Biases in Micro-level Probabilistic Reasoning and Its Impact on the Spectators' Enjoyment of Tennis Games

Stephen Zhu(✉)

Tennis Analyzer App, Atlanta, USA
stephen.zhu6@gmail.com

Abstract. In sports games, the excitement and suspense felt by the spectators are essential to their entertainment experience. The level of excitement and suspense is linked to the spectators' reasoning about the probability of winning or losing. In tennis, as in many other sports, spectators' predictions of winning probabilities largely hinge on the scores. Given tennis's hierarchical scoring system, its probabilistic reasoning is multifaceted and complex. This research examines the winning probabilities across various scoring scenarios, using data from thousands of professional tennis matches and comparing them with theoretical models generally aligned with spectators' common beliefs. The analysis reveals that the theoretical model makes accurate probability predictions at the macro level but inaccurate predictions at the micro level, pointing to possible biases in micro-level probabilistic reasoning. A recent behavioral economic theory may help explain the causes of such biases. Biases are generally seen as undesirable errors, but this study offers a counterargument that biases in micro-level probabilistic reasoning actually enhance the enjoyment of tennis matches by creating expectations, anxiety, and surprises.

Keywords: Sports analytics · entertainment · probabilistic reasoning · bias · behavioral economics

1 Introduction

Why do people enjoy watching sports? Previous research has found suspense to be crucial for the spectators' enjoyment of sports [14,16,22,24,25,28,30,34,35]. Suspense, a feeling of excitement or uncertainty about future events, is closely associated with the spectator's reasoning about the probability of winning or losing. Zillmann identified three elements for investigating the connection between suspense in sports and enjoyment: (spectators') dispositions toward participants, (un)certainty about a negative outcome for a favored participant, and repeated opportunities for the favored participant to fall behind and ultimately lose [22,33]. The second and third elements are directly related to probabilistic reasoning.

A spectator's probabilistic reasoning during a game may be influenced by many factors, such as scores, past performance statistics, the players' physical

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and mental conditions, and the environment, but empirical studies indicated that score difference is a reliable predictor of suspense [16,22,30]. The smaller the score difference, the greater the suspense [16,30], leading to greater enjoyment of the sports game [22]. Thus, it has been empirically established that spectators' enjoyment of sports is closely tied to their probabilistic reasoning about the outcome, especially based on score differences.

Research has shown that probabilistic reasoning is frequently shaped by subconscious biases, such as availability bias, representative heuristics, confirmation bias, etc. [6,7,23,32] Bias in probabilistic reasoning refers to systematic human errors in assessing the probability of future events. Given the close connection between probabilistic reasoning and the enjoyment of sports games, how do probabilistic reasoning biases affect the spectators' entertainment experience? This study seeks to shed light on this rarely explored question in the context of tennis.

Tennis was selected for this study due to its relatively complex scoring system, which leads to more complex probabilistic reasoning about the outcomes. The tennis scoring system is divided into three hierarchical layers: set scores, game scores, and point scores. In this study, the set and game scores are classified as macro-level scores and point scores as micro-level scores. Probabilistic reasoning about the outcome occurs at the macro- and micro-levels, and the predictions are interconnected.

This study makes three main contributions.

- This research analyzes winning probabilities across different tennis scoring scenarios, drawing on data from thousands of professional matches and comparing these to widely accepted theoretical models. The findings show that while the predictions from the theoretical models align well with empirical probabilities at the macro-level of game scores, the model significantly deviates from the empirical probabilities at the micro-level of point scores. Since this theoretical model is considered close to human probabilistic reasoning, these discrepancies point to possible biases in micro-level probabilistic reasoning. Such biases have not been reported before.

- The biases in the micro-level probabilistic reasoning can be explained by recent theories from behavioral economics [7]. It is a type of availability bias because limited human cognitive capacity has difficulty handling the large volume of micro-level data.

- This study suggests that spectators' entertainment experience in tennis is partially based on human errors in probabilistic reasoning. In other words, biases in micro-level probabilistic reasoning actually enhance the entertainment experience of watching tennis matches by creating expectations, anxiety, and surprises. While biases are typically viewed as detrimental due to their role in producing inaccurate predictions, this research presents a counterpoint: these biases can have positive effects on the entertainment experience.

This is the first step toward a comprehensive study of biases in micro-level probabilistic reasoning for tennis spectators.

