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Article

Examining the impact of consecutive losses on gambling: When do we decide to quit?

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SUMMARY

Gambling is defined as the act of risk-taking in the hopes of a desired result. Despite the odds of the desired outcome being unreasonably low in some cases, some individuals still choose to gamble since humans are not always perfectly rational. In the modern day, gambling has moved online, worsening its negative effects as access becomes increasingly easier. In response to the rise of online gambling, we investigated an important factor that helps us determine when people decide to stop gambling. Specifically, we studied how consecutive wins or consecutive losses in a game influence an individual's decision to quit gambling. We apply various theories such as the gambler's fallacy, loss aversion, sunk cost fallacy, and an original concept termed the "three strikes heuristic". We created a coin-flip game with 277 participants recruited via an online research platform. We hypothesized that the probability of quitting would initially decrease after a few consecutive losses but would then increase after reaching a higher threshold of consecutive losses. That is, we predicted that the threshold for which the probability of quitting would increase would be three consecutive losses. Our results showed that the probability of quitting increased after reaching a threshold of four consecutive losses. Interestingly, we also found that participants commonly had balances of 10 and 20 tokens ($0.20 and $0.40) when they decided to quit — representing an increase or decrease of 5 tokens from the starting balance of 15 tokens. This suggests possible thresholds individuals may have for deciding when to stop gambling. Our work has implications for potential intervention strategies to reduce online gambling.

INTRODUCTION

Today, gambling has grown into a significant issue globally, which is currently only worsening due to the accessibility of gambling elements in video games and other online platforms (1). In fact, in the wake of COVID-19, gambling rates across the globe dramatically increased by about 67% (1). This trend raises concerns about the possible negative effects associated with a large number of individuals developing a gambling addiction. Ranging from financial loss to a higher rate of suicide, the effects of gambling should be recognized as harmful, especially when studies are reporting staggering results, with one study estimating that individuals with a gambling disorder are almost 15 times more likely to commit suicide compared to the general public (2). Not to mention, the adverse effects of gambling spillover beyond gamblers themselves, as gambling can significantly burden friends and families and even communities via "both tangible and intangible costs" (2). Furthermore, while the gambling elements in popular video games are becoming more prevalent, there are few to no restrictions against them, and they are becoming harder to detect (3,4). Thus, it is imperative to investigate what other factors influence an individual's decision to continue or quit an online gambling game. Understanding what elements drive people to quit is crucial as it would help organizations and governments implement new rules or mechanisms that discourage continued gambling.

Previous research suggests that people have misconceptions, or irrational beliefs, about how past events affect probabilities of future events (5). The gambler's fallacy is a phenomenon in which people irrationally make assumptions about future wins or losses based on the past results they have experienced, even in cases of two independent events (5). For instance, if a player were to lose a coin-flip three times in a row, the player may believe that they now have better odds for the coin to land on their preferred side on the next attempt. Based on the gambler's fallacy, there is reason to suspect that people might be less likely to quit after consecutive losses. However, we could also theorize that the gambler's fallacy may have the opposite effect to as stated above (5). The irrational beliefs about how past results affect future outcomes could make people more likely to quit after experiencing several losses, because experiencing consecutive losses may lead a player to believe that their "luck has run out" and that future losses are now more probable.

Another key factor that may influence an individual's decision to continue playing is loss aversion (6). Loss aversion refers to a phenomenon where, from a given reference point, people are impacted more by their losses compared to their wins of equivalent value (6). Loss aversion could make an individual less likely to quit after a few losses. Ending the game immediately after a losing round could mean accepting the loss as the final result of the game, so they may choose to continue playing until they achieve a win, to avoid accepting the loss. Thus, our theory implies that people may be less likely to quit if they have just experienced a loss.

However, there are other reasons why people could be more likely to quit after several consecutive losses. Individuals may believe that experiencing several consecutive losses is highly improbable, leading them to presume the coin-flip is unfair (7). Previous research suggests that people are unable to consistently judge the randomness of sequences (8–9). Specifically, people believe that a random sequence should contain more alternation than what would actually occur in a random sequence, meaning they believe a random sequence of heads or tails should not contain many consecutive, identical outcomes (8–9). Thus, given these previous findings that people are prone to dismiss the possibility of consecutive, identical outcomes, a gambler who experiences many consecutive losses may suspect that the results are not truly random and therefore feel discouraged to continue playing. Crucially, this suggests that our tendency to misjudge random sequences can lead to a loss of trust in the fairness of the game, consequently impacting our motivations to continue gambling.

