You Only Lose Once: Blockchain Gambling Platforms

Research Paper

Lorenz Baum[1], Arda Güler[1], and Björn Hanneke[1]

[1] Chair of Information Systems and Information Management,
Goethe University Frankfurt, Germany
{baum,gueler,hanneke}@wiwi.uni-frankfurt.de

Abstract. Online gambling platforms exhibit increasing revenues, exacerbating societal issues while evading regulatory oversight. The emergence of blockchain gambling platforms aggravates these issues, luring users with the promise of transparent and verifiable gambling rules. To provide insights for regulators and user protection measures, we strive to understand how users interact with these emerging platforms. We analyze over 22,800 rounds of YOLO, a gambling platform implemented as a smart contract. In our sample, 3,306 unique users lost a total volume of USD 5.1 million. Generalized linear mixed model estimation results reveal the effects of users' cognitive biases while engaging in on-chain gambling, demonstrating the substantial risks of gambling smart contracts in exploiting users with gambling inclinations, especially given the lack of user protection measures. Enforcing user protection remains challenging for decentralized gambling smart contracts, which might exacerbate the lack of oversight, user protection, and law enforcement on traditional online gambling platforms.

Keywords: gambling platform, smart contract, gambling behavior, cognitive bias, user behavior

1 Introduction

Online gambling platforms exhibit continuous growth, accounting for almost USD 100 billion in revenue in 2024 (Statista, 2024). This development is concerning, as from a gambling platform user's perspective, gambling behaviors are associated with various adverse effects, ranging from mental health issues and suicide attempts (McCormick et al., 1984) to substance abuse and financial difficulties (Cowlishaw & Kessler, 2016). Moreover, from a societal perspective, traditional online gambling platforms often evade regulatory oversight and law enforcement, e.g., increasing corruption in sports (Turk et al., 2023), and providing the ground for money laundering and organized crime (UNODC, 2024). While gambling is associated with financial losses and psychological effects such as addiction, traditional online gambling platforms are at least partially subject to regulatory oversight.

Against this background, the emergence of blockchain-based smart contracts for gambling potentially aggravates these issues (Brown, 2022). Unlike traditional online gambling, blockchain-based gambling platforms operate via decentralized smart contracts, allowing users to engage in wagering without intermediaries, making regulatory enforcement and user protection particularly challenging. While enabling verifiable, transparent, and tamper-proof gambling rules and transactions, gambling smart contracts create unique challenges, including the circumvention of national regulations, difficulties in enforcement, oversight, and consumer protection regulation, and enhanced risks of user exploitation (Scholten, 2022). Moreover, shutting down decentralized smart contracts for violations is difficult, as they run decentralized and automatically ad infinitum on the blockchain (Nofer et al., 2017).

Previous studies have examined behavioral aspects of online gambling (Cowlishaw & Kessler, 2016; Fiedler, 2013), but research on blockchain gambling remains scarce. As highlighted by recent discussions in the Information Systems community (Davison, 2023; Kane, 2022; Struijk et al., 2022), the broader IS field risks overlooking the novel challenges and opportunities presented by decentralized systems. A significant gap remains in understanding how blockchain-enabled platforms uniquely shape user behavior, particularly concerning how cognitive biases influence user decision-making. This study seeks to bridge this gap by investigating the application of smart contracts for gambling platforms and how users interact with a blockchain-based gambling platform. Specifically, we explore the prevalence of cognitive biases in on-chain gambling, examining their impact on user engagement and financial losses. We aim to contribute to the literature on gambling behaviors by assessing how blockchain-based platforms differ from traditional gambling environments. Moreover, our findings provide valuable insights for users and regulators regarding the potential harms and policy challenges associated with decentralized gambling platforms.

In our paper, we empirically investigate over 22,800 rounds of *YOLO*, a blockchain-based (*on-chain*) gambling smart contract. On *YOLO*, users contribute cryptocurrencies (fungible tokens, e.g., ETH) or digital assets (non-fungible tokens) to a winning pool with winning chances corresponding to their relative winning pool contributions. *YOLO* runs on the Ethereum blockchain with transparent, verifiable source code, and stores gambling outcomes as transactions publicly on the blockchain, which allows us to retrospectively investigate users' gambling behavior.

In the following, we present how smart contracts qualify as platforms and introduce related works on users' gambling behavior in traditional and blockchain contexts. Afterward, we present estimation results from a generalized linear mixed model, exploring which factors contribute to users continuing to gamble on *YOLO*. These insights inform our discussion regarding the potential to address the phenomenon of smart contract on-chain gambling from a user's and regulatory perspective.

2 Conceptual Setting

2.1 Blockchains and Smart Contracts

Blockchains are distributed databases, securely storing past transactions within the chain of transaction records, while a decentralized consensus mechanism updates new records in a tamper-proof manner (Nofer et al., 2017). Building on blockchains and relying on decentralized consensus, smart contracts enable tamper-proof, self-enforcing execution of operations, such as exchanging cryptographic tokens or any other information on the blockchain (Cong & He, 2019).