2 Background and Related Work

2.1 Biases in Probabilistic Reasoning

People often need to make decisions in uncertain circumstances based on subjective probabilities of future events. Due to scarcity of data or limited human cognitive capacity, people use certain heuristic principles to simplify their probabilistic reasoning [29]. Although these heuristics may work well in many cases, they frequently lead to biases (or errors) that negatively affect people's judgments [6,31,32]. Since Tversky and Kahneman's early work [31], researchers have discovered various biases: anchoring effect, framing bias, availability bias, representative heuristics, recallability trap, survivorship bias, biased beliefs about the random sequence, biased beliefs about sampling distributions, base rate neglect, etc. [6,12,32]

In recent years, some researchers have attempted to uncover the underlying cognitive process associated with such biases. For example, Enke and Graeber [10] argued that cognitive uncertainty might cause systemic biases. Bordalo, et al. [7] proposed a theory that the bias in probabilistic reasoning is related to the similarity and interference in memory retrieval.

2.2 Biases in Sports-Related Probabilistic Reasoning

Bias and heuristics have also been studied in sports [2,9], and one of the most notable examples is the hot-hand bias [6,13]. However, relatively little research has been done on the biases and heuristics in tennis. Most related works in tennis focused on the biases in the tennis betting markets [1,11,18,19]. This work differs from previous works by focusing on the bias in game outcome (micro-level) predictions. In contrast, the previous work on the betting market focused on match outcome (macro-level) predictions. To the best knowledge of this author, the biases in the micro-level probabilistic reasoning have not been reported before.

2.3 Tennis Scoring System

Before getting into the details of predicting winning probabilities in tennis, it is important to understand the basics of the tennis scoring system. A tennis match is divided into three hierarchical layers: match, set, and game. There are three types of scores in tennis: point scores, game scores, and set scores. The two players take turns to server for each game. Each time a player scores in a game, the player's point score increases in the sequence of 0, 15, 30, 40, and Advantage(Ad). To win a game, a player must score higher than 40 and win at least two more points than the opponent. If a player wins a game, the player's game score increases by one. To win a set, a player must score higher than five games and win at least two more games than the opponent or win the tiebreak game after 6–6. If a player wins a set, the player's set score increases by one. To win a match, the player must win the best of three or five sets, depending on the tournament.

In this study, the set scores and game scores are classified as macro-level scores and point scores as micro-level scores.

2.4 Prediction Models for Tennis

There is a large body of work on predicting the winner or calculating the winning probabilities in tennis matches. Kovalchik [17] and Sarcevic, et al. [27] have conducted comprehensive reviews on the subject. The prediction models in tennis can be divided into three categories: point-based models (including regression models), paired comparison models, and machine learning models [27].

Point-based models make predictions based on past performance statistics and the scores. For example, Barnett, et al. [5] developed recursive models for calculating winning probabilities, based on a player's pre-match point-winning statistics and current scores. Based on a similar idea, O'Malley [20] also developed recursive models for calculating the winning probabilities for tennis games, sets, and matches. Sarcevic, et al. [4] developed a combinatorial prediction model that is theoretically identical to the recursive model but more efficient in practice.

Paired comparison models use the players' historical data, such as their rankings and head-to-head records, to make predictions [27]. Previous studies indicate that paired comparison models can better predict match winners than point-based models [17,27]. However, paired comparison models are generally unsuitable for micro-level predictions because there is no tennis ranking data for game-level comparisons.

The benefit of machine learning methods is that they can take in a wide variety of information that is otherwise difficult to integrate into traditional statistical models. Such information may include home-court advantage, player fatigue, court surfaces, weather conditions, player's physical and mental conditions, etc. However, current machine learning models have not generated better results than other types of models [27].

Overall, paired-based and machine-learning models are more suitable for pre-match outcome predictions, but point-based models are more suitable for real-time, in-game outcome predictions.

3 Probabilistic Reasoning and Sports Spectators' Entertainment Experience

The relationship between probabilistic reasoning and sports spectators' entertainment experience can be constructed as follows.

Before and during a sports game, a spectator estimates the probability of a player or team winning or losing, either consciously or subconsciously. This is particularly true if the spectator has a personal affinity for the player or team in question [22,34]. Although the pre-match prediction may involve many factors, such as head-to-head records, ranking differences, home-court advantage, playing venue, and weather conditions, multiple empirical studies have shown that a spectator's subjective probabilistic reasoning during a game is primarily based on the scores, particularly the score differences [16,22,30,34].

The spectator experiences different emotions depending on the winning probability of the player or team. When the spectator believes that a player or team's chance of winning is high or increasing, the spectator feels hopeful. However, if the winning probability is low or decreasing, the spectator fears the negative outcome. During the game, the spectator always has a sense of uncertainty about the game's outcome. However, this feeling of uncertainty intensifies when the probability of winning is perceived to be hovering around 50%.

