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The Illusion of Control in Sports Betting: How AI-Framed Probability Influences Wagering Decision

Haozhe Yuan[1*†], Ruimin Luo[2†], Yue Wu[3], Zejing Zhao[4]

[1]YK Pao School, Shanghai, China
[2]Oxford College, Emory University, Oxford, USA
[3]Santa Monica College, Santa Monica, USA
[4]One Direction Academy, Toronto, Canada
**Corresponding Author. Email: S19330@ykpaoschool.cn*
[†]These authors contributed equally to this work and should be considered as co-first author.

Abstract. This study investigates how framing sports betting odds as AI-predicted win rates influences wagering behavior, compared to identical predictions labeled as originating from human experts. Drawing on behavioral economics concepts such as the Illusion of Control, belief updating biases, and trust in algorithmic decision-making, we conducted an online survey experiment with 230 participants from 26 provinces in mainland China. Respondents were exposed to hypothetical football match scenarios in which betting advice was attributed either to AI or to human experts, with detailed demographic, AI trust, and Illusion of Control measures collected. Probit and OLS regressions reveal that expert framing significantly increases both the likelihood of placing a bet and the selection of the advised team, whereas AI framing has no significant effect on market entry or choice direction. However, both expert and AI labels increase intended stake sizes among participants who choose to bet, suggesting that algorithmic advice can heighten financial commitment without attracting new bettors. The results indicate a persistent trust advantage for human experts in the Chinese sports betting context, consistent with global evidence on algorithm aversion. Policy implications include the need for transparent AI performance disclosure, targeted responsible gambling measures, and public education to mitigate cognitive biases. This research contributes to the literature by empirically linking AI framing effects, cognitive bias, and demographic moderators in a high-stakes decision-making environment, offering insights for both regulators and platform designers seeking to balance innovation with consumer protection.

Keywords: Sports betting, Illusion of Control, Algorithmic trust, China, Behavioral economics

1. Introduction

Lotteries and betting have long played a significant role in the global sports economy, offering excitement for fans and profits for operators. Yet, they also represent one of the most accessible forms of high-risk gambling, where participants make decisions under uncertainty. Unlike financial

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professionals, most bettors lack advanced training in statistics or economics. Their decisions are therefore shaped less by rational probability calculus and more by heuristics and cognitive biases. As a result, betting markets exhibit structural inefficiencies, which gambling companies can and often do exploit.

A classic example is recency bias. The study conducted by Krieger et al. in 2021 [1] show that bettors in the U.S. National Football League (NFL) systematically overweights recent performance. They bet disproportionate on teams with winning streaks even when facing more stronger opponents. This bias distorts prices and creates predictable profit opportunities for operators, who strategically adjust odds to capitalize on public misperception. While a small segment of highly analytical bettor can avoid such traps, the majority cannot. Careful data analysis requires expertise, time and effort that casual participants rarely possess.

The rise of artificial intelligence (AI) complicates this picture. On one side, AI democratizes access to information. Ordinary bettors can now employ models that scrape and analyze large data sets, potentially reducing reliance on crude heuristics such as recency bias. On the other side, AI also creates new channels for manipulation. Platforms may strategically design algorithms or control information inputs to nudge consumer behavior in subtle but profitable ways. This dual potential makes AI both a tool for rationalization and a source of heightened vulnerability.

Our study focuses on AI-framed predicted win rates. That is, win–loss likelihood estimates explicitly labeled as generated by an AI system. Although these probabilities are technically identical to human-generated ones, the "AI" label may shift perceptions of credibility, precision, and fairness [2,3]. Counterintuitively, prior studies suggest mixed effects. Some shows that AI framing can enhance trust because of perceived computational objectivity [4]. Others document persistent algorithmic aversion [5]. In gambling context, however, evidence remain limited. Mihai et al. [3] , for example, examine how algorithmic advice shapes confidence judgments, but do not test its effect on actual betting stakes. This leaves open an important question: does AI labeling alter wagering behavior in ways that differ from unlabeled odds?

