Psychology of Addictive Behaviors

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Accuracy of Self-Reported Gambling Frequency and Outcomes: Comparisons With Account Data

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Objectives: The ability to accurately recall past gambling behavior and outcomes is essential for making informed decisions about future gambling. We aimed to determine whether online gambling customers can accurately recall their recent gambling outcomes and betting frequency. ***Method:*** An online survey was distributed to 40,000 customers of an Australian sports and race wagering website which asked participants to recall their past 30-day net outcome (i.e., total amount won or lost) and number of bets. We compared responses to these questions with participants' actual outcomes as provided by the online site. ***Results:*** Among the 514 participants who reported their net outcome, only 21 (4.09%) were accurate within a 10% margin of their actual outcome. Participants were most likely to underestimate their losses ($N = 333$, 64.79%). Lower actual net losses were associated with greater underestimation and overestimation of losses. Of the 652 participants who reported their gambling frequency, 48 (7.36%) were accurate within a 10% margin of their actual frequency. Most participants underestimated their number of bets ($N = 454$, 69.63%). Higher actual betting frequencies were associated with underestimating betting and lower actual frequencies with overestimating betting. ***Conclusions:*** The poor recall accuracy we observed suggests public health approaches to gambling harm minimization that assume people make informed decisions about their future bets based on past outcomes and available funds should be reconsidered. Findings also question the reliability of research outcomes predicated on self-reported gambling behavior. Research is needed to determine the best methods of increasing people's awareness of their actual expenditure and outcomes.

Public Health Significance Statement

This study found that most people who gamble online are unable to accurately recall their past 30-day gambling outcomes and betting frequency. The majority of people underestimate how much money they have lost and how many bets they have placed when asked to self-report their gambling behavior.

Keywords: self-report accuracy, recall accuracy, problem gambling, gambling disorder, gambling harm

The ability to accurately recall past gambling behavior and outcomes is important for several reasons. Foremost, an accurate understanding of one's gambling outcomes is crucial for making decisions about how much or whether to continue gambling in the future (Clark, 2010). Only by keeping track of wins and losses can one prevent overspending and ensure they are appropriately allocating funds to the different aspects of their life (bills, daily expenses, savings, etc.). Indeed, the "responsible gambling"

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All materials associated with this study can be accessed via this project's Open Science Framework page, including the survey used to collect data, the dataset, and analysis scripts: https://osf.io/8vjeh/. This manuscript first appeared as a preprint on PsyArXiv on 19/07/2021: https://psyarxiv.com/5hs7j/.

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approach to reducing gambling harm, often espoused by government and industry, places emphasis on individual responsibility, informed decision making, and self-monitoring (Miller et al., 2016; Miller & Thomas, 2018). The foundation of informed decision making is understanding whether one is winning or losing and by how much, and people's understanding of this and their ability to self-monitor outcomes is implicitly assumed when discussing the role of personal responsibility in the development of gambling problems (Shaffer & Ladouceur, 2021).

Gambling researchers frequently rely on people's ability to recall their past gambling in self-report studies. For example, Currie et al. (2017) used self-reported past-month gambling expenditure to determine a specific "low-risk" threshold for monthly spending on gambling, concluding that individuals who gamble above this level are more likely to experience harms (see also Currie et al., 2021). Notably, jurisdictional prevalence studies typically rely on self-report to determine the prevalence of gambling and related harms (e.g., Tajin et al., 2021; U.K. Gambling Commission, 2020), and these outcomes are used as the basis of determining policies and practices. The focus of the present study is the extent to which people can accurately recall their past gambling outcomes and behavior and the implications of this for reducing gambling harms and studying gambling-related phenomena.

