Proceedings of CONF-CIAP 2026 Symposium: Applied Mathematics and Statistics
DOI: 10.54254/2753-8818/2026.CH31774

The Application of Game Theory in the Analysis of "Liar's Bar"

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Abstract. This paper focuses on the game "Liar's Bar", combining game theory and psychological factors to conduct an in-depth analysis of its strategy selection and winning mechanisms. The game's rules integrate elements of "Doubt" and roulette, featuring both fun and strategy; however, existing research lacks in-depth discussions on its strategies. To fill this gap, the study constructs a simplified one-on-one model (2 players, 2 cards per player, a total of 3 "true cards" (white cards) and 5 "false cards" (black cards), with 1 card played per round). Through theoretical analysis, Python/Matlab simulations, and literature review, the study classifies player strategies and derives a payoff matrix.This study not only provides strategic guidance for "Liar's Bar" players but also enriches the application of game theory in the field of games, offering a new perspective for strategy analysis in uncertain scenarios. Meanwhile, it points out the limitations of the model in terms of strategy complexity, random factors, providing a basic reference for subsequent related research.

Keywords: Liar's Bar; Game Theory; Nash Equilibrium; Mixed Strategy; Probability Simulation; Conservative Strategy

1. Introduction

In today's society, games, as a common form of entertainment, are rich in strategies and psychological phenomena. Game theory, which studies interactive decision making, provides a powerful tool for understanding strategic choices in games. This article will focus on a recently popular game, "Liar's Bar", whose game rules are similar to a combination of Doubt and roulette, featuring high levels of fun and strategy. However, during the literature review, it is found that there is currently few in-depth research on the strategies in this type of game. This prompts an exploration of the different strategies in "Liar's Bar". This research fills that gap by providing a rigorous analysis of the game's optimal strategies and player behavior.

Since there are too many variations in this game, constructing a smaller model is reasonable. So, the question that this study intends to explore is which strategy is more likely to lead to victory in a one-on-one scenario. And carry out a more extensive discussion based on this.

This research will classify the strategies in the "Liar's Bar" game through theoretical analysis[1], computer simulation[2], and a review of the literature. By deriving the players' payoff matrix and

DOI: 10.54254/2753-8818/2026.CH31774

analyzing the risks and benefits of different strategies, this paper aims to find the strategy with the highest winning rate in different situations.

The outcomes of this study not only offer strategic guidance for ”Liar’s bar” game players, but also enrich the application research of game theory in the field of games, providing new research perspectives and methods for scholars in related fields. Such as Texas Hold’em poker or negotiations, whether you should believe the opponents’ claim or not.

This article will be divided into six sections. The first section is the introduction, which presents the research background, raises the research questions, outlines the research methods, and the practical significance. The second section is the literature review, which elaborates on the relevant background literature and research methods on game strategy optimization. The third section is the methodology, which explains how this model was set up. The fourth section is strategy, and the following results, which explains the strategies’ mathematical models and its results. All the results have been proved to be correct by python simulation. The fifth section is the conclusion, which summarizes the conclusions of the article. The sixth section is discussion, which talks about some extensions and limitations of our research and proposes practical applications.

2. Literature review

Although there is little research on the ”Liar’s bar” game, methods used in other literature on game theory can be referred to the research.

Firstly, previous studies on the Nash equilibrium help analyze the payoff matrix. Research by Slim Belhaiza(2014) is particularly useful as it shows that a perfect Nash equilibrium is an optimal response to arbitrary combination of other player’s strategy. The computational experiments conducted are perfect examples of similar approaches in the study [2]. Dionysius Glycopantis(2014) discussed the relationship between the formulation of non-anonymous Nash-Schmeidler game to Mas-Colell anonymous game, demonstrating the fact that a non-anonymous game cannot always be formulated in an anonymous form. Moreover, the explanation of the nonexistence of NE in a particular game is vital to explain the potential similar scenario in our simulation [3].