We argue that three mechanisms make such an effect plausible. First, the Illusion of Control (IoC) suggest that bettors may overestimates their influence over random outcome. This effect occurs when information is presented as expert or data-driven [6,7]. AI framing could emphasize this illusion by advocating for hidden causal insights, thus encouraging higher-risk wagers to bet. Second, belief updating biases show that individuals overweight weak signals while underweighting strong ones [8]. The AI label may function as a "signal booster," making ambiguous odds appear more reliable than they are. Third, trust in AI systems—linked to perceptions of fairness, transparency, and objectivity—may increase bettors' willingness to act on AI predictions, even if accuracy is uncertain [4,5].

The significance of these mechanisms extends beyond academic debate. Theoretically, they highlight how digital technologies reshape the boundary between rational and biased decision-making. From a policy perspective, they raise concerns about responsible gambling. Vulnerable populations—such as younger bettors, lower-income groups, or those with high institutional trust—may be disproportionately exposed to harm if AI framing systematically biases perceptions of risk and control. Yet over-regulation also risks suppressing genuinely beneficial innovations, such as tools that enhance transparency.

Despite growing interest in AI's role in behavioral decision-making, no empirical study has directly tested whether AI-labeled probabilities influence wagering decisions in sports betting markets. This absence is particularly striking in China, where rapid technological adoption, dominance of digital platforms, and strict gambling regulation create a distinctive environment.

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Against this backdrop, we ask the following research question: Do AI-framed win probabilities alter bettors' wagering decisions compared to identical probabilities presented without the AI label? To address this, we conduct a controlled experiment simulating football betting scenarios. Our study seeks to advance both academic understanding of decision-making under uncertainty and practical guidance for policymakers and industry stakeholders. Specifically, the findings will clarify whether AI serves as a corrective tool for biased gamblers or as a new source of vulnerability, thereby informing evidence-based interventions to ensure innovation in betting markets evolves alongside effective consumer protection.

2. Literature review and theoretical framework

The use of AI-framed probabilities in gambling introduces a unique psychological and behavioral dynamic. An AI-framed probability refers to a win–loss likelihood explicitly labeled as generated by an artificial intelligence system. Although technically identical to human-generated predictions, the "AI" label can still alter perceptions of credibility, precision, and fairness [2,3]. Some studies suggest that bettors trust AI more because of its perceived computational objectivity [4]. Others, however, point to persistent skepticism rooted in algorithmic aversion among gamblers [5]. In gambling contexts specifically, personalized AI predictions can make odds appear more precise or data-driven. This framing, in turn, may increase perceived certainty and shape subsequent betting behavior [3].

Theoretically, three mechanisms may provide explanation for how AI framing affects wagering decisions. First, the Illusion of Control (IoC) suggests that individuals often overestimate their influence over random outcomes, particularly when existed information indicates implied expertise or hidden knowledge [6,7,9]. When odds are labeled as "AI-predicted," this framing may amplify IoC. It creates the impression of greater certainty or even insider advantage for the gamblers [9].

Second, belief updating biases means that bettors tend to over rely on weak evidence while ignoring strong evidence [8]. Even when AI predictions are statistically equivalent to neutral probabilities (data without source), the AI-label itself can distort subjective probabilities. In this way, bettors may feel more confident in their wagers simply because the prediction is framed by AI.

Third, trust in AI provides another explanation. Algorithmic advice is often accepted when it is framed as objective, transparent, or fair [4]. Yet algorithmic aversion can still emerge when individuals fear a loss of autonomy or control [5]. This duality implies that the effect of AI framing may vary across individuals depending on their baseline trust in AI systems.

At the same time, gambling behaviors are shaped by demographic moderators. Men are more frequent sports gamblers compared to women [10]; individuals with lower income levels may display greater sensitivity to persuasive information [11]; and urban versus rural residents exhibit distinct emotional drivers and risk preferences [12]. These contextual factors are likely to condition how AI framing affects betting behavior.

Despite extensive research on behavioral biases in gambling and on algorithmic trust in other domains such as finance and healthcare, no empirical work directly investigates how AI-labeled odds influence actual wagering decisions. This gap is especially relevant in China, where online betting platforms increasingly experiment with AI-driven personalization under a strict regulatory framework. Addressing this gap, this study evaluates whether AI framing changes both the willingness to place a bet and the size of the stake committed, while accounting for individual psychological mechanisms and demographic heterogeneity.

Building on the mechanisms discussed above, we propose the following hypothesis: When sports betting odds are labeled as AI-predicted win rates, bettors will wager higher amounts compared to

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when the same odds are presented without an AI label.