The few existing studies on this topic have found that many people are unable to accurately recall their recent gambling outcomes (Auer & Griffiths, 2017), and the extent of the discrepancy between self-reported and actual outcomes is positively associated with problem gambling (Braverman et al., 2014). Braverman et al. (2014) asked 773 European subscribers to bwin.party's online gambling service to report how much money they had won or lost in the last three or 12 months and compared their responses with their actual "net outcome" (i.e., the overall amount won or lost in that period) as provided by the gambling site. Most participants (51% at three-month recall and 56% at 12-month recall) were favorably biased in their recall. That is, they were losing gamblers who underestimated their losses or, less commonly, winning gamblers who overestimated their winnings. Conversely, around one-third of participants (36% at three months and 37% at 12 months) were unfavorably biased—losing gamblers who overestimated their losses or, less commonly, winning gamblers who underestimated their winnings. The authors developed a standardized measure of inaccuracy (or "bias," as they termed it) calculated as: (self-reported outcome—actual net outcome)/average size. "Accurate recall" was defined as a bias score within the −1 to +1 range, which is equivalent to the self-reported outcome being within one average bet size of the actual outcome. Only 13% and 7% of participants accurately recalled their past three-month and 12-month outcomes, respectively.

Auer and Griffiths (2017) performed a similar study in 2015 with 1,335 Norwegian subscribers to the state-owned online gambling site *Norsk Tipping*, asking participants to recall their outcome for the past month. Like Braverman et al. (2014), they found people were more likely to be favorably biased (17%; underestimating losses or overestimating winnings) than unfavorably biased (9%; overestimating losses or underestimating winnings). However, unlike Braverman et al. (2014), considerably more participants were classified as accurately recalling their net outcome (74%) using the same standardized measure of inaccuracy, which the authors attributed to the shorter period of recall (one month as opposed to three or 12 months).

Two theories have been proposed in an attempt to explain poor recall accuracy when reporting gambling outcomes. Braverman et al. (2014) suggested increased arousal during gambling could be responsible, adducing evidence that arousal—particularly negative arousal—can selectively bias people's attention and their subsequent recall toward highly salient events (Sutherland & Mather, 2012; see also Mather et al., 2016). Such events in the gambling context could include large wins or losses, which can focus one's memory on these outcomes (Wood & Williams, 2007). Braverman et al. (2014) also implicated mood and substance disorders—which frequently co-occur with problem gambling (Bischof et al., 2013; Håkansson et al., 2018)—as these are thought to disrupt cognitive processes such as memory and attention (Bruijnen et al., 2019; Porter et al., 2015).

One explanation for recall inaccuracy not discussed in previous studies is the complexity associated with calculating one's net outcome. People may place many bets within a one or three-month period and thus accurately summing these outcomes may prove challenging. A recent analysis of nearly 40,000 online gambling customers account data in Australia found that the median number of bets placed in a year was 41, and 25% of the sample placed 184 bets or more (Heirene et al., 2021). Further, there may be different ways in which people calculate their net outcome. Some may include their stake in winnings, whereas others may not. For example, a person who places $50 worth of bets in one month and wins $100 may report their net outcome as $50 (without stake) or $100. Others may only include the money deposited into their account and not losing bets in their calculations. Someone who deposits $10 into their account, wins $50 but subsequently loses all of this might report their net outcome as −$10 or −$50.

Providing guidance on how to calculate net outcome when asking people to report their outcomes could improve recall accuracy, though neither Braverman et al. (2014) nor Auer and Griffiths (2017) did this. Braverman et al. (2014) only asked: "How much money did you win or lose during the last three (12) months on each type of gambling activity at bwin? (Record your net losses or winnings—how much you are behind or ahead)," and Auer and Griffiths (2017) did not provide the exact question asked but stated: "one survey item asked gamblers to estimate their overall loss or win during a 1-month period immediately prior to the survey." Providing guidance on standard drink sizes has been shown to alter people's self-reported alcohol consumption (Gilligan et al., 2019), suggesting a similar effect could be observed in the gambling context. Question wording may also affect self-reported outcomes. Wood and Williams (2007) asked people about their past-month net outcome using 12 different questions and found minor variations in the phrasing resulted in significantly different reported outcomes.