There may be mechanisms by which losses could make people more likely to quit after a few losses, and mechanisms by which losses could make people less likely to quit. It is possible that all of these mechanisms are at work and are competing with each other. Furthermore, depending on the number of losses, the magnitude of each effect could vary, so the question of which mechanisms have stronger effects on an individual's decision to quit or continue may depend on the exact number of consecutive losses experienced.

In our study, we posit an original theory that people will be likely to quit after three consecutive losses because of what we refer to as the "three strikes heuristic". Previous studies have demonstrated that repeated exposures to certain patterns can lead individuals to form "heuristics" or mental shortcuts (6). In games or gambling, the prototype of the number three is often deeply embedded — that is, the concept of the number three, or a triad, is cognitively salient as a result of repeated exposure through games and cultural norms (10). For instance, in baseball, three strikes results in an out. Other similar games revolving around the number three are slot machines, in which your objective is to get the same shape three times in a row. In the classic game of Tic-Tac-Toe, not only is the name composed of three words, but also, the fundamental method to win the game is by placing three of your markers consecutively along the three-by-three board. In this way, the concept of three attempts in a game is highly salient in people's minds, inducing people to perceive three consecutive losses as an important threshold for deciding when to quit gambling. Therefore, in this study, we hypothesized that losses may initially encourage individuals to continue due to loss aversion and the gambler's fallacy, but only up to a threshold, which we predicted to be three consecutive losses. After this threshold, we hypothesized that the amount of discouragement individuals experience — such as feeling unlucky, experiencing loss aversion, or suspecting that the game is unfair — would have a greater effect, leading to a higher probability of quitting.

In this paper, we investigate whether people will be more or less likely to quit after experiencing consecutive losses in a gambling game. We tested our hypothesis by having participants take part in a simple gambling game. In the end, our original hypothesis was partially supported since we found that the probability of quitting decreased after a few consecutive losses and then increased after passing a threshold of four or more consecutive losses. These findings have important implications for what interventions may be useful in discouraging online gambling.

RESULTS

Using a survey experiment, we directly tested whether experiencing consecutive losses would increase or decrease the probability of quitting in the context of gambling and whether there is a threshold at which the probability of quitting switches from decreasing to increasing. For our study, we created a simple gambling game in which participants could choose to play for as long as they wanted. We gathered participants from Prolific, an online research platform that pools eligible participants from all around the globe (11). In our study, there were 277 participants (**Table 1**). Each participant chose how many times they played the decision-making game, where participants were asked to predict the outcome of a coin-flip (**Figure 1**). The number of times played ranged from one to 104 rounds, with a mean of 26.8, a standard deviation of 29.3, and a median of 14 (**Figure 2**). In other words, most of the participants played 14 rounds, with a smaller number of participants playing up to 104 rounds (**Figure 2**)

In this game, participants played to win tokens. Participants were told that a token was worth \$0.02 USD. Each participant started with a balance of 15 tokens (\$0.30). Depending on the results of the coin-flip, a value of one token was either added or subtracted from the participant's balance. The participants' ending balances ranged from 0 to 38 tokens (\$0 to \$0.76), with a mean of 14.98 tokens (\$0.2996), a standard deviation of 29.3 tokens (\$0.586), and a median of 15 tokens (\$0.30) (**Figure 3**).

The primary goal of the study was to estimate how the probability of quitting varies depending on how many consecutive wins or losses the participant had just

Category		Number	Percentage
Age	18 to 24	75	27.08%
	25 to 34	118	42.6%
	35 to 44	52	18.77%
	45 to 54	23	8.3%
	55 Plus	9	3.25%
Sex	Male	138	49.82%
	Female	139	50.18%
Region	Africa	107	38.63%
	Asia	14	5.05%
	Europe	109	39.35%
	North America	17	6.14%
	Oceania	13	4.69%
	South America	17	6.14%
Employment Status	Full-Time	137	49.46%
	Part-Time	39	14.08%
	Unpaid	9	3.25%
	Unemployed	34	12.27%
	Expired	40	14.44%
	Other	18	6.5%
Ethnicity	Asian	25	8.96%
	Black	85	30.47%
	Mixed	18	6.45%
	White	138	49.46%
	Other	13	4.66%

Table 1: Demographic overview of sample population. Participants aged 18 and above (n = 277) filled out a Prolific survey which automatically collected their demographic information as listed in their profile.