Based on the OCC theory [8,21], a combination of hope, fear, and uncertainty generates suspense. Uncertainty is a particularly strong factor in this mix, as it creates a sense of unpredictability and keeps spectators engaged. Empirical studies indicate that the relationship between suspense and probabilistic reasoning can be represented by a bell-shaped curve between suspense and score differences [16,22,30,34]. In such experiments, the subjects usually self-reported the level of suspense they felt. When the score difference decreases, the uncertainty factor is heightened, and so is the suspense. On the other hand, when the score gap increases, the spectators experience hope or fear, but the suspense decreases. However, our research (as discussed below) indicates that the spectators' emotional response to the score differences in tennis matches is likely to be based on accurate predictions on the macro level (set and game scores) but biased predictions on the micro level (point scores).

Psychological studies have established the close correlation between suspense and the spectators' enjoyment of sports games [14,22,30,34]. In other words, the enjoyment would be higher for spectators who viewed a more suspenseful game. Based on Zillman's disposition theory [34], suspense enhances the enjoyment when the spectator's favored player or team wins a close game. Research by Hall [14] indicates that even when the spectator's favored player or team loses, the suspense still enhances the enjoyment by creating a stronger feeling of appreciation.

Therefore, it is reasonable to conclude that a spectator's subjective predictions of the outcome during a sports game generate suspense, which subsequently elevates the entertainment experience. Such assertion is not only supported by scholarly research but also by anecdotal evidence. For example, renowned European football manager Jose Mourinho once said in a press conference: "I think entertaining is emotional until the end, an open result until the end, everybody on their seats until the end, both dug-outs nervous and tense with the unpredictability of the result. For me as a football lover, not as a manager, that's entertaining."

4 Discovering Possible Biases in Probabilistic Reasoning

This part of the research aims to test the following hypothesis.

- H1: Spectators of tennis matches make highly accurate predictions of a player's probability to win a set based on the game scores.

– H2: Spectators of tennis matches make inaccurate predictions of a player's probability to win a game based on the point scores.

The author has developed these hypotheses through personal experience, observations of others, and a study of tennis-related literature.

Predicting match outcomes using the set scores is straightforward because the score scenarios are very limited. For a best-of-three match, the possible set scores are 1–0, 1–1, and 0–1. Because most of the tennis matches are best-of-three matches, analyzing such simple predictions does not offer much insight. Therefore, the focus of this study is on predicting the set winners and game winners.

To test the hypothesis, the spectators' predicted winning probabilities for different tennis score scenarios should be compared with the corresponding empirical (or historical) probabilities for their statistical correlation. The data set from the Match Charting Project [26] is used to calculate the empirical (or historical) probabilities in tennis (see Sect. 4.1). The challenge is to get the spectators' subjective winning probability predictions for different tennis score scenarios.

The ideal approach would be to conduct a controlled experiment where a large number of spectators predict a player's chances of winning under various tennis score scenarios. However, this type of subjective probability prediction data isn't readily available. As an alternative, this study employs a commonly used point-based prediction model [5,20] to simulate the spectators' subjective probability predictions about the outcomes (see Sect. 2.4).

Is it reasonable to use a point-based, theoretical prediction model to simulate the spectators' subjective predictions? Substantial evidence suggests that it is. As discussed in Sect. 3, several empirical studies have shown that spectators' estimation of winning probability during a game is primarily based on the score differences [16,22,30,34]. As discussed in Sect. 2.4, the point-based prediction models are best suited for real-time, in-game outcome predictions. In addition, anecdotal evidence and individual accounts also support the idea that spectators primarily base their assessment of a player's probability of winning or losing on the score differences. For example, when a player leads by a big game score margin (e.g., 5–1), the commentators would describe the player as "in control." If a returning player leads 40–0 in a tennis game, the commentators often say the player has a "good chance of breaking." In the US Open 2023, BBC reporter Jonathan Jurejko [15] wrote that British tennis player Lily Miyazaki "showed composure to fight back from 0–40 down," implying that the player showed mental toughness and resilience when confronted with significant odds of losing the game.

4.1 Calculating Empirical Winning Probabilities

The data set from the Match Charting Project [26] is used to calculate the empirical winning probabilities for different score scenarios. This data set is a spreadsheet that contains detailed, point-by-point data for over 10K professional tennis matches and over 1.5K male and female players. This data set is used to calculate the comprehensive statistics published on the tennisabstract.com website.

