scoring skill factor (Model 1), the application of 15%, 20%, 25%, and 30% betting win probabilities was assessed. The validity indices, ACC, EER, GM, F-1 score, and MCC, all exhibited their highest performance at a 20% betting win probability application, with respective values of 0.537 (ACC), 0.463 (EER), 0.518 (GM), 0.410 (F-1), and 0.298 (MCC).

When the betting win probability was applied to the sequential winning percentage prediction model that focused on the scoring situational factor (Model 2), the highest validity was observed with a 30% application rate, resulting in the following indexes: ACC at 0.470, EER at 0.530, GM at 0.474, F-1 score at 0.365, and MCC at 0.269.

For the model that considers the scoring-timing factor (Model 3), applying a 20% betting win probability yielded the highest validity across all indexes: ACC was 0.730, EER was 0.270, GM was 0.628, the F-1 score reached at 0.486, and MCC was 0.306.

For the sequential winning percentage prediction model that integrates scoring-skill and situational factors (Model 4), the highest validity was achieved with a 25% betting win probability application, displaying indexes of ACC at 0.520, EER at 0.480, GM at 0.515, F-1 score at 0.405, and MCC at 0.309.

When betting win probability was applied to the model combining scoring-situation and timing factors (Model 5), optimal validity indexes of ACC at 0.716, EER at 0.284, GM at 0.619, F-1 score at 0.476, and MCC at 0.286 were observed at a 25% application rate.

In the case of the model blending scoring-skill and timing factors (Model 6), all applied rates of betting win probability yielded identical validity indexes and rankings, indicating a consistent performance across different betting win probabilities.

Table 7 Validity results of scoring skill factor winning percentage prediction model in terms of betting win probability application rate

Model	Application rate	ACC	R	EER	R	GM	R	F-1	R	MCC	R	TR
1	15%	0.527	3	0.473	3	0.511	3	0.403	4	0.286	4	3
	20%	0.537	1	0.463	1	0.518	1	0.410	1	0.298	1	1
	25%	0.530	2	0.470	2	0.513	2	0.406	2	0.292	2	2
	30%	0.527	4	0.473	3	0.511	4	0.404	3	0.287	3	3
2	15%	0.463	2	0.537	2	0.469	3	0.361	2	0.267	2	2
	20%	0.459	4	0.541	4	0.467	4	0.359	4	0.264	4	4
	25%	0.463	2	0.537	2	0.469	2	0.361	3	0.266	3	3
	30%	0.470	1	0.530	1	0.474	1	0.365	1	0.269	1	1
3	15%	0.713	4	0.287	4	0.617	4	0.475	4	0.283	4	4
	20%	0.730	1	0.270	1	0.628	1	0.486	1	0.306	1	1
	25%	0.726	2	0.274	2	0.626	2	0.484	2	0.302	2	2
	30%	0.726	2	0.274	2	0.626	2	0.484	2	0.302	2	2
4	15%	0.517	2	0.483	2	0.512	2	0.402	2	0.305	3	2
	20%	0.517	2	0.483	2	0.511	4	0.401	4	0.308	2	4
	25%	0.520	1	0.480	1	0.515	1	0.405	1	0.309	1	1
	30%	0.517	2	0.483	2	0.512	2	0.402	2	0.305	3	2
5	15%	0.706	3	0.294	3	0.612	3	0.469	3	0.272	3	3
	20%	0.716	1	0.284	1	0.620	1	0.476	2	0.286	2	2
	25%	0.716	1	0.284	1	0.619	2	0.476	1	0.286	1	1
	30%	0.706	3	0.294	3	0.612	3	0.469	3	0.272	3	3
6	15%	0.730	1	0.270	1	0.628	1	0.485	1	0.303	1	1
	20%	0.730	1	0.270	1	0.628	1	0.485	1	0.303	1	1
	25%	0.730	1	0.270	1	0.628	1	0.485	1	0.303	1	1
	30%	0.730	1	0.270	1	0.628	1	0.485	1	0.303	1	1

ACC Accuracy, *EER* Error rate, *GM* Geometric Mean, *F-1* F-1 score, *MCC* Matthews correlation coefficient, *R* Ranking, *TR* Total ranking

Selecting initial prior probability based on prediction model validity according to betting win probability application rate

Table 8 and Fig. 3 present the validity results of six sequential winning percentage prediction models evaluated at betting win probability application rates of 15%, 20%, 25%, and 30%. The analysis showed that applying a 25% betting win probability produced the most reliable outcomes. Models integrating multiple factors, such as the scoring skill and situational combination model (Model 4), the situational and timing combination model (Model 5), and the scoring skill and timing combination model (Model 6), all ranked the highest. Based on these results, the method of applying a 25% probability involves evenly dividing the remaining 75% of the betting win probability to assign a baseline constant of 37.5% to each player.