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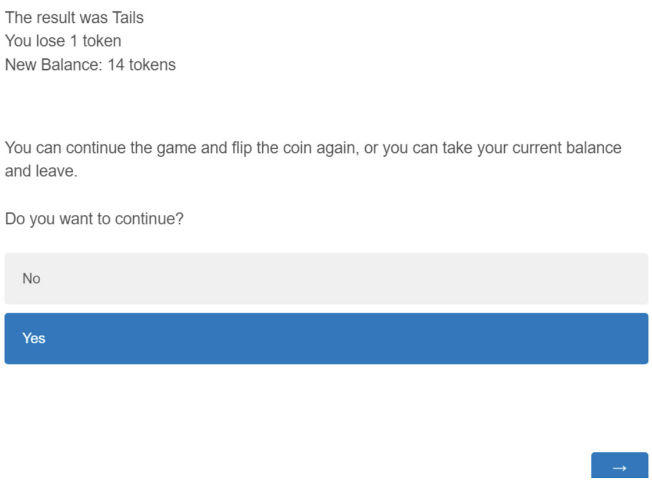

Figure 1: *Qualtrics* Survey View. The *Qualtrics* survey screen displays the coin-flip's result, the amount of tokens the participant losses or gains, and their new balance. Participants are then prompted on whether or not they would like to continue playing. This particular screen is shown to participants after choosing a side of the coin-flip.

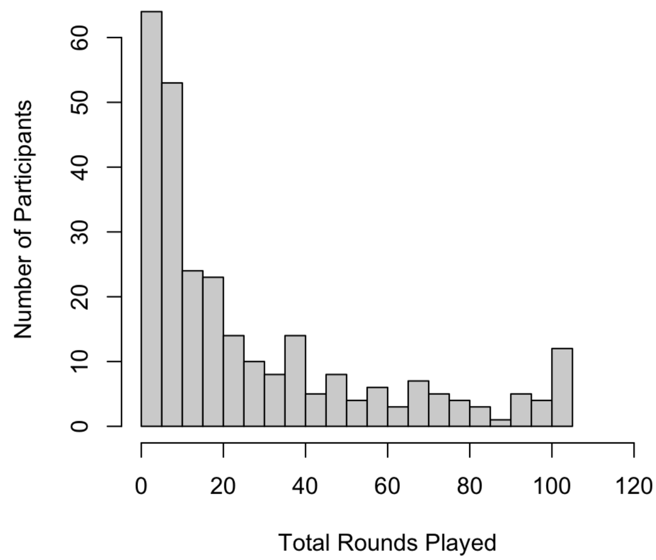

Figure 2: Frequency distribution of number of rounds played by each participant. Participants (n = 277) played repeated rounds of a gambling game in a Qualtrics survey, and after each round, they chose whether to continue the game for more rounds. The histogram above shows the distribution of the number of rounds played, ranging from 0 to 104, with a bin size of 2.6.

experienced. The probability of quitting varied significantly based on the number of consecutive losses the participants experienced (χ^2 test, $\chi^2 = 26.956$, df = 9, $p = 0.001422$) (**Figure 4**). As predicted, we found that the probability of quitting initially decreased as the number of consecutive losses increased, until it reached a threshold number of losses, after which the probability of quitting increased (**Figure 4**). However, the specific threshold is not what we had predicted. We predicted that the probability of quitting would increase after three consecutive losses, but the actual threshold was four consecutive losses (**Figure 4**). Hence, our hypothesis was partially supported.

Upon completing our data analysis, we carried out further exploratory analyses and found that the probability of quitting was notably different across different groups. The data was separated into three arbitrary groups: those who experienced one or more wins, those who have experienced one to three consecutive losses and those who have experienced four or more consecutive losses. A chi-squared test showed a significant difference between these three groups ($\chi^2=21.529$, df = 2, p-value = 0.000021). Specifically, the percentage of players who chose to quit was lower among those who had just experienced one to three losses (2.7%) compared to those who had experienced one or more wins (4.0%) (difference-of-proportion, $p = 0.0032$) (Figure 4). A difference-of-proportions test using the prop.test function in R showed a statistically significant difference between these two groups ($p = 0.0032$) (**Figure 4**). Additionally, the percentage of players who chose to quit was lower among those who had just experienced one to three losses (2.7%) compared to those who had experienced four or five losses (6.6%) (difference-of-proportion, $p = 0.000015$) (**Figure 4**). These findings seem to suggest consecutive wins may also impact the probability of quitting. This may be of interest for future researchers to investigate further. It is important to note that these findings were explored after the main analyses and therefore not part of our hypothesis.