This hypothesis integrates three theoretical strands: Illusion of Control (IoC): Perceived information quality increases risk-taking when bettors believe outcomes involve skill [6,7,9]. AI framing may reinforce this illusion by implying hidden causal insights. Trust in AI: Algorithmic framing enhances credibility and shapes decisions independent of actual accuracy [3,4]. Belief Updating Bias: AI labels may lead individuals to overweight weak signals, inflating confidence in probabilistic forecasts [8]. By testing this hypothesis through a controlled football-betting experiment, we aim to clarify whether AI serves as a corrective tool for biased gamblers or as a new source of vulnerability.

3. Methodology

3.1. Data collection

The data for this study were collected through an online survey in August 2025, distributed via Wenjuanxing on major Chinese social media platforms. A total of 230 respondents from 26 provinces participated, spanning diverse age groups, income levels, education backgrounds, and city tiers. Participants were randomly assigned to hypothetical football betting scenarios, where odds were either neutrally presented or explicitly labeled as “AI-predicted.” This experimental design allows us to isolate the causal effect of AI framing on wagering decisions. All responses were collected confidentially and analyzed by the research team.

3.2. Variables and rationale

3.2.1. Independent variable

X: AI Framing – This binary treatment indicates whether odds were presented with an “AI-predicted” label (1) or neutrally (0). This variable captures the hypothesized psychological influence of AI labeling on subjective probability perception and wagering behavior, consistent with the mechanisms discussed in Section 2 (Illusion of Control, belief updating, and trust in AI).

3.2.2. Dependent variables

Y: Wagering Decisions – Betting behavior is captured using three complementary measures to reflect both the decision to participate and the intensity of engagement:

Betting choice: binary indicator (0 = not willing to bet, 1 = willing to bet). This captures general participation under uncertainty.

Betting side: binary indicator for selecting Team 1 (0 = No, 1 = Yes). This measures directional preference and potential susceptibility to framing effects on perceived probability.

Betting amount: continuous variable (0–100%) indicating the proportion of disposable income respondents are willing to allocate. This captures risk intensity, reflecting how AI framing influences the magnitude of exposure rather than mere participation.

The combination of these three measures allows the analysis to distinguish whether AI labeling affects merely the decision to engage or also the stakes placed, providing a nuanced understanding of behavior under uncertainty.

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3.2.3. Psychological indices

Illusion of Control (IOC) Index: Comprised of six Likert-scale items (1–5), the IOC index measures participants' perceived influence over random outcomes. The average score reflects overall susceptibility to overestimating control, allowing us to examine heterogeneity in response to AI framing.

AI Belief Index: Six-item Likert scale measuring general trust in AI systems. The mean score captures overall confidence in algorithmic advice, which may moderate responsiveness to AI-labeled odds.

3.2.4. Demographic controls

Demographic variables are included to account for systematic heterogeneity in gambling behavior. Their selection is informed by prior research showing differences across gender, income, education, and location:

Age: Four categories are used—18 and under, 18–25, 25–34, and 35 and above. Age may influence both risk tolerance and familiarity with AI technologies, potentially moderating the effect of AI framing.

Gender: Male and female. Prior studies indicate that men tend to engage more frequently in sports gambling than women [10].

Education: Classified as below high school, high school, undergraduate, and above undergraduate. Higher educational attainment may be associated with greater statistical literacy and a more nuanced understanding of probabilistic information.

Occupation: Grouped as student, employed, self-employed, and freelancer. Occupation affects both disposable income and the amount of time available for engaging in betting-related analysis.

Monthly Income: Six brackets are constructed based on the national average Chinese household income (¥10,342.5) reported by the National Bureau of Statistics [11]. The median serves as a dividing point to distinguish financially constrained participants from those with greater disposable income, which may influence both risk appetite and susceptibility to persuasive AI framing [11].

City Tier: Categorized according to China's four-tier city ranking system [12]. Urbanicity shapes access to information, exposure to digital platforms, and the emotional or social drivers underlying gambling participation.

By including these variables, the model controls for both socio-economic context and structural differences in gambling behavior, ensuring that observed effects of AI framing are not confounded by demographic heterogeneity.