After that, information of more directedly related topics is retrieved. In The research ”Bluff and Learn: Comparing CFR and NFSP in Liar Bar”, two methods are employed: CFR (Counterfactual Regret Minimization) approximates the Nash equilibrium by performing regret matching on a compact information set; NFSP (Neural Fictitious Self-Play) alternates the update of Double-DQN values with supervised learning of the average policy.They present the first reinforcement-learning agents for Liar Bar, showing that tabular CFR excels in small, near-zero-sum games but cannot accommodate richer multi-agent dynamics. In contrast, NFSP’s deep self-play framework not only outperforms CFR in complex scenarios but also remains nearly unexploitable. Crucially, the integration of Double-DQN updates and per-round reward design accelerates and stabilizes learning. Their work provides feasibility in AI research in multiplayer bluffing games and other high uncertainty, imperfect information domains[4]. In the research ’A method of computing the probability of winning for Texas Hold’em poker’, linear regression is introduced to calculate the approximate effective hand strength based on an algorithm for the classification of poker hand. A hand evaluation is first performed, with hand strength calculated from hand rank. Following this, a model based on linear regression is established whose evaluation speed largely outperforms Bit Manual’s and neural network’s. The algorithm in this paper provides a good example in mathematical modeling and computer programming considering imperfect information games. It reveals potential innovative and efficient methods to quantify the initial hand strength of players which are applicable in this research. However, player strategies are not identified in this paper;thus, it is left to this research to determine possible strategies that dominate

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a player's decision mode based on physiological factors, which enables further analysis in winning rates[5]. Another research on Texas Hold'em Poker designs a data structure by training a Support Vector Machine classifier and do 5-fold cross-validation to estimate winning probabilities and verify the precision. Furthermore, the paper derives three agents with different strategies. A Simple Random Strategy indicates random choices ignoring hand strength and strategies of the opponent, whereas a Rule-based Agent utilizes the hand rank of the agent's card hand to make decision, including psychological confidence as a variable. This is a factor that influences our simulation as well[6]. Although the machine learning methods in these researches are not necessarily the focus of this paper, they do suggest important factors that need to be considered and discussed in bluffing games with imperfect information and enable this research to make comparisons between results acquired from distinct approaches on similar subjects.

Psychological literature is also consulted to classify different game strategies. In the research "Decision Making Styles and Adaptive Algorithms for Human Action", an evolutionary theory of rationality is adapted to simulate human behavioral patterns. The different decision-making styles concluded from the research conducted by Scott and Bruce (1995) present a method to determine different strategies. A rational style describes players who tend to gather all possible information before making their preferred decisions, which corresponds to the conservative strategy in "Liar's Bar" in terms of cautiousness. In contrast, players with an intuitive decision-making style tend to base their decisions more on emotions and intuition, leading to random movements, while the spontaneous style implies aggressive decisions[7]. Further evaluation includes the application of the General Decision Making Style Inventory(GDMS) to simulate individual behavioral patterns and another approach proposed by Schwartz and his group(2002) that includes the 'optimizer' and 'satisficer', distinguishing between players who tend to seek the best option and those whose decision contain a fair level of satisfaction[8]. These models provide theoretical support in the classification of strategies in terms of psychological factors.

Finally, cross-subject application of game theory is discovered. In the research "The Nancy Pelosi Game: to Reveal or Not to Reveal", game theory is applied to analyze whether Pelosi should reveal the fact that she possessed secret information that would stop GOP candidate Newt Gingrich from competing for presidency against Barack Obama. The model assumes two players: Nancy Pelosi who decides between revealing or concealing the secret information and GOP voters who either nominate Newt Gingrich or Mitt Romney. Based on the strategies and payoffs, a payoff matrix is formed. Results from matrix analysis show that although Pelosi should publicize that she has the secrets, she should not reveal the exact information, which corresponds to the situation that GOP voters would have turned to Romney who was a stronger candidate and the actual strategy Pelosi had used, suggesting that she had made the optimal decision. Although the methodology applied in this essay is fairly basic and simple, it demonstrates the possibilities of game theory as a mathematical tool to describe real-world phenomena[9]. This gives inspiration to extend the methodology to a broader field, such as international trade which also contains similar features like bluffing.

3. Methodology

3.1. Introduction

In this part, a simplified version of one-on-one game will be analysed, since in real games, player can play 1-3 cards from 5 cards, and the proportion of genuine cards is 8/20. After viewing many game live streams, we find in one-to-one scenario, many people play 2 or 3 cards at a time. So it's reasonable to assume that players will play cards twice in this simplified version. At the same time,

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we also assume that there are 3 true cards(white cards), 5 fake cards(black cards), which proportion is close to the original game.

3.2. Game rule

The discussion in this paper will focus on the basic rules of the game.