Another interesting pattern was discovered through exploratory analysis. The distribution of balances seemed to be almost a normal distribution, other than the notable spikes at a balance of ten tokens ($0.20) and a balance of 20 tokens ($0.40) (**Figure 3**). This indicates that many players chose to end when they had either a balance of 10 or 20 tokens. The probability of quitting varied depending on the player's current balance, with a clear spike at a balance of 10 tokens and a balance of 20 tokens (**Figure 5**). Thus, it seems that many participants may be using the numbers 10 and 20 as thresholds for their ending balance. If they lose many times and their balance goes down to 10 tokens, they quit. If they win many times and their balance reaches 20 tokens, they also quit.

DISCUSSION

We studied the relationship between the percentage of individuals quitting and the number of consecutive losses experienced in order to understand the factors that lead to an individual quitting a session of gambling. In our study, we had hypothesized that the probability of quitting would initially decrease after a few consecutive losses and would then increase after reaching a higher threshold of consecutive losses. Consistent with our hypothesis, experiencing a few consecutive losses initially decreased the probability of quitting, but after passing a threshold, this led to an increase in the probability of quitting. However, instead of a threshold of three consecutive losses, the probability of quitting increased after reaching four or more consecutive losses. Therefore, our hypothesis was partially supported since there was indeed a threshold of losses before quitting, but our hypothesis was not fully supported since this threshold varied from the one we predicted.

One possible explanation for this is that people's beliefs about the probability of future wins or losses may change depending on whether they have just experienced consecutive

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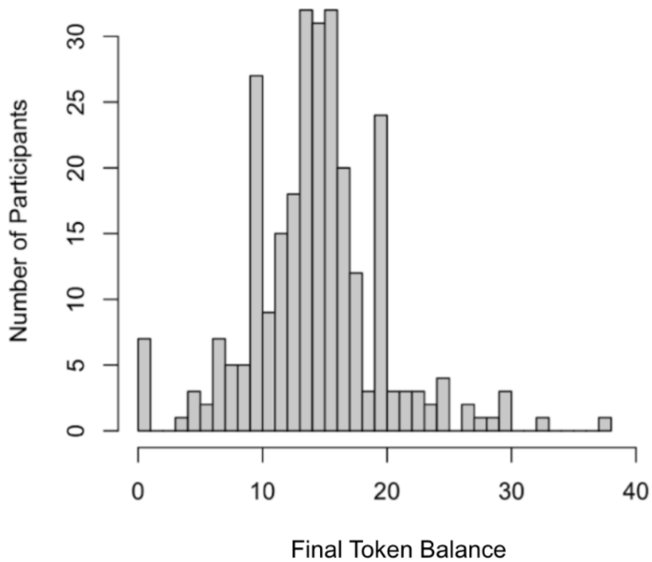

Figure 3: Frequency distribution of participants' final point balance. Participants (n = 277) played repeated rounds of a gambling game in a Qualtrics survey, and after each round, they chose whether to continue the game for more rounds. When the participant chose to quit, the participant's final point balance was recorded in the data. Each of these tokens was worth $0.02, which was awarded to the participant.

wins as opposed to consecutive losses. The gambler's fallacy states that people tend to believe that their probability of winning is affected by the outcome of the previous event (9). When participants have just experienced a few losses, this could lead them to believe that they are more likely to get a win and thus could lead them to be less likely to quit in that situation (9). In other words, if an individual loses a coin toss three times in a row, that individual may believe that a win is due soon.

Additionally, another interpretation of this finding is that loss aversion could lead people to be less likely to quit after a few losses because people might strongly dislike ending the game on a loss (6). So, they may continue playing until they are able to achieve a win. After a loss, players may believe that if they quit now, they will have to accept that they lost the game today. If they continue playing until they get a win, the loss is not realized. If this theory is correct, then one way to mitigate this effect could be to force players to fully process the loss before they make a decision to play another round. (12). Policymakers who wish to reduce gambling behaviors could impose a mandatory pause period after a loss, which could force players to accept that they lost the game today. The results suggest the possibility that this memory of having lost the game could create a long-term mental association of this game with the idea of losing. The memory that they lose in this game could then lead the player to have less positive feelings toward playing this game, which could make them less likely to play again. However, this intervention would only be effective if the loss aversion theory holds true. Future studies should test this hypothesis.