4. Results

4.1. Baseline results

The evidence shows a clear separation between expert framing and AI framing for both the decision to participate and the direction of choice, while any labeled advice substantially raises stake size once a person decides to bet. In the full sample, 43.0 percent report willingness to bet, the average intended stake is 27.987 on a 0 to 100 scale, and 34.3 percent select Team 1. These baselines help interpret magnitudes throughout. All models use N=230.

Providing advice increases entry by 0.221 in the unadjusted specification, significant at the 1 percent level. This corresponds to roughly 22 additional bettors per 100 respondents, or about 51

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extra bettors in our sample of 230. After adding controls, the effect is 0.124, significant at the 10 percent level, which corresponds to about 12 additional bettors per 100 respondents, or 29 in the sample. Decomposing the advice indicator shows that the entire effect comes from the expert label. The expert coefficient is 0.343 without controls and 0.227 with controls, both significant at the 1 percent level. These magnitudes correspond to about 34 and 23 additional bettors per 100 respondents respectively. In contrast, the AI label is near zero and not significant. Adding controls raises the R^2 from 0.040 to 0.117, confirming that individual differences explain part of the raw variation but do not eliminate the expert effect.

Expert advice also steers choices toward the recommended team. In the group 1 columns of Table 6, the expert coefficient is 0.237, significant at the 1 percent level, while the AI coefficient is 0.040 and not significant. An effect of 0.237 means that about 24 more bettors out of every 100 follow the expert's side compared to those with no advice.

Both labels produce large increases in intended stake size. The pooled advice coefficient is 14.476, significant at the 1 percent level. Disaggregated effects are 14.437 for AI and 14.506 for expert, each significant at the 1 percent level. With a mean stake of 27.987, these coefficients imply increases of about 52 percent of the baseline mean. In practical terms, once someone chooses to participate, both expert and AI labels induce them to plan wagers that are half again as large as those in the baseline. AI framing does not expand entry but substantially raises financial exposure among those who are already betting.

Split samples highlight a trust advantage for human experts. Expert advice raises entry among women by 0.158, among men by 0.341, and in Tier 1 cities by 0.324, each significant at the 10 percent level. These correspond to 16, 34, and 32 additional bettors per 100 people in those groups. Expert is not significant in other tiers, and the AI label is not significant across all subsamples. The stronger entry response to expert advice is therefore present for both genders and is strongest in the most urban areas.

Controls show patterns consistent with economic intuition. Higher income predicts lower entry with coefficients around –0.094 and –0.091, both significant at the 1 percent level, and predicts smaller stakes with a coefficient of –7.421, significant at the 1 percent level. With mean stakes around 28, this implies high-income individuals bet about 25 percent less. Being female is associated with lower entry and choice probabilities and reduces stake size by about 6.6 points, significant at the 10 percent level, which equals roughly a quarter of the baseline mean. Age also shows negative associations with entry and with choosing the advised side. These findings suggest that resources, risk literacy, and experience moderate both gambling intensity and responsiveness to framing.

Descriptive means align with regression results. The treatment group has higher entry than the control group, 0.491 compared to 0.270, and a higher mean stake, 33.341 compared to 13.794. Within treated participants, Treatment 2 shows higher entry at 0.613 and a larger mean stake at 35.151, compared to 0.279 and 30.197 in Treatment 1. These descriptive means are not causal estimates but illustrate the regression patterns.

Mechanism checks provide further context. The expert group shows a positive association with the mechanism index equal to 0.195, significant at the 10 percent level, while the AI group shows a negative association with mechan_1 equal to –0.240, also significant at the 10 percent level. Although small in magnitude, these results are consistent with expert framing strengthening the path from advice to action, while AI framing does not create the same sense of credibility unless the person is already engaged.

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The overall message is consistent. Expert framing significantly increases market entry and steers directional choice. AI framing does not affect entry or choice direction, yet it significantly raises the amount staked once people choose to participate. Since both labels increase planned stakes by about one half of the baseline average, platform design and policy should emphasize transparency about historical performance, clear probability explanations, and frictions at the point of advice such as default stake limits or timed prompts. These measures target the margins where the largest and most significant effects occur while preserving potential benefits from high quality information.