This author developed Python programs to clean and analyze the data set. The data was grouped by players and then by specific score scenarios, such as 30–15, 30–30, and 30–40. Winning probabilities for each player under all possible score combinations are calculated. Based on tennis' hierarchical scoring system, the match-winning probabilities were calculated based on the set scores, the set-winning probabilities were calculated based on the game scores, and the game-winning probabilities were calculated based on the point scores. In this study, the empirical winning probability means the winning probability calculated from the historical data from the Match Charting Project.

4.2 Theoretical Prediction Model

This study adopts a point-based, recursive model very close to the ones developed by Barnett, et al. [5] and O'Malley [20]. This type of model is widely accepted and often used in calculating the winning odds for real-time betting.

Suppose $Player1$ and $Player2$ are playing a tennis match. The point scores are $ps1$ and $ps2$, game scores are $gs1$ and $gs2$, and the set scores are $ss1$ and $ss2$. The probability of $Player1$ winning a service point is $SPWP1$, and the probability of $Player1$ winning a return point is $RPWP1$. In tennis, a service game for $Player1$ is a game where $Player1$ serves for each point. Every point in such a service game is a service point for $Player1$. A return game for $Player1$ is when $Player2$ serves for each point. Every point in such a return game is a return point for $Player1$. The probabilities of a professional player winning a service point ($SPWP1$) and return point ($RPWP1$) can be found on the Association of Tennis Professionals (ATP) and Women's Tennis Association (WTA) websites or tennisabstract.com [26]. In this study, we use the statistics from tennisabstract.com.

To simplify the score calculation, the traditional tennis point scores are converted to a simple incremental score system, where 15 is converted to 1, 30 to 2, 40 to 3, and Advantage to 4. For example, 15–40 is converted to 1–3, and Ad-40 is converted to 4–3. Each time a player wins a point, the player's point score increases by 1.

Thus, the probability of $Player1$ winning a service game is given by the recursive equation below.

$$\begin{aligned} SGWP1(ps1, ps2) = (SPWP1 * (SGWP1(ps1+1, ps2)) \\ + ((1 - SPWP1) * (SGWP1(ps1, ps2+1)) \end{aligned} \quad (1)$$

The probability of $Player1$ winning a return game is given by the recursive equation below.

$$\begin{aligned} RGWP1(ps1, ps2) = (RPWP1 * (RGWP1(ps1+1, ps2)) \\ + ((1 - RPWP1) * (RGWP1(ps1, ps2+1)) \end{aligned} \quad (2)$$

The algorithm for calculating $Player1$'s probability to win a tiebreak game $TBGWP1$ considers the rule that $Player1$ and $Player2$ take turns to serve.

The probability of $Player1$ winning a set is given by the recursive equation below.

$$SWP1(gs1, gs2) = (NGWP1(0,0) * (SWP1(gs+1, gs2)) + ((1 - NGP1(0,0)) * SWP1(gs1, gs2+1)) \quad (3)$$

where $NGWP1(0,0)$ is either $SGWP1(0,0)$, $RGWP1(0,0)$, or $TBGWP1$, depending on whether the next game is $Player1$'s service game, return game, or a tiebreak game.

The probability of $Player1$ winning a match is given by the recursive equation below.

$$MWP1(ss1, ss2) = SWP1(0,0) * MWP1(ss1+1, ss2) + (1 - SWP1(0,0)) * MWP2(ss1, ss2+1) \quad (4)$$

The model has some limitations, most notably the assumption that each point is independent and identically distributed (IID), meaning that the outcome of one point does not affect the outcome of the next point, and the player's probability of winning each point is constant. The situation is more complicated in real matches. For example, winning a critical point after a long rally or losing a critical point with an unforced error could affect the mental states of both players for the next point. The audience's response at critical points could also affect the players' mental and emotional states.

4.3 Comparing Theoretical Probabilities and Empirical Probabilities at the Macro Level

Table 3 shows $Player1$'s theoretical and empirical set-winning probabilities for both male and female professional players under different score scenarios, with $Player1$ serving first in the set. The theoretical probabilities are calculated using the models discussed in Sect. 4.2. The empirical probabilities are calculated using the Match Charting Project data as discussed in Sect. 4.1.

The theoretical probabilities for male players are calculated based on the male players' average service point winning percentage of 66% and average return point winning percentage of 37% [26]. The theoretical probabilities for female players are calculated based on the female players' average service point winning percentage of 59% and average return point winning percentage of 44% [26].

Since the theoretical probabilities are not normally distributed, Spearman's rank correlation coefficient is used to analyze the relationship between the theoretical and empirical probabilities. The result shows that the theoretical set-winning probabilities and empirical probabilities are highly correlated. For both male and female players, $Spearman's\, r = 0.99, p = 0.001$ at the 95% confidence level.