If recall accuracy is partially mediated by the complexity and variability involved in calculating net outcome, then people's ability to recall more simple aspects of their gambling behavior, such as the number of times they have gambled, should be more accurate. However, no studies have investigated gambling recall accuracy beyond net outcome. This remains an important and yet unexplored area of study as gambling studies frequently ask people not only to report their outcomes, but also the frequency or regularity of their gambling (e.g., Gainsbury et al., 2014; Raisamo et al., 2013; U.K. Gambling Commission, 2020). The aim of the present study was to extend previous work in this area (Auer & Griffiths, 2017; Braverman et al., 2014; Wood & Williams, 2007) in two ways. First, by asking online gambling customers to self-report their past one-month net outcome and providing them with some guidance on how to calculate their outcomes. With this added guidance, observing improved recall accuracy by comparison to previous studies may imply that poor recall of gambling outcomes can be ameliorated via improving people's understanding of how to calculate their outcomes. This could have important implications for developing strategies that aim to increase consumers' informed decision making. Second, we extended previous research by asking participants to also report their past one-month gambling frequency. If recall rates for betting frequency are also poor, then greater caution is warranted when interpreting the findings of studies where the outcomes are predicated on self-reports as recall issues extent beyond net outcome reporting. Better understanding the prevalence and extent of biases when recalling both outcomes (e.g., underestimating losses) and frequency (e.g., underestimating bets) will assist with determining the extent to which these may be distorting informed decision making.

We did not preregister any a priori hypotheses, although we anticipated that net outcome recall accuracy would be more accurate here than in previous studies due to the instruction provided. We also anticipated that participants would be more accurate when recalling their betting frequency compared to net outcome due to the complexity associated with calculating the latter.

Method

Transparency and Openness

All relevant materials associated with the study can be found on our Open Science Framework; OSF project page (https://osf.io/8vjeh/), including the full survey completed by participants, the raw data, the analysis script used to produce the results reported here, and an analysis document outlining the full process of processing and analyzing the data that includes all outcomes produced from this process. This manuscript—including all outcomes, tables, and figures reported—was produced computationally in R Markdown and can therefore be independently reproduced (see guidance on reproduction in *Analysis and code* subsection). In the following methods sections, we follow the Journal Article Reporting Standards (JARS; Appelbaum et al., 2018) and report how we determined our sample size, all data exclusions, and all measures used in the study. This study's design and its analysis were not preregistered.

Design and Procedures

We worked with a large online wagering operator based in Australia to collect survey responses and match these with actual betting data. The operator sent an email containing a link to our survey to a random selection of 40,000 customers in October 2020. Customers were told that participation in the survey was voluntarily and that they would not be reimbursed for completion. Email invitations framed the study to focus on responsible gambling as opposed to self-report accuracy which may have impacted participation rates. The online survey was hosted by the operator on the Qualtrics platform and remained open for one week after the initial email was sent to customers. The survey asked participants about their gambling frequency and outcome over the last 30 days:

1. Approximately how many bets did you place with [operator] in the last 30 days?
2. Approximately what was your net outcome with [operator] of the last 30 days (i.e., the amount you won or lost)? Calculating your net outcome—here's two examples: (a) You had three bets in the last 30 days. $10 on a horse at odds of $3.00 which won, and two $20 bets on Australian Football League (AFL) games that lost. In total, you collected $30 after placing $50 worth of bets, so your net result is −$20 ($30 minus $50). You lost $20. (b) You had five bets in the last 30 days, all of them $50 on $2 favorites. Three of the favorites won. So, in total you received $300 after placing a total of $250 in bets. Your net result is $50 ($300 minus $250). You won $50.

The examples of how to calculate net outcome were developed in combination with the gambling operator to use terminology and phrasing familiar to their customer base. In these examples, the dollar sign on the odds values can be considered redundant and may not be included on other sites. For example, odds at $2 mean that the operator will deposit two times the bet if successful (i.e., a return two times the value staked, including the stake). To make the calculation as simple as possible for participants, net outcome was defined as "all bet winnings minus stake" so that net losses were minus values and net wins were positive values (previous studies have defined net outcome as "stake minus winnings," making net wins minus values and net losses positive values). We compared participants' responses with the above questions with their actual betting frequency and net outcome using their account data. Participants were unaware that we were planning to make these comparisons. The survey also contained questions relating to people's preferences for different responsible gambling messages presented to them. The outcomes from this component are not yet available and plan to be reported separately. The gambling operator provided us with the following variables for each participant alongside their survey responses: unique customer id, age, gender, and (for the 30 days preceding their date of completion) number of active betting days, betting frequency (i.e., total number of bets placed), number bets per active day, net outcome, and proportion of bets that were placed on sports and proportion placed on races. Ethical approval to carry out the study was obtained from the the University of Sydney Human Research Ethics Committee (protocol number: 2020/583).