5. Conclusion

Our empirical analysis demonstrates that the framing of predictive information significantly shapes wagering behavior in the Chinese sports betting context. The treatment effect on betting amount was statistically significant across the full sample (0.221***); however, this effect was driven entirely by predictions labeled as coming from human experts (0.343***), whereas AI-labeled predictions exhibited no significant effect (0.009). This indicates that bettors were far more likely to increase their stake size when presented with expert predictions, while AI-labeled predictions did not elicit the same behavioral change. The negative correlation between income and betting amount is consistent with prior findings that higher-income, often higher-educated individuals tend to exhibit greater risk moderation in gambling contexts [11,13-16].

The demographic composition of our sample shows a slight overrepresentation of female participants, with 58.3% identifying as female. The treatment group contained 56.3% females, while the control group contained 63.5%, suggesting a modest imbalance that was controlled for in our regressions. The negative correlation between income and city tier (-0.113***) aligns with expectations, as higher-tier cities in China generally correspond to higher incomes, providing a validity check on the accuracy of self-reported demographic information [12]. While most demographic variables were statistically insignificant in predicting betting amount, this does not imply irrelevance; rather, it may reflect limited statistical power to detect subgroup-specific effects, multicollinearity between education and income, or a genuinely universal treatment effect across demographic groups. Consequently, interventions in sports betting policy should be designed with population-wide applicability in mind, while still offering targeted protections for potentially vulnerable subgroups [17].

The pattern of results aligns closely with prior findings in behavioral research. Verdickt and Stradi demonstrated in four experiments with over 3,600 U.S. investors that AI-labeled forecasts were less trusted than identical forecasts attributed to humans. In both contexts [2], the human label carries authority and social accountability cues that enhance perceived credibility, while AI labels may evoke skepticism, particularly when transparency regarding the model's workings or historical performance is absent [5]. The effect of expert framing can also be explained through the Illusion of Control [6,7], whereby bettors may misinterpret expert commentary as evidence of actionable skill, overweighting weak signals and inflating their stakes. Belief-updating biases further support this interpretation, as individuals tend to overreact to weak signals and underreact to strong ones [8]; expert labeling appears to elevate such weak signals to a level perceived as much stronger than they objectively are.

In contrast, the negligible effect of AI labels can be interpreted as algorithm aversion, which has been documented in various decision-making contexts [4,18]. Transparency about an algorithm's accuracy metrics can partially mitigate this aversion [3], suggesting that the absence of such disclosures in our experimental setup contributed to participants' reluctance to act on AI predictions. In the Chinese sports betting context—where betting often occurs in informal or grey-market

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environments—trust is built through localized, personal networks such as trusted tipsters or key opinion leaders, rather than impersonal, data-driven systems [19]. This structural factor likely compounds the trust gap between AI and human experts.

An intriguing aspect of our findings is the relationship between income and education in shaping betting behavior. Higher income implies greater disposable capital, allowing larger bets, whereas higher education is associated with increased risk literacy and lower gambling propensity [10,16]. Since income and education are closely correlated, the observed negative relationship between income and betting amount could be mediated by education rather than income per se. Disentangling these effects is crucial for designing consumer protection strategies. The driving effect of risk-taking may not be the same for everyone. For instance, high-income but less-educated bettors may behave differently from low-income but highly educated bettors [14].

The implications of these findings are twofold. First, without transparency and performance disclosure, AI predictions may struggle to gain trust among bettors [5,18]. This would limit the potential of AI to influence behavior responsibly. Second, human expert framing—while effective at stimulating betting volumes—raises ethical concerns. It can encourage higher monetary betting levels without necessarily improving bettors' decision accuracy [20]. It is evident that a persistent mistrust toward AI forecasts remains, even in an era of widespread technological adoption. Many people continue to favor human judgment because it feels more familiar, accountable, and emotionally engaging [4].

The study does have limitations. It relies on hypothetical betting scenarios and self-reported behavior, which may not fully capture real-world risk-taking. Even so, the findings carry strong policy relevance. Platforms employing artificial intelligence should prioritize communicating probabilistic information transparently [3]. This includes sharing historical performance data and providing clear contextual explanations to users. The government may also consider mandating such disclosures through "prediction fact labels," similar to the FDA's nutrition labeling model [21]. In addition, safeguards such as cooling-off periods or default stake limits—especially for online betting platforms—could help reduce imprudent betting triggered by framing effects [13]. Public education campaigns should further aim to improve AI literacy and rational thinking [9]. These efforts could lower both algorithm aversion and the Illusion of Control in gambling contexts, and in general AI usage [7].