Liar's Bar is a multiplayer card game designed for 2 to 4 players, where the objective is to be the last player remaining. Each round begins with the revelation of a table card, determining the "True" card type for that round, while all other cards are considered "liars." Players take turns playing 1 to 3 cards face down, claiming them to be of the true type, or challenging the previous player's claim by calling "LIAR" If a challenge occurs, the accused player's cards are revealed: if any are liars, the accused faces a Russian Roulette penalty; otherwise, the challenger does. [1]

Moreover, if a player is the only player who has cards in a round, then he must challenge the previous player's claim, this mechanism prevents the situation that every player finishes playing their cards without any challenge.

3.3. Game setup

The analysis of such a game presents significant challenges, necessitating the simplification of the setup for effective discussion.

Observe tht Once one card type is declared, the total cards split into 2 group: The declared cards and its complement. Let "W" "White" cards be declared cards, and "B" "Black" be the complement. Let the hand of each player be a non-ordered list of W and B. textbfe.g. $[W, W, B, B, B]$ mean a Player's hand has 2 "white" cards and 3 "black" cards.

Considering the simplest setup,

1. 2 player
2. given 2 card to each player
3. each player could only throw 1 card each round
4. 3 white cards, 5 black cards

In this configuration, the game strategy could be analyzed using a two-dimensional probability field.

3.4. Probability in cases

Let w, b be the total number of true cards and false cards. In this setup, let $P(x, y)$ be a function of probability, where x, y are the true cards that Player 1 and Player 2 have,

$$P(x, y) : \{0, 1, 2\}^2 \to [0, 1]$$

If $x + y > w$ or $4 - x - y > b$, then,

$$P(x, y) = \frac{\binom{w}{x}\binom{b}{2-x}\binom{w-x}{y}\binom{b-(2-x)}{2-y}}{\binom{n}{2}\binom{n-2}{2}}$$

In this case, $w = 3$ and $b = 5$. The full probability table is as below (Table 1).

4. Strategy

4.1. Strategy: Player 1

The strategy for Player 1 is trivial when Player 1 has $[W, W]$ and $[B, B]$.

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Table 1: Probability of all cases

Event	Probability
$P(0,0)$	0.0714
$P(0,1)$	0.214
$P(0,2)$	0.0714
$P(1,0)$	0.214
$P(1,1)$	0.286
$P(1,2)$	0.0357
$P(2,0)$	0.0714
$P(2,1)$	0.0357
$P(2,2)$	0

- $[W, W]$: Player 1 throws without calling.
- $[B, B]$: Player 1 throws B, then call in next round.

The strategy for Player 1 when has $[W, B]$ is as Table 2.

Table 2: Strategies of Player 1

Rounds	Strategy A	Strategy B
1	W	B
2	call	not call
3		W

Let probability of Player 1 chooses Strategy A over B be p. This is that Player 1 has probability of p using Strategy A, and $1 - p$ using Strategy B.

4.2. Strategy: Player 2

For Player 2, when Player 2 has $[W, B]$ or $[W, W]$, the strategy is identical, since Player 2 will not throw all the cards, then 2 strategy for Player 2 in this condition is as table 3,

Table 3: Strategies of Player 2

Rounds	Strategy I	Strategy II
1	call	not call
2		W
3		call

When Player 2 has $[B, B]$, using simulation, Player 2 has a better winning chance when calling on the first round. There is other strategy, but for simplification reason, it will not be discussed in this paper. Let probability of Player 2 chooses Strategy I over II be q. This is that Player 2 has probability of q using Strategy I, and $1 - q$ using Strategy II.

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In this configuration, p and q serve as two independent variables, thereby generating a probability field. Consequently, game theory can be effectively applied to this scenario.

Using such construction, obverse that Player 1 wins when has $[W, W]$, and loses when has $[B, B]$. In the case of Player 1 has $[W, B]$ and Player 2 has $[W, W]$ or $[W, B]$,

- Strategy A wins over Strategy I
- Strategy I wins over Strategy B
- Strategy B wins over Strategy II
- Strategy II wins over Strategy A

When Player 1 has $[B, B]$, Strategy I wins and Strategy II loses.

There are various strategies that can be employed in this game. If a Player exclusively uses one strategy, their winning rate becomes quite extreme. However, mixing strategies is a more effective approach to playing this game.