While loss aversion may explain why participants continue gambling after experiencing a few losses, we believe that another psychological bias that could reinforce this behavior is the sunk cost fallacy. The sunk cost fallacy is the phenomenon in which people who have invested more resources into a course of action are more likely to continue that course and not quit (13). In the case of this study, when an individual has lost one or two rounds, the amount of money they have just lost could be thought of as a sunk cost or investment. Thus, they could be more likely to continue because they want to get some benefit from the costs they have already sunk into the game. However, the chance of winning does not change after investing resources, which means that this action is irrational. To sum, the sunk cost fallacy and loss aversion may both be potential reasons for why people are less likely to quit after a few losses.

However, once the number of losses passes a threshold, we theorize that the accumulating losses may become too emotionally and financially distressing for the player to justify continuing, in which case they may then decide to quit. Individuals who have experienced several consecutive losses may hold an irrational belief that their luck has run out, causing them to be discouraged from continuing to play.

Another possible factor could be that individuals who have experienced several consecutive losses begin to doubt the legitimacy of the game. Previous research suggests that people expect a random string to have more alternation and fewer consecutive identical results compared to what would actually occur in a true random sequence (8,9). This may cause people to doubt the fairness or true probability of the coin-flip after experiencing consecutive wins or losses. It is possible that this could be part of the reason why people become more likely to quit our game after several consecutive losses.

This study has several limitations. First, the sample used in this study was not randomly selected; rather, it was a convenience sample consisting only of volunteers recruited via Prolific. This approach opened up the possibility of bias, as volunteers on Prolific may behave differently compared to the general public. Broadly, researchers in social sciences have argued that, although responses collected via such online research platforms like Prolific and Amazon Mechanical Turk (MTurk) can be more generalizable to populations than typical in-person convenience samples (e.g. college students), these responses still come from individuals who self-selected themselves (14). For example, it could be that people who voluntarily join these online platforms are individuals who are more technologically savvy because they would need to be able to navigate these platforms to successfully complete requested tasks. In such a case, these respondents, who are relatively more competent with technology, could be younger or more educated. In fact, given Prolific's official disclosure which states that their volunteer respondents were initially recruited on social media platforms, it could be possible our sample of respondents were generally more familiar with online platforms generally, which could be associated with increased likelihood of engaging with online gambling platforms (15). These are some speculations within the context of our study. Future studies should be mindful of the limitations that are inherent to online research platforms like Prolific.

Another limitation of this study was that the financial stakes of the game were small. These lower stakes could result in different risks compared to games with higher financial rewards and losses, possibly impacting the overall quitting behavior observed in the study. For example, in a

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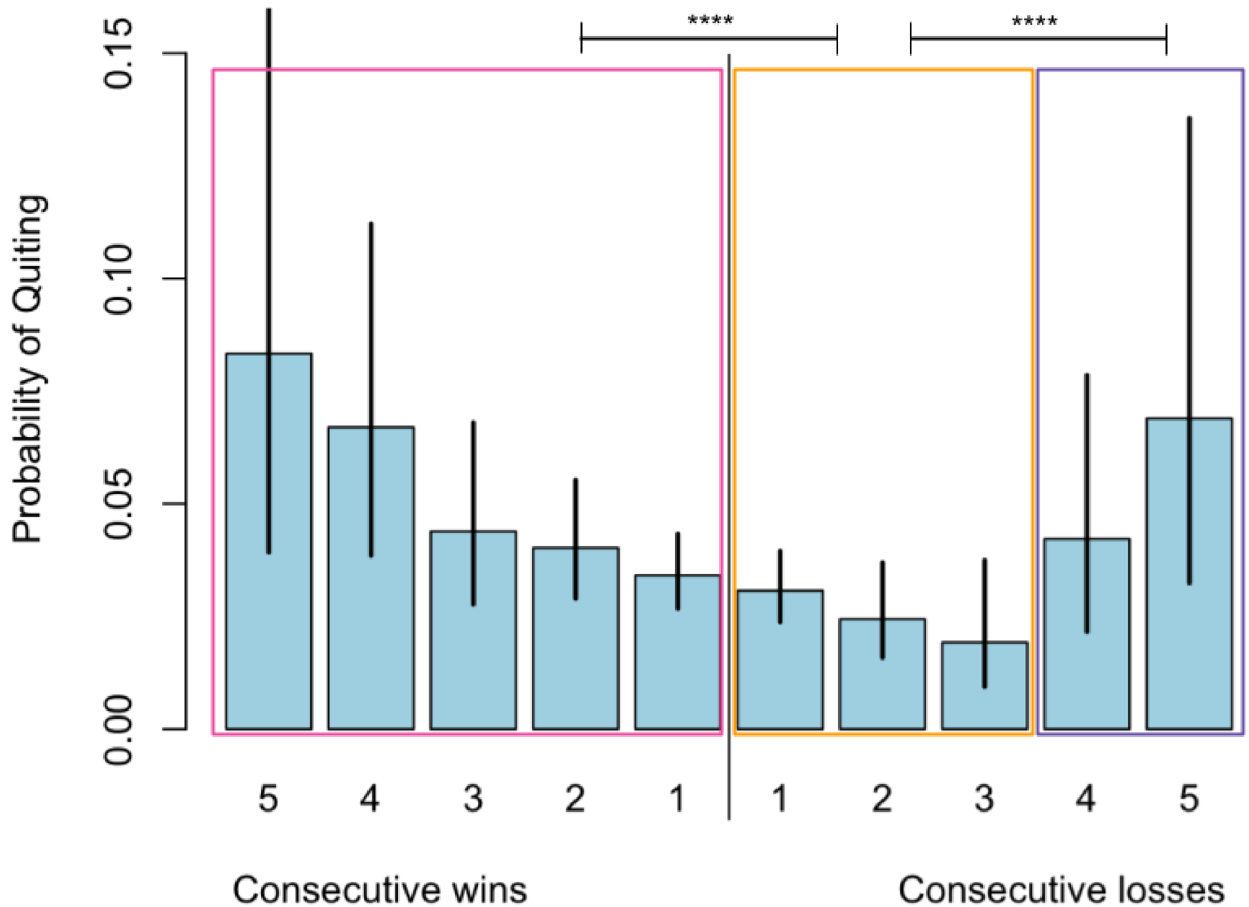