Online Operator

The online wagering operator involved in this study offers their customers opportunities to bet on sports (e.g., football, boxing, basketball) and races (e.g., horses, dogs). Like all online gambling sites in Australia, they do not offer live ("in-play") betting. Customers of the operator can view their history of bets and transactions on their online account, as with most online gambling sites. In addition to this, customers of this site can download a .csv spreadsheet file listing their full transaction history. However, the information provided in this statement may not be an effective way of communicating net outcomes to all customers, particularly over any specific period. The files do not contain the dates of bets or

Table 1
Example Betting Statement From Wagering Operator

Type	Summary	Transaction.Id	Bet.Id	Amount	Balance
Bet stake	Team A v Team B; Match betting; Choice: Team A @ 1.64 (Win)	5	3	−13.1	0.0
Win	Person 1 v Person 2; Match betting; Choice: Person 2 @ 2.62 (Win)	4	2	13.1	13.1
Bet stake	Person 1 v Person 2; Match betting; Choice: Person 2 @ 2.62 (Win)	3	2	−5.0	0.0
Bet stake	Person 3 v Person 4; Match betting; Choice: Person 3 @ 3.34 (Win)	2	1	−5.0	5.0
Deposit	Debit/credit card (************1,111)	1	NA	10.0	10.0

Note. This table displays a fictitious, example transaction history for a customer from the wagering site involved in this study. In this simple example, a customer deposits $10, wins one bet and loses two bets, ultimately ending up losing the $10 they deposited. Determining net outcome using such statements becomes more difficult to calculate, particularly for any duration of time other than overall, when multiple deposits are made, and the balance >0.

transactions and do not separately list losses. In addition, customers require some reason and/or self-motivation to access and analyze the spreadsheet, as well as an awareness that they can do this. See Table 1 for an example transaction history offered by the operator.

Participants

Of the 40,000 customers invited to take part in study, 754 (1.88%) opened the survey. After we removed those who did not bet at least once in the preceding month, 652 (91.57%) completed the first question about their gambling frequency, and 514 (72.19%) completed the second question about their net outcome.[1] Table 2 presents the demographic and gambling-related characteristics of all those who completed the net outcome question and Table 3 contains the corresponding statistics for those who completed the bet frequency question.

Data Analysis

Data analysis was performed using statistical programming language R (version 4.0.2; R Core Team, 2020). An "Absolute discrepancy" score representing the difference between self-reported and actual gambling values was calculated for each participant, along with a "Percentage discrepancy" score representing the absolute discrepancy as a percentage of the person's actual outcome (net outcome or bet frequency). As an example, here are the calculations for the discrepancy variables relating to net outcome: Absolute discrepancy = actual net outcome—self-reported net outcome; Percentage discrepancy = (absolute discrepancy/actual net outcome) × 100. These variables provided an indicator of recall accuracy that was relative to each participant's actual gambling outcomes and behavior. For example, two people with an absolute discrepancy of $50, one whose actual net outcome was $200 and one whose was −$50, would have percentage discrepancy scores of 25% and 100%, respectively (we made all percentage discrepancy scores positive values for ease of interpretation).

Based on absolute discrepancy scores, participants were grouped into "estimation categories" for net outcome (i.e., accurate recall, underestimating losses, over estimating winnings, underestimating winnings, and overestimating losses) and betting frequency (i.e., accurate recall, underestimating, and overestimated). Unless otherwise stated, customers whose self-reported and actual values perfectly matched were included within the "accurate recall" group for both variables. For net outcome, customers who indicated they lost less money than they actually lost (based on actual net outcome), or who stated they won money when they lost, were classed as "underestimating losses." Customers who indicated they lost more money than they actually lost were classed as "overestimating losses." Customers who indicated they won more money than they actually won were classed as "overestimating winnings." Customers who indicated they won less money than they actually won, or who stated they lost money when they won, were classed as "underestimating winnings."