Ultimately, our study challenges the assumption that AI-labeled predictions spontaneously inspire greater confidence or risk-taking among gamblers. Focusing on the Chinese sports betting market, we find that—consistent with international patterns—the public continues to place more trust in human experts than in AI systems, as demonstrated through our experimental evidence [2,5]. This pattern holds across age, gender, income, and education groups [10,12].

This aligns with broader evidence from other domains showing that while AI can improve efficiency and accuracy—such as in customer service, where generative AI has been shown to increase resolution rates by 15 percent—it still faces a trust barrier in decision-making tasks involving uncertainty and high stakes [21]. Bridging this trust gap will require not only technical advancements in AI systems but also deliberate strategies to increase transparency, contextual relevance, and user understanding. By addressing these factors, AI integration into sports betting can evolve beyond novelty, becoming a trusted and responsible tool that complements rather than competes with human expertise [3-5].

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Appendix

Table 1. Summary statistics

Variable	Mean	Std. dev.	Min	Max
Overall sample (N: 230)				
Choose to Bet	0.430	0.496	0	1
Team 1	0.343	0.476	0	1
Betting amount	27.987	30.229	0	100
IOC Score	2.552	0.714	1	5
AI Belief Score	2.352	0.804	1	5
Advice Intervention	0.726	0.447	0	1
AI Group	0.265	0.442	0	1
Expert Group	0.461	0.500	0	1
Education Background	2.578	0.742	1	4
Female	0.583	0.494	0	1
Occupation	1.804	0.852	1	4
Income	4.213	1.565	1	6
City Tier	2.300	1.086	1	4
Sports	0.265	0.442	0	1
Age	2.213	1.326	1	4

Notes: Descriptive statistics (means, standard deviations, minimums, maximums) for the full sample N = 230. Binary variables: Choose to Bet and Team 1 (0/1). Betting amount is on a 0–100 scale. IOC Score and AI Belief Score are 1–5 Likert indices (higher = more agreement). No regression is estimated in this table; standard errors and significance stars do not apply. Source: Authors' own calculation from online survey (August 2025, Wenjuanxing).

Table 2. Statistics divided by treatment and control group

Variable	Mean	Std. dev.	Min	Max
Treatment group (N: 167)				
Choose to Bet	0.491	0.501	0	1
Team 1	0.407	0.493	0	1
Betting amount	33.341	29.903	0	100
IOC Score	2.579	0.723	1	5
AI Belief Score	2.329	0.780	1	5
AI group	0.365	0.483	0	1
Expert Group	0.635	0.483	0	1
Education Background	2.569	0.764	1	4
Female	0.563	0.498	0	1
Occupation	1.832	0.833	1	4

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Table 2. (continued)

Income	4.174	1.544	1	6
City Tier	2.335	1.079	1	4
Sports	0.228	0.421	0	1
Age	2.102	1.274	1	4
Control group (N: 63)				
Choose to Bet	0.270	0.447	0	1
Team 1	0.175	0.383	0	1
Betting amount	13.794	26.439	0	100
IOC Score	2.482	0.690	1	4.375
AI Belief Score	2.413	0.867	1	5
Education Background	2.603	0.685	1	4
Female	0.635	0.485	0	1
Occupation	1.730	0.902	1	4
Income	4.317	1.625	1	6
City Tier	2.206	1.109	1	4
Sports	0.365	0.485	0	1
Age	2.508	1.424	1	4

Notes: Descriptive statistics by group: Treatment N = 167, Control N = 63. Treatment includes both advice sources (AI and Expert); Control receives no advice. Means and standard deviations are reported; no regressions are estimated here, so standard errors and significance stars do not apply. Causal estimates are reported in Tables 4–6. Source: Authors' own calculation from online survey.