Table 1. Linear regression analysis for the set-winning probabilities and score differences (Player1 serving first). $SWP1$ is Player1's set-winning probability. $gs1$ is Player1's game score. $gs2$ is Player2's game score.

Probability	Linear Regression Line	Standard Error	F Statistics	Coeff. of Determination
Theoretical probability (male players)	$SWP1 = 0.50 + 0.13 * (gs1 - gs2)$	0.007	361.0	0.90
Empirical probability (male players)	$SWP1 = 0.45 + 0.14 * (gs1 - gs2)$	0.007	350.6	0.90
Theoretical probability (female players)	$SWP1 = 0.53 + 0.13 * (gs1 - gs2)$	0.006	501.9	0.93
Empirical probability (female players)	$SWP1 = 0.48 + 0.13 * (gs1 - gs2)$	0.006	562.3	0.93

The data analysis also shows a linear relationship between the game score differences and empirical set-winning probabilities (Table 1).

Table 4 shows $Player1$'s theoretical and empirical set-winning probabilities for both male and female professional players under different score scenarios, with $Player1$ returning first in the set. Spearman's correlation coefficient also indicates a strong correlation between the theoretical and empirical probabilities. For both male and female players, $Spearman's\ r = 0.99, p = 0.001$ at the 95% confidence level. Again, the data analysis also shows a linear relationship between the score differences and probabilities (Table 2).

Table 2. Linear regression analysis for the set-winning probabilities and score differences (Player1 returning first). $SWP1$ is Player1's set-winning probability. $gs1$ is Player1's game score. $gs2$ is Player2's game score.

Probability	Linear Regression Line	Standard Error	F Statistics	Coeff. of Determination
Theoretical probability (male players)	$SWP1 = 0.59 + 0.13 * (gs1 - gs2)$	0.007	342.7	0.90
Empirical probability (male players)	$SWP1 = 0.55 + 0.14 * (gs1 - gs2)$	0.007	350.6	0.90
Theoretical probability (female players)	$SWP1 = 0.58 + 0.13 * (gs1 - gs2)$	0.006	500.0	0.93
Empirical probability (female players)	$SWP1 = 0.52 + 0.13 * (gs1 - gs2)$	0.006	563.0	0.94

The macro-level analysis has shown a straightforward linear relationship between the set outcome and game score differences. **This means that a spectator in tennis can make highly accurate predictions about the outcome of a set based solely on the game score differences.**

Table 3. This table shows $Player1$'s theoretical and empirical set-winning probabilities for both male and female professional players under different game score scenarios, with $Player1$ serving first in the set. The theoretical probabilities for male players are calculated based on the male players' average service point won percentage of 66% and average return point won percentage of 37% [26]. The theoretical probabilities for female players are calculated based on the female players' average service point won percentage of 59% and average return point won percentage of 44% [26].

Player1 game score	Player2 game score	Theoretical set-winning probability (male)	Empirical set-winning probability (male)	Theoretical set-winning probability (female)	Empirical set-winning probability (female)
0	0	0.60	0.48	0.60	0.50
0	1	0.33	0.20	0.42	0.28
0	2	0.26	0.15	0.32	0.19
0	3	0.08	0.03	0.15	0.07
0	4	0.04	0.02	0.08	0.03
0	5	0.00	0.00	0.01	0.00
1	0	0.65	0.56	0.68	0.61
1	1	0.59	0.48	0.60	0.51
1	2	0.29	0.18	0.39	0.28
1	3	0.22	0.12	0.28	0.19
1	4	0.05	0.02	0.10	0.06
1	5	0.02	0.01	0.04	0.02
2	0	0.86	0.84	0.83	0.80
2	1	0.65	0.56	0.68	0.62
2	2	0.58	0.49	0.59	0.50
2	3	0.25	0.16	0.35	0.26
2	4	0.17	0.09	0.22	0.15
2	5	0.02	0.01	0.05	0.04
3	0	0.90	0.90	0.89	0.88
3	1	0.88	0.86	0.85	0.82
3	2	0.64	0.57	0.68	0.63
3	3	0.58	0.49	0.58	0.51
3	4	0.19	0.13	0.29	0.22
3	5	0.10	0.06	0.14	0.11
4	0	0.98	0.99	0.97	0.97
4	1	0.93	0.92	0.91	0.89
4	2	0.91	0.88	0.87	0.84
4	3	0.65	0.58	0.69	0.64
4	4	0.57	0.50	0.57	0.50
4	5	0.12	0.08	0.20	0.19
5	0	0.99	1.00	0.99	0.99
5	1	0.99	1.00	0.99	0.98
5	2	0.96	0.95	0.95	0.94
5	3	0.95	0.93	0.92	0.90
5	4	0.65	0.59	0.72	0.67
5	5	0.56	0.50	0.56	0.52
5	6	0.11	0.09	0.19	0.17
6	5	0.64	0.60	0.71	0.70
6	6	0.55	0.51	0.55	0.54