Moreover, so-called oracles connect smart contracts with off-chain environments, enabling the exchange of information between smart contracts and any other off-chain database (Cong, Prasad, & Rabetti, 2023). As smart contracts are self-enforcing, they autonomously continue their operation if the blockchain on which they are deployed provides consensus, and new transactions potentially trigger smart contract executions.

This technical implementation constitutes a major difference from traditional platforms, which rely on a centralized set-up and an operator, e.g., a company, to be functional and continuously operational. Once the operator ceases to exist or stops its operation, its platform typically stops working, e.g., servers and databases are shut down. Moreover, smart contracts provide more functionality than typical peer-to-peer networks, e.g., traditional peer-to-peer networks are not self-enforcing or tamper-proof.

Ultimately, smart contracts rely on blockchains while sharing features with platforms and peer-to-peer networks. These new technical properties might induce new or different platform user behaviors, as we will explore in the context of gambling.

Recent IS literature highlights that blockchain-based platforms, including decentralized finance (DeFi) and decentralized applications (Dapps) for gambling, foster new forms of user interaction, shaped by pseudonymity, algorithmic transparency, and immutable execution (Beck et al., 2018; Davison, 2023; Scholten, 2022). These socio-technical dynamics distinguish blockchain gambling not merely in terms of mechanics but in how they fundamentally reshape governance, user trust, and behavioral feedback loops. Features like immutable execution, transparent transaction histories, and pseudonymous participation may reinforce cognitive biases by amplifying perceived patterns or reducing perceived control. Thus, blockchain affordances do not just support decentralization, they might actively shape user behavior in distinct ways.

2.2 User Gambling Behavior

Our study draws on established theories of cognitive biases in gambling behavior, particularly Prospect Theory (Kahneman & Tversky, 1979): Users often rely on heuristics and mental shortcuts when making gambling decisions, leading to systematic biases.

While gambling, users make decisions under uncertainty and risk. Gambling constitutes placing monetary stakes with the prospect of either winning an augmented sum or forfeiting the waged funds. The users' behavioral decisions regarding uncertain events rely on judgment heuristics, or cognitive shortcuts, to simplify assessing probabilities and taking actions (Sundali & Croson, 2006; Tversky & Kahneman, 1974). Judgment heuristics may be reliable for many decisions; however, deviations from probability theory may result in systematic errors and suboptimal decisions (Kahneman & Tversky, 1979). The decision-making literature has revealed numerous cognitive biases serving as shortcuts (Goodie & Fortune, 2013). We focus on the biases emerging from the representativeness heuristic and the irrational belief in the law of small numbers (Tversky & Kahneman, 1971), where gamblers mistakenly believe that the probabilistic properties of the law of large numbers hold for a small (finite) sample. Thus, gamblers perceive the probability of independent random events as conditional on past events (Kovic & Kristiansen, 2019). We briefly introduce three cognitive biases that have been shown to drive user behaviors in traditional gambling contexts: the gambler's fallacy and the hot/cold hand as biases in assessing probabilities, and the anchoring effect as a shortcut for taking actions (Sundali & Croson, 2006). These biases have been widely studied in traditional gambling contexts (Sundali & Croson, 2006) but remain underexplored in blockchain-based gambling environments. Our analysis examines how these biases manifest in on-chain gambling and their implications for user behavior.

The *gambler's fallacy* describes the observation that after a streak, i.e., the same outcome of a random event, gamblers falsely believe that the opposite outcome is more likely to occur, to balance out perceived deviations from the law of large numbers (Tversky & Kahneman, 1974). The *hot hand* is the mistaken belief that the probability of winning (losing, i.e., *cold hand*) is higher when experiencing consecutive wins (losses) in a sequence of random events because the user believes to be on a "hot (cold) streak" (Green & Zwiebel, 2018; Sundali & Croson, 2006). Long streaks in short samples make the sequence appear non-random, leading users to falsely perceive recent wins (losses) as an indicator of continued wins (losses) (Gilovich et al., 1985). Finally, the *anchoring effect* biases judgments or estimates towards a reference point, the anchor, such as when gamblers tend to bet similar amounts as their initial wager regardless of changing circumstances (Teovanović, 2019).

Building on Prospect Theory and the broader literature on behavioral decision-making (Kahneman & Tversky, 1979; Kovic & Kristiansen, 2019; Sundali & Croson, 2006), our study posits that cognitive biases play a central role in influencing gambling behavior on blockchain platforms. The selection of variables for our regression analysis is theoretically grounded in these insights. I.e., measures for gambler's fallacy, hot/cold hand effects, and anchoring effect are chosen not only because they have been widely documented in traditional gambling contexts but also because blockchain systems, with their inherent transparency and immutability, may amplify these biases. This integration addresses a notable gap in prior research (e.g., Meng & Fu, 2020; Scholten, 2022) by directly linking observed on-chain behavior with established cognitive theories.

2.3 Traditional and Blockchain Gambling

Blockchain-based gambling differs from traditional online gambling in several key aspects. First, traditional platforms operate under centralized governance, where a company manages transactions, sets rules, and ensures compliance with legal frameworks. By contrast, blockchain gambling platforms execute wagering processes through immutable smart contracts, eliminating the need for intermediaries (Cong & He, 2019).