Construct Expected Value of the winning probability of Player 1 (Table 4),

Table 4: Analysis of all the cases

Player 1's hand	Player 2's hand	Win% Player 1	Win% Player 2
$[W, W]$	$[W, B]$	1	0
$[W, W]$	$[B, B]$	1	0
$[W, B]$	$[W, W]$	$pq + (1-p)(1-q)$	$q(1-p) + p(1-q)$
$[W, B]$	$[W, B]$	$pq + (1-p)(1-q)$	$q(1-p) + p(1-q)$
$[W, B]$	$[B, B]$	p	$1-p$
$[B, B]$	$[W, W]$	0	1
$[B, B]$	$[W, B]$	0	1
$[B, B]$	$[B, B]$	0	1

Then putting all the cases together, let E_1 be a function of probability. and let $E_1(p, q)$ be the expected value of Player 1 wins under the condition of $p = p, q = q$. Similarly, let E_2 be the expected value of Player 2 wins, and $E_2 = 1 - E_1$.

$$E_1, E_2 : [0, 1]^2 \to [0, 1]$$

$$E_1(p, q) = [\sum_{i=0}^{2} P(2, i)] + [\sum_{i=1}^{2} P(1, i) \times (2pq + 1 - p - q)] + [P(1, 0) \times p] \tag{1}$$

In particular, under the setup,

$$E_1(p, q) = \frac{3}{28} + \frac{9}{27}(2pq - p - q) + \frac{3}{14}p$$

Observe that E are bilinear functions. Using Python, visualization is done using a 101 $\times$101 grid with increasing simulation amount (Figure 1-3). These are functions $E(p, q)$ with p on the vertical axis and q on the horizontal axis.

DOI: 10.54254/2753-8818/2026.CH31774

Figure 1: 1 game

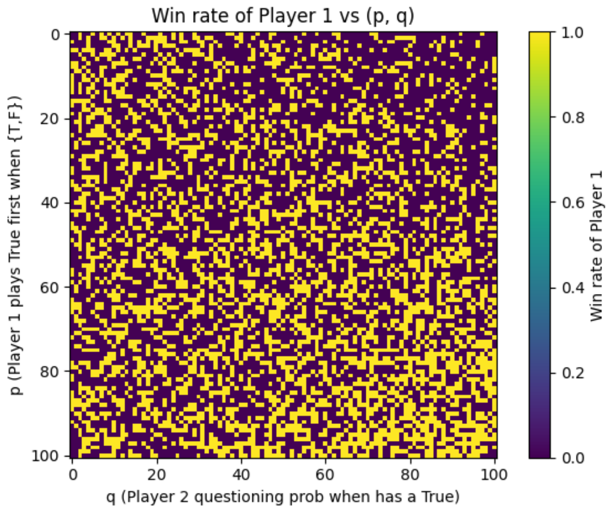


Figure 2: 100 games

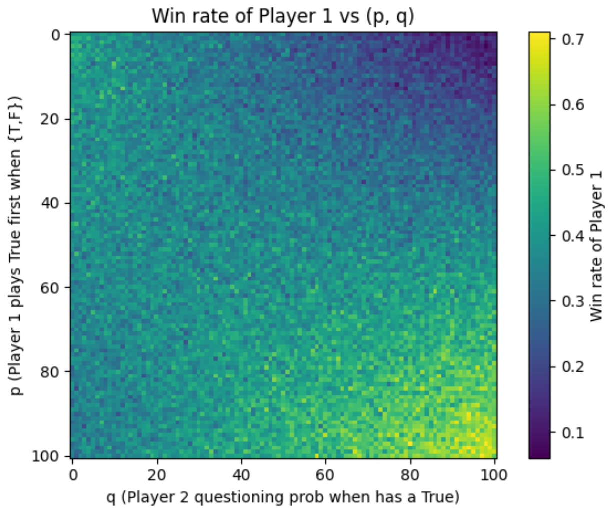
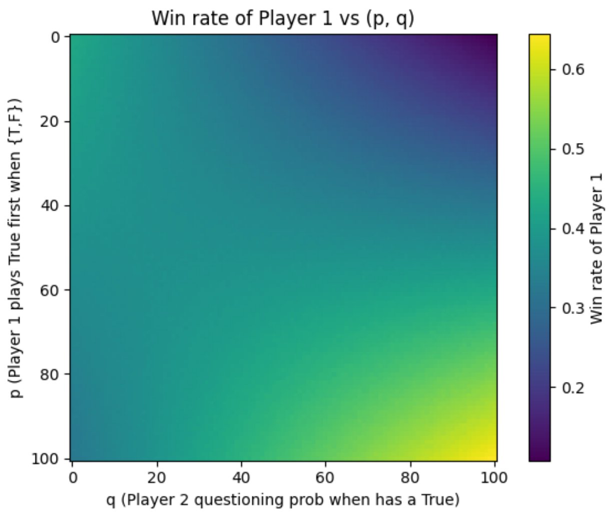