Table 3. Treatment group statistics

Variable	Mean	Std. dev.	Min	Max
Treatment 1 (N: 61)				
Choose to Bet	0.279	0.452	0	1
Team 1	0.230	0.424	0	1
Betting amount	30.197	26.776	0	100
IOC Score	2.352	0.722	1	3.75
AI Belief Score	2.197	0.955	1	5
Education Background	2.803	0.813	2	4
Female	0.557	0.501	0	1
Occupation	1.770	0.824	1	4
Income	4.115	1.664	1	6
City Tier	2.246	1.150	1	4
Sports	0.328	0.473	0	1
Age	2.607	1.417	1	4
Treatment 2 (N: 106)				
Choose to Bet	0.613	0.489	0	1
Team 1	0.509	0.502	0	1

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Table 3. (continued)

Betting amount	35.151	31.543	0	100
IOC Score	2.709	0.694	1	5
AI Belief Score	2.406	0.651	1	4.5
Education Background	2.434	0.704	1	4
Female	0.566	0.498	0	1
Occupation	1.868	0.840	1	4
Income	4.208	1.478	1	6
City Tier	2.387	1.038	1	4
Sports	0.170	0.377	0	1
Age	1.811	1.088	1	4

Notes: Descriptive statistics for the two advice conditions (Treatment 1: N = 61; Treatment 2: N = 106). "Treatment 1" and "Treatment 2" correspond to the two advice sources used in the experiment (see §3.2.1 for definitions). No regressions are estimated; standard errors and significance stars do not apply. Causal effects are estimated in Tables 4–6. Source: Authors' own calculation from online survey.

Table 4. The effect of the advice intervention on betting decisions

Dependent variable: bett			
	(1)	(2)	(3)
Panel A			
Advice Intervention	0.221***		
	(0.072)		
Ai group		0.009	0.027
		(0.084)	(0.240)
Expert Group		0.343***	0.901***
		(0.075)	(0.210)
Constant	0.270***	0.270***	-0.613***
	(0.061)	(0.059)	(0.169)
N	230	230	230
R-sq	0.040	0.117	
Panel B			
Advice Intervention	0.124*		
	(0.068)		
Ai group		-0.009	-0.004
		(0.079)	(0.252)
Expert group		0.227***	0.683***
		(0.075)	(0.232)
Education level	-0.088*	-0.066	-0.216
	(0.041)	(0.041)	(0.136)
Female	-0.142*	-0.130*	-0.432*

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Table 4. (continued)

	(0.067)	(0.066)	(0.207)
Occupation	0.060	0.041	0.134
	(0.041)	(0.041)	(0.128)
Income	-0.094***	-0.091***	-0.307***
	(0.024)	(0.023)	(0.080)
Occupation	0.038	0.037	0.120
	(0.029)	(0.029)	(0.093)
Sports	-0.176*	-0.153*	-0.479*
	(0.070)	(0.069)	(0.218)
Age	-0.088***	-0.063*	-0.219*
	(0.029)	(0.029)	(0.099)
Constant	1.090***	0.980***	1.695***
	(0.199)	(0.199)	(0.657)
N	230	230	230
R-sq	0.217	0.250	

Notes: All columns are estimated using OLS, which is estimated using a Probit model. Reported coefficients in column (3) are average marginal effects. Robust standard errors are shown in parentheses. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' own calculation from online survey.

Table 5. The effect of gender and city tier on betting behavior

Dependent variable: Bett				
	(1)	(2)	(3)	(4)
	Female	Male	City tier 1	other tiers
AI Group	0.030	-0.017	0.048	-0.063
	(0.106)	(0.124)	(0.129)	(0.103)
Expert Group	0.158*	0.341*	0.324*	0.147
	(0.094)	(0.130)	(0.139)	(0.092)
Education level	-0.142*	0.016	-0.029	-0.075
	(0.055)	(0.063)	(0.083)	(0.047)
Female	-	-	-0.125	-0.130
			(0.103)	(0.088)
Occupation	0.007	0.076	-0.042	0.107*
	(0.048)	(0.086)	(0.067)	(0.053)
Income	-0.086*	-0.074*	-0.113***	-0.076*
	(0.035)	(0.034)	(0.034)	(0.033)
City Tier	0.045	0.025	-	-0.003
	(0.040)	(0.044)	-	(0.056)
Sports	-0.225*	-0.062	0.029	-0.222*

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Table 5. (continued)

	(0.086)	(0.124)	(0.119)	(0.089)
Age	-0.005	-0.095*	-0.077	-0.068*
	(0.043)	(0.044)	(0.055)	(0.036)
Constant	0.984***	0.667*	1.069***	1.028***
	(0.260)	(0.358)	(0.332)	(0.295)
N	134	96	79	151
R-sq	0.190	0.342	0.303	0.266

Notes: Probit models estimated separately by subgroup; reported coefficients are average marginal effects. Subsamples: Female (N = 134), Male (N = 96), Tier-1 cities (N = 79), Other tiers (N = 151). Robust standard errors in parentheses. Controls (where applicable): education, occupation, income, city tier (or gender), sports participation, age. Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' own calculation from online survey.