Second, while traditional gambling platforms may implement responsible gambling measures such as deposit limits, age restrictions, and self-exclusion tools, blockchain-based platforms lack such enforcement mechanisms. Users can participate pseudonymously, and permissionless access to blockchains makes enforcing consumer protection measures nearly impossible (Beck et al., 2018). Also, winnings and losses are processed directly on-chain, bypassing traditional financial oversight (Scholten, 2022).

Finally, blockchain gambling platforms introduce unique incentives and risks. The transparency of smart contracts allows users to verify game rules, yet this does not necessarily mitigate exploitative gambling mechanisms. For instance, decentralized applications may implement game mechanics that encourage repeated betting behavior, exacerbating losses. Recently, Mills (2024) argued that blockchains may reduce harm by creating safer and cross-platform tracking for bet limit enforcement.

Prior studies on online gambling behaviors (Cowlishaw & Kessler, 2016; Fiedler, 2013) serve as a replication reference for several studies exploring user behaviors in the context of blockchain gambling. For example, Scholten et al. (2020) derive the spending behaviors of users on decentralized gambling applications. Based on Ethereum transaction data, they report that the average on-chain gambler spends less money than in comparable online casinos. However, they do not consider the effects of cognitive biases. Related to biases in on-chain gambling, Meng & Fu (2020) investigate on-chain transactions, identifying gambling patterns and strategies, e.g., strategic time inconsistencies, gain-exit and loss-exit strategies, and loss-chasing behavior. However, they do not measure biases directly but only infer their existence overall. From an online gambling platform operator's perspective, Chagas et al. (2024) provide qualitative evidence that blockchain technology provides transparency, which has the potential to impact online gambling business models. However, initial investment, technological skepticism, and complexity, amongst others, prevent an immediate implementation.

These studies provide valuable starting points and input for investigating on-chain gambling user behavior and profiling users based on on-chain transaction data. We extend these works by identifying cognitive biases at every gambling round, allowing us to predict user behaviors based on occurring biases. Moreover, we derive and discuss implications for regulators and users based on these observations. Our study complements recent IS research that applies behavioral analytics to DeFi and gambling contexts (e.g., Scholten, 2022; Steinmetz, 2023; Wang et al., 2023) and contributes a novel, high-frequency empirical lens to wallet-level user profiling on decentralized platforms.

3 Empirical Study

We analyze transaction data from *YOLO*, a smart contract gambling platform deployed on the Ethereum blockchain. Our dataset includes gambling rounds involving 3,306 unique users over six months. Using a generalized linear mixed model (GLMM), we estimate the probability of continued gambling based on various factors, including cognitive biases, bet size, and prior outcomes.

3.1 *YOLO*, a Smart Contract Gambling Platform

Our empirical setting, *YOLO*, is a gambling smart contract deployed by the team behind LooksRare, a non-fungible token (NFT) trading marketplace. *YOLO*, the aphorism for "you only live once", is a smart contract that implements the functionality for a round-based gambling game. During these rounds, each lasting for 15 minutes, users may deposit cryptocurrencies (i.e., fungible tokens) or digital assets (i.e., non-fungible tokens) to the winning pool (see Figure 1).

Users' relative contributions to the winning pool correspond to their winning chances: Following the example from Figure 1, if three users contribute 1 ETH, 2 ETH, and 3 ETH, then user 1 has a winning chance of 17%, user 2 of 33% and user 3 of 50%. After the round, *YOLO* (i.e., LooksRare) withholds a fee of 5 percent (0.3 ETH) of the winning pool, reducing the winner's payout to 5.7 ETH. Thus, *YOLO* qualifies as a gambling game due to the random element and negative expected pay-off, as the expected total payoff for user i is 0.95 times the amount wagered due to the 5 percent fee. If there are less than two users in a single round, the round is not played, refunding the deposited amounts. Also, within one round, users can increase their bet size by depositing multiple times and, thus, increase their winning chances while at the same time increasing their potential losses (LooksRare, 2024).

3.2 Methodology

We retrieve all *YOLO* transactions from dune.com, a major blockchain analytics platform. Dune.com decodes raw blockchain transaction data and enriches it with additional information, such as exchange rates for fungible tokens. Overall, our sample comprises over 22,800 rounds of *YOLO*, containing 3,306 unique users, during the observation period between August 16, 2023, and February 2, 2024.

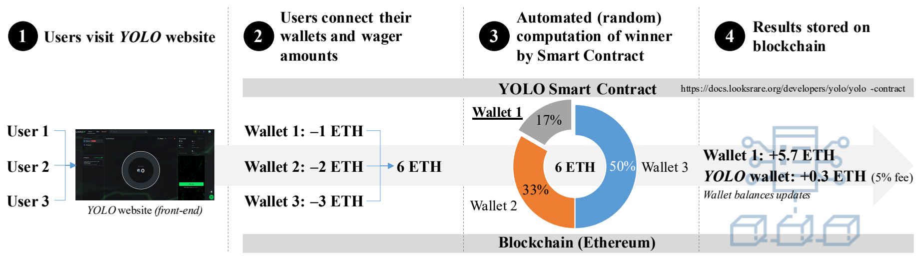

Figure 1. Gambling process on *YOLO*

Description of Variables. For our empirical analysis of the *YOLO* gambling behavior, we consider the following variables:

- **continues playing:** Binary variable measured for each user i in each round j played: continues $\text{playing}_{ij} = 1$ denotes that the user gambles in the next round, and continues $\text{playing}_{ij} = 0$ if not.
- **is winner; is first losing; is too little gambler:** Indicator variables measured for each user i in each round j: is $\text{winner}_{ij} = 1$, if the user is the winner of the round; is first $\text{losing}_{ij} = 1$, if it is the first round lost; is too little $\text{users}_{ij} = 1$, if the game is canceled because there is no other user.
- **#users in round; #deposits in round of user:** Variables that count the number of users i in the current round j and the number of times each user deposited.

- **exchange rate; user bet size:** Variables include the exchange rate (USD 1,000 per ETH) and the total amount of USD per round j for each user i in USD 1,000.
- **average bet size; average amount won/lost:** Variables that measure the average bet size for each user i; and the average amount won/lost for each user i; both in USD 1,000 until the current round j.
- **expected win probability; winning ratio; rounds played:** Variables that present the winning probability for user i in each round j; the winning ratio for user i until current round j (proportion of won rounds); and the $\log_2$ (to account for exponential distribution) of the number of rounds played for user i until the current round j.
- **winning/losing streak (length):** Variables that count the current number of consecutive wins and consecutive losses for each user i and round j.
- **anchoring effect, gambler's fallacy (w & l), hot/cold hand:** Binary variables that take the value 1 if users i express the corresponding biases in round j (see below).

Measuring Biases. First, we examine the anchoring effect by tracking occurrences of repeated bet sizes in ETH. We assign anchoring effect$_{ij} = 1$, if the user i's bet size in round j already occurred in previous rounds.

Second, following the definitions of cognitive biases and findings from Prospect Theory that users weigh losses more negatively than wins positively (Kahneman & Tversky, 1979), we identify patterns where users win or lose consecutively and then analyze betting behaviors within these streaks. We define being on a winning (losing) streak as at least two consecutive identical outcomes. Within a winning (losing) streak, users may increase or decrease their bet size, resulting in four different observations:

(1) **Winning streak & increase of bet size:** We define users exhibiting hot hand as being on a winning streak and increasing their bet sizes, e.g., believing they will continue winning, i.e., hot hand$_{ij} = 1$.

(2) **Winning streak & decrease of bet size:** We define that users who reduce their bet size within a winning streak exhibit the gambler's fallacy. Users believe the opposite outcome (losing) is due, hence, reducing their bet size, i.e., gambler's fallacy (w)$_{ij} = 1$.

(3) **Losing streak & increase of bet size:** Similarly to observation (2), we define users reducing their bet sizes within a losing streak to exhibit the gambler's fallacy. Users believe that the opposite outcome (winning) is due, hence increasing their bet size, i.e., gambler's fallacy (l)$_{ij} = 1$.

(4) **Losing streak & decrease of bet size:** We define users who decrease their bet size after consecutive losses to exhibit cold hand, believing they will continue losing, i.e., cold hand$_{ij} = 1$.

Regression Analysis. For our empirical analysis, we consider whether a user continues gambling in the next round. To estimate this probability per user and round, we take continues playing as the dependent variable $Y_{ij} \in \{0,1\}$ and deploy a GLMM to account for the longitudinal data. Let m denote the number of users and n_i the number of observations for user i. The response Y_{ij} is the outcome of user i at measurement j, with x_{ij} as the fixed-effects covariate vector for the fixed effects $\beta \in R^p$ and random intercept $\gamma_i \sim \mathcal{N}(0, \tau^2)$, accounting for unobserved heterogeneity across users. Since the outcome is binary, the conditional expected value $\mu_{ij} = E[Y_{ij}|x_{ij}, \gamma_i]$ is linked to the linear predictor $x_{ij}^T\beta + \gamma_i$ by a logit-link function, allowing us to model the probability $\pi_{ij} = P(Y_{ij} = 1|x_{ij}, \gamma_i)$. To this end, we fit a random intercept logistic regression model $\log\left(\pi_{ij}/(1-\pi_{ij})\right) = x_{ij}^T\beta + \gamma_{i1}$ (1), using the *melogit* module in STATA (StataCorp, 2023). As covariates, we include the independent variables described before, and we report standard errors obtained through robust estimations (Huber, 1967; White, 1980). Finally, we compare the models using Akaike's information criterion (AIC) and Bayesian information criterion (BIC) (Burnham & Anderson, 2004). The GLMM assumes that repeated observations for a user are independent once we account for individual characteristics (random effects) and relevant covariates. This is reasonable in our setting, as we explicitly include variables capturing previous outcomes and behavioral biases that potentially drive gambling persistence.