Figure 3: 100,000 games



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4.3. Simulation result and interpretation

As depicted in the diagrams, the Law of Large Numbers emerges. Due to the property of bilinearity, extreme values are observed at the corners of the diagram, indicating that this game is neither symmetric nor fair.

For each Player, the "average" shows the standard winning rate, which is the average value on each vertical and horizontal line. Consider the average function Avg_1 for player 1 and Avg_2 for player 2.

$$\mathrm{Avg}_1, \mathrm{Avg}_2 : [0, 1] \to [0, 1]$$

$$\mathrm{Avg}_1(p) = \int_0^1 E_1(p, y)w(y)\underset{\cdot}{\mathrm{y}},\ \mathrm{Avg}_2(q) = \int_0^1 E_1(x, q)h(x)\underset{\cdot}{\mathrm{x}} \tag{2}$$

where w, h are weight function, $\int_w = \int_h = 1$. If assume other player switch the strategy uniformly, then $w = h = 1$ in $[0, 1]$. For simplicity, assume the distribution is uniform, then the calculation of the total average is,

$$\mathrm{Avg}_i = \int_{[0,1]\times[0,1]} E_i(x, y) \tag{3}$$

Additionally, the construction of variants is also of significance. With a larger variant, the selection of p or q becomes a more "risky" decision compared to a smaller variant. With variants small, the winning rate in each round is closer to overall average.

$$V : [0, 1] \to$$

$$V_1(p) = \int_I \left|E_1(p, x) - \mathrm{Avg}_1(p)\right|^2 \underset{\cdot}{\mathrm{x}},\ V_2(q) = \int_I \left|E_2(x, q) - \mathrm{Avg}_2(q)\right|^2 \underset{\cdot}{\mathrm{x}} \tag{4}$$

where, V_1, V_2 are the winning variant for each p, q.

Using simulation, it finds the result of maximal of Avg, the minimal of V , and the overall average. It also find the maximal of Avg + $\sqrt{V}$. Taking the partition of 1/100, 000 on each p, q, the result is done using Matlab.

Table 5: Computation Simulation

=== Player 1 (p) ===	
p^* (max avg)	$= 1$, avg $= 0.482$
p^* (min var)	$= 0.5$, avg $= 0.375$, var $= 5.87 \times 10^{-33}$
p^* (max avg $+\sqrt{\text{var}}$)	$= 1$, score $= 0.575$
=== Player 2 (q) ===	
q^* (max avg)	$= 0.976$, avg $= 0.625$
q^* (min var)	$= 0.167$, avg $= 0.625$, var $= 3.83 \times 10^{-13}$
q^* (max avg $+\sqrt{\text{var}}$)	$= 1$, score $= 0.78$
=== Overall Means ===	
Player 1 overall mean	$= 0.375$
Player 2 overall mean	$= 0.625$

4.4. Result

Observing the grid as a whole:

1. No pure Nash Equilibrium, but if considering the payoff be the average, the Nash Equilibrium is approximately at $(1, 1)$
2. Highest values are at the corners
3. Player 2 has advantage after large amount of games
4. For Player 1, playing consistently results in a low winning rate
5. The better chance for Player 1 is to gamble on the extreme value, otherwise Player 1 has smaller chances
6. The better chance for Player 2 is to play consistently, with a greater 0.6 winning chance, after many game, Player 2 wins more

5. Discussion

5.1. Further discussion

A strategy is called Switch: a switch move is to take p or q to the other extrema from an extrema. This is trying to simulate some psychology factors.