Table 6. The effect of the advice intervention on betting behavior

Dependent variable:	join	join	group1	group1	money	money
	(1)	(2)	(3)	(4)	(5)	(6)
Advice Intervention	0.131*		0.151*		14.476***	
	(0.068)		(0.068)		(4.058)	
AI Group		0.009		0.040		14.437***
		(0.080)		(0.079)		(4.822)
Expert Group		0.226***		0.237***		14.506***
		(0.075)		(0.075)		(4.541)
Education Level	-0.091*	-0.071*	-0.053	-0.035	-0.835	-0.828
	(0.041)	(0.041)	(0.041)	(0.041)	(2.430)	(2.472)
Female	-0.140*	-0.130*	-0.181***	-0.171***	-6.585*	-6.582*
	(0.067)	(0.066)	(0.066)	(0.065)	(3.964)	(3.979)
Occupation	0.056	0.038	0.051	0.036	1.702	1.697
	(0.041)	(0.041)	(0.041)	(0.041)	(2.451)	(2.484)
Income	-0.096***	-0.093***	-0.061*	-0.058*	-7.421***	-7.420***
	(0.024)	(0.024)	(0.024)	(0.023)	(1.420)	(1.424)
City Tier	0.044	0.043	0.030	0.028	2.512	2.512
	(0.029)	(0.029)	(0.029)	(0.029)	(1.742)	(1.747)
Sports	-0.159*	-0.138*	-0.063	-0.044	-9.604*	-9.598*
	(0.070)	(0.069)	(0.069)	(0.068)	(4.135)	(4.168)
Age	-0.089***	-0.067*	-0.100***	-0.080***	-4.143*	-4.136*
	(0.029)	(0.029)	(0.028)	(0.029)	(1.706)	(1.776)
Constant	1.098***	0.996***	0.808***	0.716***	57.596***	57.564***
	(0.200)	(0.200)	(0.197)	(0.198)	(11.844)	(12.067)
N	230	230	230	230	230	230
R-sq	0.215	0.242	0.164	0.189	0.254	0.254

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Notes: Columns (1)–(2) Choose to Bet and columns (3)–(4) Team 1 are Probit models; reported coefficients are average marginal effects. Columns (5)–(6) Betting amount are OLS estimates (0–100 scale). Robust standard errors in parentheses. Controls in all columns: education, gender, occupation, income, city tier, sports participation, age. Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' own calculation from online survey.

Table 7. The effect of demographics on betting behaviour

Dependent variable:	mechan	mechan	mechan_1	mechan_1
	(1)	(2)	(3)	(4)
Advice Intervention	0.044		-0.149	
	(0.107)		(0.122)	
AI Group		-0.149		-0.240*
		(0.125)		(0.145)
Expert Group		0.195*		-0.078
		(0.118)		(0.136)
Education Level	0.056	0.087	0.048	0.063
	(0.064)	(0.064)	(0.073)	(0.074)
Female	0.027	0.043	-0.147	-0.140
	(0.105)	(0.103)	(0.119)	(0.120)
Occupation	0.062	0.034	0.052	0.039
	(0.065)	(0.064)	(0.074)	(0.075)
Income	-0.054	-0.050	-0.060	-0.058
	(0.037)	(0.037)	(0.043)	(0.043)
City Tier	-0.111*	-0.113*	-0.038	-0.039
	(0.046)	(0.045)	(0.052)	(0.052)
Sports	-0.130	-0.098	0.009	0.024
	(0.109)	(0.108)	(0.125)	(0.125)
Age	-0.094*	-0.058	-0.120*	-0.103*
	(0.045)	(0.046)	(0.051)	(0.053)
Constant	2.974***	2.813***	2.932***	2.856***
	(0.313)	(0.313)	(0.357)	(0.362)
N	230	230	230	230
R-sq	0.069	0.103	0.042	0.048

Notes: OLS regressions with dependent variables mechan and mechan_1 (psychological indices; see §3.2.3). Coefficients reported with robust standard errors in parentheses. Controls: education, gender, occupation, income, city tier, sports participation, age. Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' own calculation from online survey.