Table 4. This table shows *Player*1's theoretical and empirical set-winning probabilities for both male and female professional players under different game score scenarios, with *Player*1 returning first in the set. The theoretical probabilities for male players are calculated based on the male players' average service point won percentage of 66% and average return point won percentage of 37% [26]. The theoretical probabilities for female players are calculated based on the female players' average service point won percentage of 59% and average return point won percentage of 44% [26].

Player1 game score	Player2 game score	Theoretical set-winning probability (male)	Empirical set-winning probability (male)	Theoretical set-winning probability (female)	Empirical set-winning probability (female)
0	0	0.60	0.52	0.60	0.50
0	1	0.54	0.44	0.52	0.39
0	2	0.26	0.16	0.32	0.20
0	3	0.19	0.10	0.22	0.12
0	4	0.04	0.01	0.08	0.03
0	5	0.01	0.00	0.03	0.01
1	0	0.82	0.80	0.76	0.72
1	1	0.59	0.52	0.60	0.49
1	2	0.53	0.44	0.50	0.38
1	3	0.22	0.14	0.28	0.18
1	4	0.14	0.08	0.17	0.11
1	5	0.02	0.00	0.04	0.02
2	0	0.86	0.85	0.83	0.81
2	1	0.84	0.82	0.77	0.72
2	2	0.58	0.51	0.59	0.50
2	3	0.51	0.43	0.48	0.37
2	4	0.17	0.12	0.22	0.16
2	5	0.08	0.05	0.10	0.06
3	0	0.97	0.97	0.93	0.93
3	1	0.88	0.88	0.85	0.81
3	2	0.86	0.84	0.79	0.74
3	3	0.58	0.51	0.58	0.49
3	4	0.50	0.42	0.45	0.36
3	5	0.10	0.07	0.14	0.10
4	0	0.98	0.98	0.97	0.97
4	1	0.98	0.98	0.95	0.94
4	2	0.91	0.91	0.87	0.85
4	3	0.89	0.87	0.82	0.78
4	4	0.57	0.50	0.57	0.50
4	5	0.47	0.41	0.40	0.33
5	0	1.00	1.00	1.00	1.00
5	1	0.99	0.99	0.99	0.98
5	2	0.99	0.99	0.98	0.96
5	3	0.95	0.94	0.92	0.89
5	4	0.93	0.92	0.87	0.81
5	5	0.56	0.50	0.56	0.48
5	6	0.47	0.40	0.39	0.30
6	5	0.93	0.91	0.87	0.83
6	6	0.55	0.49	0.55	0.46

4.4 Comparing Theoretical Probabilities and Empirical Probabilities at the Micro Level

Table 5 shows *Player*1's theoretical and empirical game-winning probabilities for both male and female professional players under different point score scenarios, with *Player*1 serving in the game. The theoretical probabilities are calculated using the models discussed in Sect. 4.2. The empirical probabilities are calculated using the Match Charting Project data as discussed in Sect. 4.1.

The theoretical probabilities for male players are calculated based on the male players' average service point won percentage of 66% [26]. The theoretical probabilities for female players are calculated based on the female players' average service point won percentage of 59% [26].

Table 5. This table shows *Player*1's theoretical and empirical game-winning probabilities for both male and female professional players under different point score scenarios, with *Player*1 serving in the game. The theoretical probabilities for male players are calculated based on the male players' average service point won percentage of 66% [26]. The theoretical probabilities for female players are calculated based on the female players' average service point won percentage of 59% [26].

Player1 point score	Player2 point score	Theoretical game-winning probability (male)	Empirical game-winning probability (male)	Theoretical game-winning probability (female)	Empirical game-winning probability (female)
0	0	0.85	0.80	0.71	0.66
0	15	0.71	0.79	0.55	0.66
0	30	0.50	0.82	0.35	0.67
0	40	0.23	0.86	0.14	0.70
15	0	0.92	0.80	0.83	0.66
15	15	0.82	0.76	0.69	0.65
15	30	0.64	0.76	0.49	0.64
15	40	0.34	0.79	0.23	0.65
30	0	0.96	0.82	0.92	0.67
30	15	0.91	0.77	0.83	0.65
30	30	0.79	0.74	0.67	0.63
30	40	0.52	0.73	0.40	0.62
40	0	0.99	0.86	0.98	0.71
40	15	0.98	0.79	0.95	0.66
40	30	0.93	0.73	0.87	0.63
40	40	0.79	0.72	0.67	0.62
Ad	40	0.93	0.72	0.87	0.61
40	Ad	0.52	0.72	0.40	0.62
Average		0.74	0.78	0.64	0.65

No statistically significant correlation is found between the theoretical probabilities and empirical probabilities. For male players, $Spearman's\, r = 0.07, p = 0.4$. For female players, $Spearman's\, r = 0.13, p = 0.32$.