3.3 Results

We fit five different models (A-E) using eq. 1 and report all estimates with robust standard errors and significance levels in Table 1. We display estimated coefficients β of the independent variables as odds ratios, where $\exp(\beta)$ equals the odds ratio, allowing a straightforward interpretation, e.g., $\exp(\beta) > 1$ indicates a positive association of the independent variable to the probability of continued gambling, whereas $\exp(\beta) < 1$ indicates a negative association. Our primary goal is to assess the influence of different cognitive biases in on-chain gambling behavior. For each variable, we test whether the estimated odds ratio $\exp(\beta)$ is statistically different from 1. Specifically, we evaluate the null hypothesis H_0: $\exp(\beta) = 1$ against the alternative hypothesis H_1: $\exp(\beta) \neq 1$.

Model A includes all independent variables except for the biases; model B additionally includes the gambler's fallacy for winning and losing streaks; model C includes the hot hand and cold hand; model D includes the anchoring bias; finally, model E includes all independent variables and the biases. Overall, estimates' directions, standard deviations, and significances remain robust across all models. In the following, we focus on results from the complete Model E, additionally supported by the AIC criteria.

4 Discussion

4.1 Empirical Results

Our estimation results (Table 1) reveal several concerning factors driving user engagement with the on-chain gambling platform. We discuss these factors and their implications for users and platforms based on (1) cognitive biases and (2) other positively and negatively associated variables to the probability of continued gambling.

First, the anchoring effect is positively associated with the probability of continued gambling. Hence, users continued gambling with higher probability when repeatedly depositing the same bet size. Leveraging the anchoring effect, platforms might entice all users (even those previously not showing the anchoring effect) to continue gambling by displaying predefined (potentially higher) bet sizes as anchors. This platform strategy might further encourage users to deposit repeated bet sizes regardless of the winning probabilities and to continue gambling, ultimately increasing the platform's profits at the expense of the users.

Second, the expression of the gambler's fallacy within a winning streak is also positively associated with the probability of continued gambling. Thus, instead of stopping gambling in expectation of a potential loss, users would rather lower their deposited amount. From the platform's perspective, gambling platforms could be designed to respond to changes in betting patterns, such as displaying messages to maintain or increase bet sizes, e.g., "Warning: By decreasing your bet size, you lower your chances of winning." This also holds for the gambler's fallacy in the losing streak, where users could be encouraged to substantially increase their bet size and corresponding winning probabilities. Overall, platforms can use these insights to their advantage by designing features that deceive users into believing that they have control over random events.

From a user's behavioral perspective, we observe that winning and a higher expected winning probability both lead to a higher probability of continued gambling. This observation indicates addictive gambling behavior, leading to potential losses, as the users' expected payoffs are negative. Also, the negative association of bet size with the probability of continued playing hints at the final users' attempts to make up for losses from previous rounds by depositing larger bet sizes.

Regulators' efforts to protect users and enforce taxes in online gambling settings seem fruitless for *YOLO* and potentially other on-chain gambling smart contracts (Cong, Grauer, et al., 2023). For example, user protection measures, such as deposit limits (e.g., monthly EUR 1,000 in Germany), the option to blacklist oneself, and general minimum age limits can hardly be enforced in a decentralized and permissionless setting (Beck et al., 2018).

Table 1. Mixed-effects logistic regressions based on 84,394 observations of 3,306 users

Y = continues playing	**Model**				
Odds ratio (Robust std. err.)	**A**	**B**	**C**	**D**	**E**
Intercept	275.18^{***} (131.72)	270.94^{***} (129.33)	289.78^{***} (138.46)	196.19^{***} (94.39)	231.50^{***} (111.13)
is winner	1.61^{**} (0.30)	1.76^{**} (0.32)	1.68^{**} (0.31)	1.66^{**} (0.30)	1.91^{***} (0.34)
is first losing	1.90^{***} (0.18)	1.88^{***} (0.18)	1.84^{***} (0.18)	2.04^{***} (0.20)	1.92^{***} (0.19)
is too little users	1.35 (0.35)	1.29 (0.33)	1.43 (0.37)	1.28 (0.33)	1.32 (0.34)
#users in round	1.03^{***} (0.01)	1.03^{***} (0.01)	1.03^{***} (0.01)	1.03^{***} (0.01)	1.03^{***} (0.01)
#deposits in round of user	1.10 (0.11)	1.13 (0.11)	1.08 (0.11)	1.16 (0.12)	1.16 (0.12)
exchange rate	0.03^{***} (0.01)	0.03^{***} (0.01)	0.03^{***} (0.01)	0.02^{***} (0.01)	0.03^{***} (0.01)