Discussion

The ongoing effort to improve the accuracy of sports competition outcome prediction is well documented [6, 39–41]. However, most previous studies have primarily relied on prematch data, such as game history, stadium conditions, and player information, for predicting outcomes, posing a limitation. These approaches do not consider dynamic real-time events that occur after the game begins, including changes in player condition, stadium climate, and fluctuations in spectator numbers.

Table 8 Validity ranking of six sequential winning percentage prediction models based on the application rate of betting win probability

Ratio	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Total	Ranking
15%	3	2	4	2	3	1	15	4
20%	1	4	1	4	2	1	13	3
25%	2	3	2	1	1	1	10	1
30%	3	1	2	2	3	1	12	2

Model 1: Sequential winning percentage prediction model reflecting scoring skill factor

Model 2: Sequential winning percentage prediction model reflecting scoring-situation factor

Model 3: Sequential winning percentage prediction model reflecting scoring-timing factor

Model 4: Sequential winning percentage prediction model reflecting scoring-skill and situational factor combination

Model 5: Sequential winning percentage prediction model reflecting scoring-situation and timing factor combination

Model 6: Sequential winning percentage prediction model reflecting scoring-skill and timing factor combination

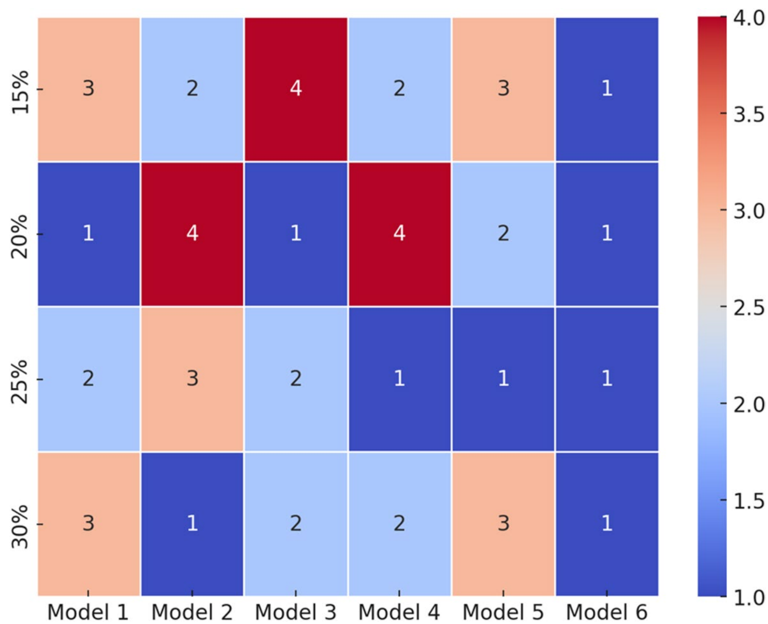

Fig. 3 Heatmap of average validation rankings for models based on betting win probability application rate

Recent advances in real-time sports win-loss prediction have shown considerable progress. For instance, Saito et al. [42] used first-half soccer match data to develop strategies for the second half, whereas Song et al. [41] applied a gamma process to predict real-time total score distributions in NBA basketball games based on betting odds. Nevertheless, limitations remain; for example, Saito et al. [42] did not address first-half outcome prediction, and Song et al. [41] relied solely on betting odds, neglecting real-time in-game progress.

The EXSPRT model proposed by Welch and Frick [16], however, offers a method for real-time prediction of match outcomes by incorporating the ongoing match situation and events. This approach applies to sports such as badminton, where match results depend on the sequential accumulation of points up to a predetermined score (usually 21 points). Considering that in-game events substantially impact the outcome, real-time success prediction can be achieved by employing an extended SPRT model.

This study pursued two primary objectives: first, to assess the difficulty of the events occurring during badminton matches, focusing on factors such as scoring technique, situation, and timing; second, to establish the initial prior probability (prematch player win rate) necessary to develop the EXSPRT model based on validity indices.