No statistically significant correlation is found between the score differences and empirical probabilities. Linear regression can only explain 44% of the data for male players and 42% of the data for female players.

Table 6 shows $Player1$'s theoretical and empirical game-winning probabilities for both male and female professional players under different point score scenarios, with $Player1$ returning in the game.

No statistically significant correlation is found between the theoretical probabilities and empirical probabilities. For male players, $Spearman's\, r = 0.06, p = 0.41$. For female players, $Spearman's\, r = 0.12, p = 0.32$. Again, no statistically significant correlation is found between the score differences and empirical or theoretical probabilities.

Table 6. This table shows $Player1$'s theoretical and empirical game-winning probabilities for both male and female professional players under different point score scenarios, with $Player1$ returning in the game. The theoretical probabilities for male players are calculated based on the male players' average return point won percentage of 37% [26]. The theoretical probabilities for female players are calculated based on the female players' average return point won percentage of 44% [26].

Player1 point score	Player2 point score	Theoretical game-winning probability (male players)	Empirical game-winning probability (male players)	Theoretical game-winning probability (female players)	Empirical game-winning probability (female players)
0	0	0.21	0.20	0.35	0.34
0	15	0.12	0.20	0.22	0.34
0	30	0.05	0.18	0.11	0.33
0	40	0.01	0.14	0.03	0.29
15	0	0.35	0.21	0.52	0.34
15	15	0.23	0.24	0.37	0.35
15	30	0.12	0.23	0.21	0.35
15	40	0.04	0.21	0.07	0.34
30	0	0.57	0.18	0.71	0.33
30	15	0.42	0.24	0.57	0.36
30	30	0.26	0.26	0.38	0.37
30	40	0.09	0.27	0.17	0.37
40	0	0.81	0.14	0.89	0.30
40	15	0.70	0.21	0.81	0.35
40	30	0.53	0.27	0.65	0.38
40	40	0.26	0.28	0.38	0.38
Ad	40	0.53	0.28	0.65	0.38
40	Ad	0.09	0.28	0.17	0.39
Average		0.30	0.22	0.40	0.35

Unlike the macro-level analysis, the micro-level analysis shows significant discrepancies between theoretical and empirical probabilities for different score scenarios. This study is unable to find a statistically significant correlation between the theoretical and empirical probabilities or statistically significant correlations between score differences and empirical game-winning probabilities.

Somewhat surprisingly, the empirical probabilities of a player winning a game are consistent across different score scenarios. For example, a serving male player has, on average, an 87% chance of winning the game even when he is 0–40 down. A female player has a 70% chance of winning the game when she is 0–40 down. In contrast, the theoretical model predicts a 23% winning chance for male and 14% chance for female players if the score is 0–40 (see Table 5).

Similarly, a returning male player has, on average, only 14% chance of winning the game even if he is 40–0 up. A returning female player has only a 30% chance of winning the game if she is 40–0 up. In contrast, the predictions from the theoretical model are 80% chance for male and 89% chance for female players if the score is 40–0 (see Table 6).

This means that if a typical tennis spectator makes similar micro-level predictions as the theoretical model, the spectator will make systematic errors. In other words, there are biases in the spectator's micro-level probabilistic reasoning. The question is whether the theoretical model is consistent with the spectators' beliefs. There is plenty of evidence to support this. First, the micro-level predictions made by the theoretical model make intuitive sense (see Table 5 and Table 6). The theoretical winning probability goes up and down as the score difference goes up and down. This pattern is consistent with findings from the previous empirical studies [22,30,34] and anecdotal evidence. The BBC reporter is unlikely to use the word "composure" to describe Lily Miyazaki fighting back from 0–40 down to win the game if the reporter believes Miyazaki has a 70% winning chance at 0–40. It's more likely that the reporter believes Miyazaki only has a 14% chance, as the theoretical model predicts.