Figure 4: Probability of quitting and number of consecutive wins or losses. Participants (n = 277) played repeated rounds of a gambling game in a Qualtrics survey. Each estimated probability is shown with a 95% confidence interval. A chi-squared test using the ten groups shown here finds that there is significant variation between groups (χ^2 = 26.956, df = 9, p = 0.001422). When testing pairwise differences, there are no significant differences between any adjacent pair of groups shown here. .However, when the groups were put into larger arbitrary groups, there is a significant difference between the group who experienced one to three losses (indicated by the orange box) and the group who experienced four or more losses (indicated by the purple box) (p = 0.0032) There was also a significant difference between those who experienced one or more wins (indicated by the pink box) and those who experienced one to three losses (indicated by the orange box) (p = 0.000015).

scenario with low stakes, individuals may be more willing to continue playing for a longer period due to the minimal financial impact of their losses. This could lead to a higher number of rounds played before they decide to quit. On the other hand, when the stakes are high, participants might adopt a more cautious approach due to the greater financial risk involved. The pressure of high stakes might prompt more conservative behavior, leading to a lower number of rounds played. Therefore, future studies are encouraged to use larger stakes to ensure participants have a higher financial incentive to make thoughtful decisions in the survey game the way they likely would in the real world.

The appearance of our coin-flip game was simple, featuring only text-based choices between heads and tails with no additional visual or physical stimulation. This could make participants bored with the game, causing them to quit sooner than they would quit a more engaging game. Furthermore, the game's appearance was intended to be straightforward, but this simplicity might have also led to concerns about the fairness of the game. For instance, participants who experienced a long series of consecutive losses might have become suspicious about the coin-flip's randomness, especially if they encountered a streak of four losses in a row. The absence of any visual cues or feedback may have increased these suspicions, influencing participants' decisions to quit based on their perception of the game's fairness. In future studies, researchers should consider performing the coin-flip in person to reduce the skepticism about the legitimacy of the experiment. Although this does come with the downside of a larger expense during the research. If this research were performed on a digital platform, it may be beneficial to incorporate special effects or flashing lights when a win or loss is made in order to better mimic an actual casino game.

For the sake of testing the fundamental question of when people decide to quit, it is important that there is no limit to how many rounds a participant can choose to play. However, due to limitations on the *Qualtrics* platform, there was a finite, albeit large, number of rounds available to the participants. In our data, we only had 12 out of 277 participants reach the end, meaning this did not have a significant impact on our results. Nevertheless, future researchers may use a different