Y = continues playing	**Model**				
Odds ratio (Robust std. err.)	**A**	**B**	**C**	**D**	**E**
user bet size	0.85^{***} (0.04)	0.86^{***} (0.04)	0.84^{***} (0.04)	0.86^{***} (0.04)	0.86^{***} (0.04)
expected win probability	1.51^{*} (0.31)	1.61^{*} (0.34)	1.39 (0.32)	1.64^{*} (0.34)	1.59^{*} (0.33)
winning streak	1.11 (0.12)	1.06 (0.11)	1.10 (0.11)	1.11 (0.11)	1.05 (0.10)
losing streak	0.95^{***} (0.01)	0.95^{***} (0.01)	0.95^{***} (0.01)	0.95^{***} (0.01)	0.96^{***} (0.01)
rounds played	1.19^{***} (0.05)	1.20^{***} (0.05)	1.22^{***} (0.05)	1.20^{***} (0.05)	1.22^{***} (0.05)
winning ratio	5.93^{***} (1.47)	5.39^{***} (1.34)	5.54^{***} (1.38)	5.69^{***} (1.40)	4.89^{***} (1.21)
average bet size	1.03 (0.15)	< 1.00 (0.15)	1.06 (0.15)	1.03 (0.15)	1.03 (0.15)
average amount won/lost	2.00^{**} (0.50)	1.98^{**} (0.50)	1.95^{**} (0.48)	1.96^{**} (0.47)	1.90^{**} (0.45)
gambler's fallacy winning	–	1.65° (0.46)	–	–	1.61° (0.45)
gambler's fallacy losing	–	0.81* (0.07)	–	–	0.77^{**} (0.07)
hot hand	–	–	0.97 (0.25)	–	1.01 (0.26)
cold hand	–	–	0.69^{***} (0.06)	–	0.65^{***} (0.06)
anchoring effect	–	–	–	1.31^{***} (0.09)	1.22^{**} (0.09)
user id: Intercept	4.75 (0.64)	4.75 (0.64)	4.63 (0.64)	4.30 (0.64)	4.42 (0.63)
Residual intraclass correlation	0.59	0.59	0.58	0.57	0.57
Wald χ^2	577.2^{***}	579.3^{***}	604.9^{***}	608.5^{***}	623.9^{***}
Log pseudolikelihood	-8369.2	-8364.3	-8358.4	-8361.4	-8345.6
AIC	16770.4	16764.5	16752.9	16756.8	16733.2
BIC	16919.9	16932.7	16921.0	16915.7	16929.4

Notes: Estimates are transformed only in the fixed-effects equation to odds ratios.
Intercept estimates baseline odds (conditional on zero random effects).
Robust standard errors adjusted for 3,306 clusters in user id (min=1; avg=25.5; max=10939).
Significance levels ($P > |z|$): $^{***}\ p < 0.001$, $^{**}\ p < 0.01$, $^{*}\ p < 0.05$$, $^{\circ}\ p < 0.10$.

4.2 Implications of Gambling Smart Contracts

Our findings contribute to the literature by empirically validating the influence of cognitive biases within the context of blockchain-based gambling. The evidence that biases, such as anchoring and the gambler's fallacy, are significantly associated with continued gambling not only extends the application of Prospect Theory (Kahneman & Tversky, 1979) to decentralized environments but also underscores the unique behavioral dynamics emerging from smart contract-based platforms. Theoretically, these results encourage a reexamination of established gambling models by incorporating the role of blockchain transparency in amplifying cognitive biases.

Decentralized smart contracts for on-chain gambling are alarming for three reasons: First, on-chain gambling applications based on smart contracts can be deployed on permissionless blockchains (Beck et al., 2018), like Ethereum, by anyone, adversely taking advantage of trust-enhancing features in on-chain applications, luring users to gamble. Second, a "wild west mentality" with protocols founders and operators using pseudonyms without registered legal entities, e.g., ignoring data protection regulations and user protection measures for gambling. This is very critical for regulators and users with conditions to gamble. Third, law enforcement in permissionless blockchain environments has proven to be even more difficult than in online settings (Cong, Grauer, et al., 2023). Regulators and law enforcement might still take down gambling smart contracts with dedicated frontends, as the domain-hosting typically resides with standard centralized services. Thus, the domains can be blocked.

Practically, the insights derived from our study signal the need for enhanced user protection mechanisms and regulatory frameworks that address the distinct challenges posed by decentralized systems. While traditional regulation relies on licensed intermediaries, blockchain-based platforms operate autonomously and pseudonymously, disabling standard enforcement tools. However, blockchain's public ledger also enables novel forms of behavioral monitoring and user protection, such as real-time flagging of risky betting patterns or on-chain self-exclusion logic (Mills, 2024):

- **Enhanced Monitoring**: Regulators should leverage blockchain's transparency through address-level analytics to identify high-risk gambling behavior (Mills, 2024; Wang et al., 2023).
- **User Protection Mechanisms**: Smart contract developers could integrate voluntary deposit limits or "cooling-off" periods to help users regulate gambling behavior (Mills, 2024).
- **Cross-Platform Regulation**: Governments may explore collaborative frameworks for regulating blockchain gambling, like existing financial oversight mechanisms.
- **Contract blacklisting and blocking**: As seen in cases like Tornado Cash, gambling smart contract addresses could be blacklisted, allowing central infrastructure providers (e.g., wallets, exchanges) to block user transactions with these contracts.