In the six initial sequential win prediction models developed, key elements include scoring technique, scoring situation, and scoring time. In practical application, however, various unpredictable and unique events specific to each match can arise, affecting prediction accuracy. The study's focus on scoring technique, situation, and timing elements is deliberate because they are easy to collect from real-time match footage and are supported by existing literature. Moreover, the study's results align with prior research [26–28, 37], which analyzed events related to these factors.

For the first objective, data from 100 men's singles matches (totaling 222 sets) from 2018 BWF international tournaments were utilized. The selection rationale is the accessibility of match videos provided by the BWF, facilitating data collection. Notably, all matches in the dataset are high-level men's singles competitions involving the top 100 players. Thus, acknowledging that results may not generalize to events with different player levels, genders, or match types (e.g., doubles) is essential.

While this study focuses on badminton, its implications extend beyond this sport. The findings of this study hold significant implications for other sports that involve sequential scoring, such as tennis, volleyball, and table tennis [23]. These sports share a reliance on point-by-point accumulation to determine match outcomes, making them suitable candidates for applying the EXSPRT model. To expand its applicability to these and other multievent sports, enhancing real-time data processing capabilities and integrating diverse event types are essential. Sport-specific modifications of the model can address unique gameplay characteristics, while improving robustness against environmental and contextual factors. By incorporating real-time event data and leveraging the model's adaptability to various match scenarios, future studies can validate its utility across multiple sports disciplines and enhance the accuracy of outcome predictions.

To achieve the second objective, the initial prior probability was determined using betting odds from Odds Portal site [33]. Based on this, a 25% winning probability was assigned to each player, whereas the opponent's initial prior probability was determined by adding a fixed rate of 37.5%. Betting odds were utilized to set the prior probability because they reflect recent match performance, player condition, and game circumstances [43–45]. However, owing to the wide range of betting odds (19.50–1.00; [33]), the range was limited to 15%, 20%, 25%, and 30% to validate the model's effectiveness.

In this study, when the original distribution of betting odds and a 50% winning probability were allocated to each player, a tendency for greater prediction errors was observed. Therefore, following prior research that adjusted betting odds to predict winning probabilities [46], the analysis was conducted by applying a range of 15%–30%. The results indicate that the 25% rate produced the highest classification accuracy, F1 score, and MCC, confirming it as the most valid winning probability.

The 15% and 20% rates resulted in overly conservative judgments owing to the allocation of excessively low probabilities, whereas the 30% rate led to overly hasty predictions because of the high winning probability. In contrast, the 25% rate avoided excessive errors and produced stable and reliable predictive outcomes.

However, the reliance on betting odds presents a limitation in this study. In scenarios where such data is unavailable or unreliable, the applicability of this model may be restricted. To address this, future research should explore methods for setting independent initial prior probabilities by utilizing players' match data and statistical information.

To set the initial prior probability for the second objective, betting odds from www.oddsportal.com were used, resulting in a decision to apply a betting win rate of 25% to each player. Specifically, the 25% win rate is assigned per player, with an additional fixed ratio of 37.5% added to determine the initial prior probability of the opponent. The use of betting odds in setting prior probability is justified by the fact that odds consider recent performance, player condition, and match context [43–45]. However, instead of using the entire odds amount, only 25% was applied because of the wide range of odds (19.50–1.00; [33]) assigned per player. This considerable variation could lead to overly quick judgments or incorrect outcome predictions; therefore, a validation of models with 15%, 20%, 25%, and 30% win probabilities was conducted, with 25% being the most valid.

The 3×3 classification table was employed to calculate indicators such as classification accuracy, EER, GM, F-1 score, and MCC, providing validation for the initial prior probability. Although traditional metrics such as sensitivity, specificity, and area under the ROC curve are often used, this study focused on indicators assessing program performance. Recent studies [47–49] also support the use of such validity indices.

The EXSPRT model assesses win-loss outcomes based on alpha and beta thresholds. To improve accuracy, four error rates ($\alpha=\beta<0.30$, $\alpha=\beta<0.10$, $\alpha=\beta<0.05$, and $\alpha=\beta<0.01$) were incrementally applied. Despite these efforts, when a slight performance difference exists between players, the model may still fail to determine the outcome by the match end or produce inaccurate results.