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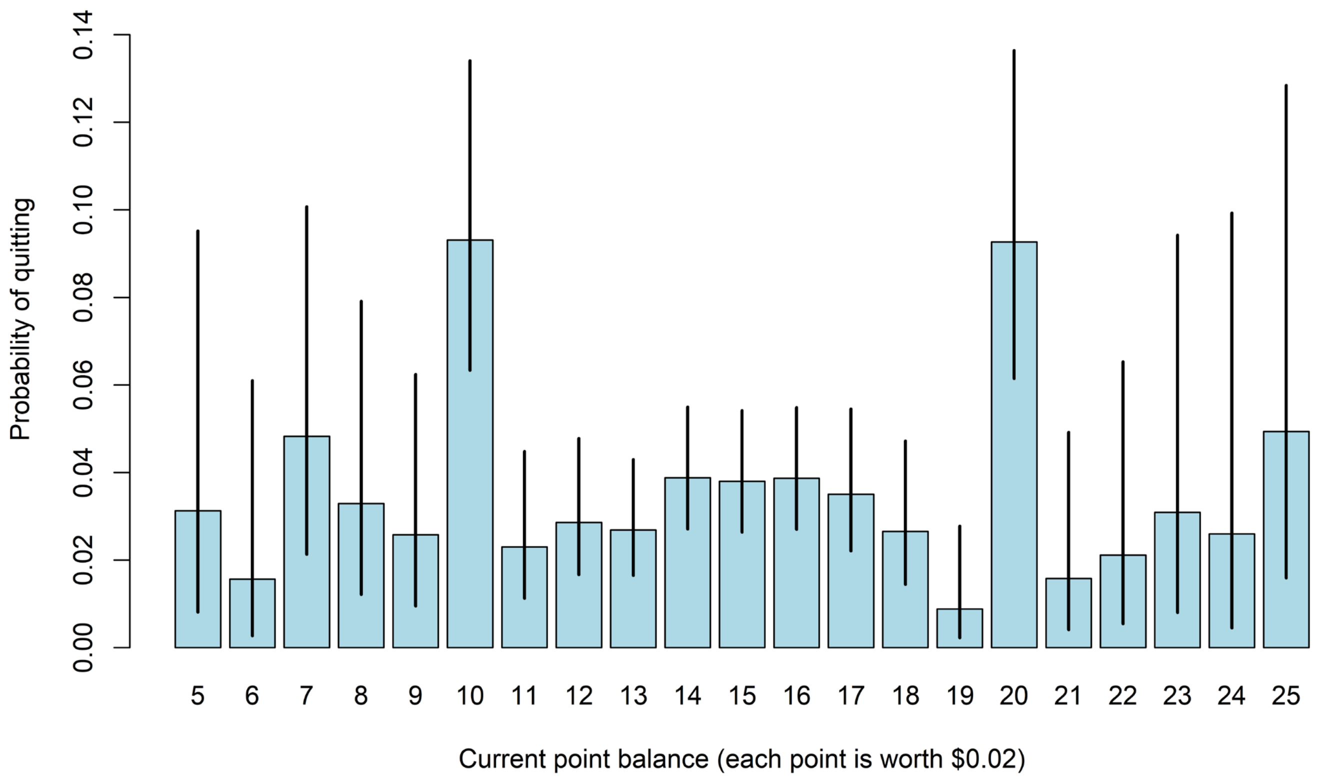

Figure 5: Probability of quitting compared to current balance. Participants (n = 293) played repeated rounds of a gambling game in a Qualtrics survey. The probability of quitting in each round of the game is plotted in relation to the participant's current balance. Each estimated probability is shown with a 95% confidence interval. This figure presents an exploratory analysis.

survey platform or method to avoid running into this problem.

In our study, another limitation was that participants started with a finite amount of money. This limitation meant that participants whose balance reached zero were forced to quit even if they wanted to continue. Thus, this limits our ability to observe how long these participants would have chosen to continue playing. However, there were only seven participants who ran out of money, so this would have a minimal impact on this study. In future studies, it might be beneficial to start with a larger balance to reduce the chance of running out of money. Prior to this study, we used computer simulations to calculate the likelihood of running out of money for a given starting balance. From this, we chose to use a starting balance to give a low probability of running out of money. However, participants chose to play more rounds than we had originally guessed.

Additionally, the differences mentioned in the Results between the three specific groups, those who experienced one or more wins, those who experienced one to three consecutive losses, and those who experienced four or more consecutive losses, were not predicted in advance (**Figure 4**). This part of the analysis is therefore exploratory and should be interpreted cautiously.

Finally, the findings of the present study have significant implications about gambling behavior for adults and adolescents alike, but we would like to note that the sample population of this study was limited to consenting adults. We see great value in replicating this study with an adolescent sample population: after all, adolescents in their developmental stage may be more vulnerable to pathological gambling than their adult counterparts (15). Therefore, we encourage future researchers to gather youth samples, with appropriate ethical practices, to improve the external validity of our findings, potentially addressing the issue of adolescent gambling behavior as well.