4.3 Future Work

We have investigated one gambling smart contract with a distinct probability and payoff function. We must acknowledge potential confounding factors, such as the influence of platform-specific design features on user decisions. Importantly, our study does not include a comparative baseline with traditional online gambling platforms. Therefore, we cannot isolate the effects of blockchain-specific technological features such as immutability, transparency, or decentralization on user behavior. A comparative analysis with conventional platforms would be valuable for future research to clarify how these blockchain characteristics influence gambling behavior. Future work might also benefit from investigating various settings, e.g., different on-chain gambling smart contracts. Although related works report observed biases for different on-chain gambling settings, our approach to directly measuring biases based on transaction data could be applied to those settings as well. While our study is observational, we propose avenues for future research to incorporate natural experiments or exogenous shocks to better isolate causal effects. Moreover, a cross-gambling smart contract investigation might reveal more information on gamblers who are active on several gambling platforms simultaneously. Also, more complex gambling smart contracts might affect decision-making and gambling behavior differently than in our setting (Beck et al., 2018). Finally, future research should explore targeted interventions and design modifications on platforms that can mitigate the adverse effects of cognitive biases on user gambling behavior.

5 Conclusion and Outlook

While traditional online gambling has long been scrutinized for its social and financial risks, our study demonstrates that blockchain gambling platforms introduce additional layers of complexity due to their decentralized and transparent nature. In summary, the title *You Only Lose Once* encapsulates a paradox: although users may initially perceive a singular loss as an isolated event, the cumulative impact of cognitive biases often leads to a cycle of repeated losses.

We find that blockchain-based gambling platforms introduce new complexities compared to traditional online gambling. While they promise transparency and fairness, their decentralized nature creates significant risks related to user protection and regulatory enforcement. Our study provides empirical evidence on how cognitive biases influence gambling behavior in on-chain environments. This observation reinforces the urgency for both regulatory oversight and the implementation of consumer protection measures specifically tailored to the unique characteristics of on-chain gambling. As blockchain technology continues to evolve, further research is essential to develop robust frameworks that safeguard users while preserving the innovative potential of decentralized systems.

Thus far, regulators and law enforcement still can restrict access to smart contract gambling platforms, by blocking their centrally hosted frontends. However, this does not restrict users with technical knowledge from interacting directly on-chain with the gambling smart contracts. Recent innovations in blockchain gambling, such as decentralized peer-to-peer betting (BlockWorks, 2024) and lotteries (Mmxicoders, 2024), suggest a future that may be even harder to regulate. Users might ultimately switch if these protocols deliver lower fees and transparent enforcement. However, there is no lobby to protect gamblers with health conditions in peer-to-peer gambling networks. Even though regulated gambling providers might eventually lobby against those protocols, it might be difficult to contain them. Where peer-to-peer file sharing has failed to persist, blockchain-based peer-to-peer gambling protocols might endure. Ultimately, gamblers, especially those with health conditions, and society will bear the costs.

References

Beck, R., Müller-Bloch, C., & King, J. L. (2018), 'Governance in the Blockchain Economy: A Framework and Research Agenda', *Journal of the Association for Information Systems*, **19**, 1020–1034, https://doi.org/10.17705/1jais.00518.

BlockWorks, (2024), *Decentralized Sports Betting*, https://blockworks.co/news/decentralized-sports-betting.

Brown, S. H. (2022), 'Gambling on the Blockchain: How the Unlawful Internet Gambling Enforcement Act Has Opened the Door for Offshore Crypto Casinos', *Vanderbilt Journal of Entertainment & Technology Law*, **24**(3).

Burnham, K. P., & Anderson, D. R. (2004), 'Multimodel Inference', *Sociological Methods & Research*, **33**(2), 261–304, https://doi.org/10.1177/0049124104268644.

Chagas, B. T., Jesus, D., & Palma-dos-Reis, A. (2024), 'Blockchain's value proposition for online gambling: The operators' perspective', *Technological Forecasting and Social Change*, **200**, 123130, https://doi.org/10.1016/j.techfore.2023.123130.

Cong, L., Grauer, K., Rabetti, D., & Updegrave, H. (2023), 'Blockchain Forensics and Crypto-Related Cybercrimes', *SSRN Working Paper.* Advance online publication, https://doi.org/10.2139/ssrn.4358561.

Cong, L., & He, Z. (2019), 'Blockchain Disruption and Smart Contracts', *The Review of Financial Studies*, **32**(5), 1754–1797, https://doi.org/10.1093/rfs/hhz007.

Cong, L., Prasad, E. S., & Rabetti, D. (2023), 'Financial and Informational Integration Through Oracle Networks', *SSRN Working Paper.* Advance online publication, https://doi.org/10.2139/ssrn.4495514.

Cowlishaw, S., & Kessler, D. (2016), 'Problem Gambling in the UK: Implications for Health, Psychosocial Adjustment and Health Care Utilization', *Eur. Addict. Res.*, **22**(2), 90–98, https://doi.org/10.1159/000437260.

Davison, R. M. (2023), 'Impact and implications for practice', *Information Systems Journal*, **33**(2), 187–191, https://doi.org/10.1111/isj.12411.

Fiedler, I. (2013), 'Gamblers' habits: Empirical evidence on the behavior of regulars, newcomers and dropouts', *Journal of Gambling Studies*, **29**(2), 289–309, https://doi.org/10.1007/s10899-012-9306-0.

Gilovich, T., Vallone, R., & Tversky, A. (1985), 'The hot hand in basketball: On the misperception of random sequences', *Cognitive Psychology*, **17**(3), 295–314.