Second, as shown in Sect. 4.3, tennis spectators can use the score differences to accurately predict the set outcome at the macro level. It is reasonable to assume that the spectators would subconsciously use the same method to predict the game outcome at the micro level. Besides, very few spectators know the game-level empirical probabilities discussed in Sect. 4.4. Such data is not publicly available. Even tennisabstract.com, which publishes comprehensive and up-to-date statistics about professional tennis players, does not provide winning probabilities for different score scenarios at the micro-level. As behavioral economics theories suggest, when people do not know the true statistics, they are likely to use mental shortcuts (heuristics) to make predictions.

Third, the theoretical model [5,20] has been around for a long time, and most people have accepted it as statistically reasonable [27]. Many people use the model to make predictions, which may further influence the tennis spectators' beliefs.

This study has shown that the theoretical prediction model is very accurate at the macro level but seriously flawed at the micro level. It is very likely that tennis spectators use the same intuitive model to make predictions at both the macro and micro levels. A possible cause for this phenomenon is discussed in the next section.

5 Possible Causes of the Biases

Herbert Simon [29] proposed that humans have cognitive limitations and must operate within those bounds, leading people to seek "good enough" rather than optimal solutions. When faced with complex or ambiguous situations, people rely on heuristics or shortcuts to make decisions. A possible cause of the biases in tennis in micro-level probabilistic reasoning is its relatively complex scoring system (see Sect. 2.3). The three hierarchical layers of set scores, game scores, and point scores, plus the tiebreak scoring rules, make it harder to retrieve historical information from memory and compare results from the same score scenarios. As a result, tennis spectators are likely to resort to simple heuristics for predicting the outcome.

A recent theory proposed by Bordalo, et al. [7] may explain the biases discussed in this paper. Bordalo, et al. argue that probabilistic reasoning is influenced by the structural similarity between the hypothesis and the information stored in the memory and interference in memory retrieval. If tennis spectators try to predict a player's winning probability at 15–40, they need to recall many cases of 15–40, who scored 15, who was serving, and who eventually won the game. It is difficult to retrieve and classify such information from memory. Instead, it is easier to recall a structurally similar question on the macro level: Who won the set when the game score was 2–4? There are far fewer cases of 2–4, and more importantly, as discussed in Sect. 4.3, their intuitive predictions (based on the score difference) are quite accurate on the macro level. As a result, the spectator is likely to apply the simple and intuitive heuristic to make predictions at both the macro and micro levels. This is likely a type of availability bias.

6 Biases in Probabilistic Reasoning and the Entertainment Experience

Biases in probabilistic reasoning are generally seen as undesirable human errors. But from a tennis spectator's perspective, biased micro-level probabilistic reasoning is actually better for the entertainment experience than the accurate prediction. First, in Table 5 and Table 6, the theoretical probabilities are inaccurate, but they create emotional roller-coasters for the spectators as the probabilities go up and down for different score scenarios. In contrast, the empirical probabilities remain more or less consistent for different scores, arousing no significant emotional change.

Second, discrepancies between theoretical and empirical probabilities create surprises. In the context of sports, surprise can be derived from win probability changes [3]. If a tennis spectator makes systematic errors in micro-level predictions, the spectator is more likely to experience surprises. For instance, a spectator may be surprised when a player wins a game where the perceived winning probability is low, or the reverse. As in films and literature, surprises enhance the entertainment experience and can significantly impact the spectators. In the US Open 2023, Lily Miyazaki fighting back to win the game from 0–40 [15] was objectively not a surprise because she had a 70% empirical (or historical) probability of winning that game at 0–40. However, the BBC reporter Jonathan Jurejko probably thought it was a surprise and highlighted it in the report [15] about Miyazaki's performance. This minor surprise created a strong impression on the reporter.

7 Conclusion and Future Work

This study explores possible biases in probabilistic reasoning for sports and their connections to the sports entertainment experience. It reveals that the well-accepted point-based prediction model for tennis is highly accurate in making predictions at the macro level but inaccurate in making predictions at the micro level. Since evidence suggests that tennis spectators' subjective probability prediction is aligned with the theoretical model, this study reveals likely biases in tennis spectators' micro-level probabilistic reasoning. An explanation for such biases has been offered using a recent behavioral economic theory. Furthermore, this author argues that biases in micro-level probabilistic reasoning are actually beneficial for the sports entertainment experience because they keep the spectators emotionally engaged and create surprises that enhance the enjoyment of the games.

This is the first step toward a comprehensive study of biases in micro-level probabilistic reasoning for tennis. The author plans to carry out user studies to collect subjective probability predictions. The comparison between different theoretical prediction models and empirical probabilities will be explored. It will also be useful to test if similar biases exist in other sports with hierarchical scoring systems, such as volleyball, table tennis, etc.

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