Nonetheless, the badminton win prediction model developed in this study is adaptable to various disciplines, offering valuable insights through real-time win rate predictions and providing new match data. For real-time prediction in actual badminton contexts, the following potential challenges must be addressed. First, managing real-time data stream processing is critical. This requires identifying the optimal model among the six developed in this study, followed by program development based on the optimal model. The program should handle input of match records, sequential updating of win rates, and reliable output of predictions. Such a system can maintain the model's predictive performance by efficiently processing rapidly updating game data [50, 51]. Moreover, designing a user interface to deliver immediate feedback on predictions, making it accessible for audiences and coaching staff, is crucial [52].

Second, confirming the robustness of the real-time prediction model is necessary for practical application. In actual matches, various conditions such as changes in player condition, environmental factors (lighting, humidity), and crowd size can influence the outcome [53, 54]. Therefore, evaluating how these conditions impact the model's predictions is essential to assess its robustness across different scenarios. This could involve comparing pre- and post-match data, and testing model performance under varying match conditions with mock data or actual match data. Recording performance by condition can verify reliability and predictive accuracy, supporting real-world application of the model. These considerations provide practical insights into model design, serving as foundational data for future development of real-time sports prediction models.

Conclusions

The integration of real-time badminton game dynamics into predictive models remains underexplored. This study aimed to address this gap by developing a real-time prediction model for badminton match outcomes using the EXSPRT framework proposed by Welch and Frick. Specifically, the study focused on evaluating event difficulty based on skill, situational, and timing factors and determining initial prior probability values for each player.

This research successfully developed six sequential win prediction models, comprising three single-factor models addressing skill, situational, and timing factors independently, and three combined models incorporating skill-situation, situation-timing, and skill-timing elements. Notably, setting the initial prior probability at 25% of the betting win probability for each player, while adding a fixed rate of 37.5% for the opponent, proved to be the most effective approach, resulting in improved prediction accuracy. These findings contribute significantly to sports science by enabling real-time win probability predictions, which can enhance strategic decision-making and audience engagement.

The implications of this study extend beyond badminton to other sports that rely on sequential scoring, such as tennis, volleyball, and table tennis. These sports share a reliance on point-by-point accumulation to determine match outcomes, making them suitable candidates for applying the EXSPRT model. To expand its applicability, enhancing real-time data processing capabilities and customizing the model to accommodate diverse event types is crucial. For instance, integrating the model into live broadcasts could provide viewers with dynamic real-time win probabilities, enhancing audience engagement. Additionally, coaching tools incorporating the EXSPRT model could help identify key moments for strategic interventions during a match.

Future research should explore the integration of advanced data sources, such as player motion tracking through sensors and detailed performance analytics, to enhance the model's accuracy and robustness. Moreover, deploying the model in real-world settings, such as international tournaments, and validating its performance under varying conditions will be essential to demonstrate its practical utility. These efforts could include designing user-friendly dashboards that provide immediate feedback to coaches and broadcasting teams, ensuring the model's effectiveness in high-pressure, real-time scenarios.

Finally, a detailed cost–benefit analysis of implementing the EXSPRT model in live sports scenarios is imperative. This analysis should assess the technical requirements, computational costs, and the added value for broadcasters, coaching staff, and audiences. Considering the economic feasibility and practical benefits of the EXSPRT model, it has the potential to become a versatile real-time predictive tool across a variety of sports disciplines.

Abbreviations

EXSPRT	EXpert system Sequential Probability Ratio Test
IRT	Item Response Theory
BWF	Badminton World Federation
PR	Posterior Probability
ACC	Accuracy
EER	Error rate
GM	Geometric Mean
F-1	F-1 score
MCC	Matthews Correlation Coefficient

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

This paper was solely authored by Eunhye Jo. Eunhye Jo was responsible for all aspects of the research, including the conception and design of the study, data collection, analysis and interpretation of data, drafting the manuscript, and revising it critically for important intellectual content. Eunhye Jo also approved the final version to be published and agrees to be accountable for all aspects of the work.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

The study was approved by the Korea National Sports University ethics committee (approval number: 1263–202003-HR-008–01). The data used in this research were collected from publicly available match videos provided by the BWF and quantified for research purposes. Because the data collected from these videos do not contain sensitive personal information, the requirement for informed consent was waived. This waiver of consent was also approved by the appropriate ethics committee.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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