Goodie, A. S., & Fortune, E. E. (2013), 'Measuring cognitive distortions in pathological gambling: Review and meta-analyses', *Psychology of Addictive Behaviors*, **27**(3), 730–743, https://doi.org/10.1037/a0031892.

Green, B., & Zwiebel, J. (2018), 'The hot-hand fallacy: Cognitive mistakes or equilibrium adjustments? Evidence from major league baseball', *Management Science*, **64**(11), 5315–5348.

Huber, P. J. (1967), 'The behavior of maximum likelihood estimates under nonstandard conditions, **1**(1), 221–233.

Kahneman, D., & Tversky, A. (1979), 'Prospect Theory: An Analysis of Decision under Risk', *Econometrica*, **47**(2), 263–291.

Kane, G. C. (2022), 'How to Write an "A" Paper', *Journal of the Association for Information Systems*, **23**(5), 1071–1079, https://aisel.aisnet.org/jais/vol23/iss5/9.

Kovic, M., & Kristiansen, S. (2019), 'The gambler's fallacy fallacy (fallacy)', *Journal of Risk Research*, **22**(3), 291–302.

LooksRare, (2024), *LooksRare Yolo Documentation*, https://docs.looksrare.org/developers/category/looksrare-yolo.
McCormick, R. A., Russo, A. M., Ramirez, L. F., & Taber, J. I. (1984), 'Affective disorders among pathological gamblers seeking treatment', *Am. J. Psychiatry*, **141**(2), 215–218, https://doi.org/10.1176/ajp.141.2.215.
Meng, J., & Fu, F. (2020), 'Understanding gambling behaviour and risk attitudes using cryptocurrency-based casino blockchain data', *Royal Society Open Science*, **7**(10), 201446, https://doi.org/10.1098/rsos.201446.
Mills, D. J. (2024), 'On the Potential Benefits of Blockchain Technology in Gambling: A Perspective on Harm Reduction', *Current Addiction Reports*, **11**(3), 425–436, https://doi.org/10.1007/s40429-024-00561-3.
Mmxicoders, (2024), *Peer-to-peer Lottery Software Revolutionizing the Gambling Industry*, https://www.mxicoders.com/peer-to-peer-lottery-software-revolutionizing-the-gambling-industry/.
Nofer, M., Gomber, P., Hinz, O., & Schiereck, D. (2017), 'Blockchain', *Business & Information Systems Engineering*, **59**(3), 183–187, https://doi.org/10.1007/s12599-017-0467-3.
Scholten, O. J. (2022), *On the Behavioural Profiling of Gamblers using Cryptocurrency Transaction Data* [Doctor of Philosophy], University of York, https://etheses.whiterose.ac.uk/31121/6/thesis.pdf.
Scholten, O. J., Zendle, D., & Walker, J. A. (2020), 'Inside the decentralised casino: A longitudinal study of actual cryptocurrency gambling transactions', *PloS One*, **15**(10), e0240693, https://doi.org/10.1371/journal.pone.0240693.
StataCorp, (2023), *Stata Statistical Software: Release 18*, https://www.stata.com/.
Statista, (2024), *Online Gambling - Worldwide*, https://en.statista.com/outlook/dmo/eservices/online-gambling/worldwide.
Steinmetz, F. (2023), 'The interrelations of cryptocurrency and gambling: Results from a representative survey', *Computers in Human Behavior*, **138**, 107437, https://doi.org/10.1016/j.chb.2022.107437.
Struijk, M., Ou, C. X. J., Davison, R. M., & Angelopoulos, S. (2022), 'Putting the IS back into IS research', *Information Systems Journal*, **32**(3), 469–472, https://doi.org/10.1111/isj.12368.
Sundali, J., & Croson, R. (2006), 'Biases in casino betting: The hot hand and the gambler's fallacy', *Judgment and Decision Making*, **1**(1), 1–12, https://doi.org/10.1017/S1930297500000309.
Teovanović, P. (2019), 'Individual differences in anchoring effect: Evidence for the role of insufficient adjustment', *Europe's Journal of Psychology*, **15**(1), 8.
Turk, M. A., Murphy, C., McCaffrey, J., & Murray, K. (2023), 'Predictors of adverse gambling behaviours amongst elite athletes', *Sci Rep*, **13**(1), 823, https://doi.org/10.1038/s41598-023-27469-8.
Tversky, A., & Kahneman, D. (1971), 'Belief in the law of small numbers', *Psychological Bulletin*, **76**(2), 105.
Tversky, A., & Kahneman, D. (1974), 'Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty', *Science*, **185**(4157), 1124–1131.
UNODC, (2024), *Casinos, Money Laundering, Underground Banking, and Transnational Organized Crime in East and Southeast Asia: A Hidden and Accelerating Threat*, https://www.unodc.org/roseap/uploads/documents/Publications/2024/Casino_Underground_Banking_Report_2024.pdf.

Wang, J., Mao, Q., Yan, J., Sun, H., & Qi, P. (2023), 'Identifying Crypto Addresses with Gambling Behaviors: A Graph Neural Network Approach', *PACIS 2023 Proceedings*, https://aisel.aisnet.org/pacis2023/210.

White, H. (1980), 'A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity', *Econometrica: Journal of the Econometric Society*, 817–838.