Consider the Switch strategy:

1. if lose a round, switch
2. if win 3 in a row, switch

After the simulation:

1. Switch vs Switch: Player 1 winning rate: $\approx 38\%$
2. $p(= 0.5)$ vs Switch: Player 1 winning rate: $\approx 37\%$
3. Switch vs $q(= 0.5)$: Player 1 winning rate: $\approx 38\%$

This is not an interesting result, since all Player 1 winning rates are less than 45%. If putting a weighted function w on the expect(average) value, $\int_I w = 1$, **e.g.** If Player 2 tended to have a weight more strategy, the function would be:

$$\int_I E_1(p, x)w(x)\,\mathrm{d}x$$

Then the game theory part would change by function w.

5.2. Roulette part

By adding the roulette part of the research above, it is found that for each situation, the win rate has been balanced to fifty-fifty. For example, when p=0.5, q=0.5, win rate of Player 1 without roulette is 37.5%, while there is roulette, it is 46.1%. We tested several combinations of (p q1), the result is the same (balance the win rate to fifty-fifty).

5.3. 4 players' simulation

An author on "bilibili" designed various strategies for the AI players in a 4-player real-mode "Liar's Bar" game, simulated 100,000 times, and counted their rankings, death counts, and shooting situations. [10]

Strategies:

DOI: 10.54254/2753-8818/2026.CH31774

1. Randomly play cards and randomly challenge
2. First play real cards with random counts; challenge if no real cards left
3. First play real cards, one card each time; challenge if no real cards left
4. Try to play all fake cards first, then play real cards
5. Try to play all real cards first, then play fake cards
6. Play one card each time, alternating between real and fake cards
7. Must challenge if the previous player played 3 cards; otherwise follow Strategy 4
8. Must challenge if the previous player played 3 cards; otherwise follow Strategy 5
9. Play real cards as much as possible; must challenge if no real cards left
10. Must challenge in the first round; follow Strategy 9 afterwards
11. Only challenge
12. First play one fake card, then play real cards as soon as possible

The final simulation results show that Strategy 8 has a winning rate (first place) far ahead, followed by 5, 3, 7, 2, 9, 10, 4, 11, 1, 6, 12. The ranking of death counts from smallest to largest is the same as this order.

This result indicates that from a statistical perspective, the more conservative game strategies (those that favor playing with real cards and not questioning) have a higher winning rate, while the more aggressive strategies (those that favor playing with fake cards and questioning) have a lower winning rate. This serves as a reminder that in actual card games or even in real life, we should adopt more conservative strategies.

5.4. Constraints

1.The strategy combination of “Liar’s Bar” can be very complex. For example, players can deliberately display a certain pattern to mislead the competitors, or make dynamic adjustments based on the competitors’ strategy.

2.Random factors in the game, such as the order of card drawing and Russian roulette penalties, can cause fluctuations in the winning rate of strategies. Although we conducted numerous simulations using Python, such as 10,000 times, we still could not tell that these factors make no differences.

3.The psychological characteristics of players cannot be quantified directly, which may cause the model unable to reflect the decision-making behavior in real games.

4.In actual games, players can adjust their strategies according to the strategy of competitors. We simulated that the player could change their strategies immediately after they won 3 times or lost 1 time. Then we compared the new win rate with the old one, and found that the win rates were the same. Therefore, in the vast number of game rounds, strategic adjustments might not be crucial. But we cannot deny that in actual situation, in few rounds, there might be a difference between adjustments and not adjustments. In short, the conclusions only provide a probability of win rate, giving a suggestion of strategy decision. It may not match the actual situations in the real game.

6. Conclusion

This paper primarily focuses on the analysis of a simplified one-on-one version of the game ”Liar’s Bar”, where each player is given two cards from a deck consisting of 3 ”True” cards and 5 ”Liar” cards. Using game theory and probability theory, the research first defines mixed strategies for Player

1 (Strategies A/B, with selection probability p) and Player 2 (Strategies I/II, with selection probability q), calculates the expected winning probabilities (E_1, E_2) for both sides, and introduces "average winning rate" ($\text{Avg}_1, \text{Avg}_2$) and "winning variance" (V_1, V_2) to evaluate strategy stability. Simulation results show that: the game has no pure Nash equilibrium, but the equilibrium point is close to $(1, 1)$ when based on average payoffs; Player 2 has a long-term advantage (overall average winning rate of 62.5%), while Player 1 needs to adopt an extreme strategy ($p = 1$) to improve the winning probability (average 48.2%).

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