In sum, the results of this study indicate that experiencing a few consecutive gambling losses initially encourages people to continue gambling, although this only holds true up to four consecutive losses, where individuals are rather discouraged from continuing to gamble. Our study can inform policymakers and regulators about what interventions can be implemented in games such that players are not encouraged to continue gambling. Future research should also seek to replicate the findings of the current study in more realistic and engaging games with larger financial stakes.

MATERIALS AND METHODS

Participant recruitment

A total of 277 participants were recruited through Prolific, an online research platform where individuals receive money for answering surveys (16). All participants were consenting adults, which means that participants were over the age of 18 (16). The Prolific platform screened the participants to only pool those who "speak English fluently". Each participant was only allowed to answer the survey once. The participants were required to sign a consent form before being allowed to see or enter the survey. From the Prolific website, participants were redirected to Qualtrics (17). Qualtrics is an online survey platform where our original survey was drafted and published (17).

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Coin-flip game

Participants were shown a set of instructions explaining the rules for a coin-flip game. They had an initial balance of 15 tokens. This specific starting balance was chosen from our previous computer simulation (18). It was calculated that this starting balance had a less than one percent chance of running out of tokens after playing 30 rounds. Correctly predicting the coin-flip led to gaining a token, and incorrectly predicting it led to losing a token. Each game token was equivalent to $0.02. This money was awarded to the participants after they chose to quit. At the beginning of each round, participants were shown their current balance of tokens and were given the choice between heads and tails. After they made their selection, the participant was shown a randomly selected result of the coin-flip, either heads or tails, how much they earned or lost, and their new balance. Then, they were asked if they wanted to continue playing. If they chose to quit the game, the survey ended by revealing the number of losses, wins, and their final balance, which was awarded to the participant after the tokens were converted to cash rewards. If they chose to continue the game, the *Qualtrics* survey redirected the participant back to choosing their side of the coin-flip until they decided to quit.

This game was created within a *Qualtrics* survey using an embedded data field to track each participant's balance. The balance was updated based on the participant's outcomes in the game. In each round, after the participant made a selection, a randomizer determined one of two possible survey flows: either increasing the balance by one or decreasing it by one. The corresponding value was updated and stored as an embedded data field, which was then used as piped text to inform the participant of the coin-flip result, their updated balance, and their number of wins and losses. Since *Qualtrics* did not have an infinite loop feature, the survey-flow elements were copied and pasted more than 100 times to make it seem like an infinite loop. This allowed the participant to play up to a hundred rounds of the game if they chose, but in the case that the participant reached this limit, the survey automatically directed them to the ending screen displaying their statistics. *Qualtrics* recorded the total number of times the participant played, the order of wins and losses, the total number of wins and losses, and the final balance of tokens.

Data analysis

This data was then downloaded as a CSV file with one row per participant. However, for the data analysis, each time a participant decided to continue the game or quit was treated as a separate observation in the data. Thus, the data was reformatted to have one row per decision rather than one row per participant. This process of reformatting was done by importing the CSV file into R, and then R code was used to calculate the values for the reformatted data. The data contained 7655 observations (277 participants × average of 27.64 rounds per participant) (19). Each row of the reformatted data showed the participant ID number, whether the most recent coin-flip was a win or a loss, the number of consecutive wins and losses, the participant's balance, and the participant's decision to either quit or continue. The primary dependent variable was whether the participant chose to quit or continue. The percentage of the time the participant chose to continue was calculated. This percentage was calculated separately for each possible number of consecutive wins and losses, ranging from five consecutive wins to five consecutive losses. This enabled us to see whether the probability of quitting was greater when the participant had experienced three consecutive losses. In 96.4% of the observations, the participants chose to continue, while in the other 3.6%, they chose to quit. These percentages varied based on the number of consecutive losses the participants experienced. To test the statistical significance of these differences, we conducted a chi-squared test using the chisq.test() function in the "stats" package default in R (Version 4.4.1). For this test, we used ten groups defined by how many consecutive wins or losses the participant had just experienced, ranging from five consecutive wins to five consecutive losses.

Finally, as an exploratory analysis, the percentage of quitting for each possible level of current balance was also calculated, ranging from a balance of five to 25 tokens ($0.10 to $0.50). The prop.test() function in the "stats" package in R (Version 4.4.1), which is available as default, was used to calculate confidence intervals for each estimated percentage and to calculate *p*-values for difference-of-proportions tests (20).

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