The discrepancy scores and actual values for net outcome and bet frequency were nonnormally distributed (Shapiro–Wilk's test p-values <.05) and contained multiple outliers (z scores > 3.29). As such, we used mostly nonparametric statistical tests to analyze the data. Where relevant, all tests were two-tailed.

We performed ordinary least squares multiple linear regression analyses to determine whether participants' age, mean number of bets per active day, and actual gambling value (i.e., betting frequency or net outcome as determined from their account data) predicted the degree of inaccuracy in self-reports as determined by percentage discrepancy scores. In all models, participant's mean bets per active day was included as an indicator of "betting intensity," as previous research has found this variable to be associated with problematic gambling online (Braverman & Shaffer, 2012). When predicting the extent of inaccuracy, a separate linear model was performed for each type of estimation error (e.g., underestimating betting frequency, underestimating losses) to provide the most comprehensive understanding of recall biases. The "performance" R package was used to explore whether models met the underlying statistical assumptions. Multicollinearity was not problematic for any of the models (variable inflation factors were all <5), although the residuals were nonnormally distributed, the error the variance was nonconstant, and there were multiple influential data points (Cook's distance >4/N). As such, we removed all influential data points and transformed the following two right-skewed variables in all models using a cube-root transformation: (a) percentage discrepancy scores and (b) the relevant actual variable (bet frequency or net outcome) derived from account data.

[1] We did not perform an a priori power analysis as we simply aimed to recruit as many participants as possible through the operator's contact with customers and could not control the ultimate number who would volunteer to participate.

Table 2
Self-Reported Net Outcome Accuracy: Sample Characteristics Overall and by Estimation Type

		Favorable bias		Unfavorable bias		
Variable	Overall, $N = 514$	Accurate recall, $N = 2$	Underestimated losses, $N = 333$	Overestimated winnings, $N = 50$	Underestimated winnings, $N = 66$	Overestimated losses, $N = 63$
Age	43.7 (15.5)	66.5 (7.8)	43.3 (15.5)	44.9 (14.7)	44.4 (16.6)	43.3 (14.9)
Gender						
Unknown	35 (6.8%)	0 (0%)	21 (6.3%)	1 (2.0%)	3 (4.5%)	10 (16%)
Male	439 (85%)	2 (100%)	285 (86%)	42 (84%)	58 (88%)	52 (83%)
Female	40 (7.8%)	0 (0%)	27 (8.1%)	7 (14%)	5 (7.6%)	1 (1.6%)
Self-reported outcome						
M (*SD*)	105.2 (1,073.8)	4.5 (41.7)	42.1 (481.9)	819.7 (1,948.4)	310.7 (1,945.0)	−340.2 (806.7)
Mdn [IQR]	5.0 [−60.0, 100.0]	4.5 [−10.2, 19.2]	5.0 [−50.0, 100.0]	150.0 [62.5, 500.0]	10.0 [−8.2, 187.5]	−150.0 [−300.0, −40.0]
Actual outcome						
M (*SD*)	−143.1 (1,030.3)	4.5 (41.7)	−375.2 (623.2)	282.7 (650.4)	684.7 (2,217.8)	−126.0 (216.1)
Mdn [IQR]	−82.2 [−314.7, −3.1]	4.5 [−10.2, 19.2]	−201.5 [−443.2, −69.6]	65.3 [28.0, 181.0]	142.3 [34.6, 520.6]	−43.6 [−152.1, −14.4]
Absolute discrepancy						
M (*SD*)	−248.3 (872.9)	0.0 (0.0)	−417.3 (677.5)	−537.0 (1,627.0)	374.0 (683.5)	214.2 (642.5)
Mdn [IQR]	−100.2 [−338.9, 0.0]	0.0 [0.0, 0.0]	−200.0 [−470.4, −83.6]	−68.2 [−346.6, −21.1]	105.1 [31.5, 270.1]	50.0 [16.2, 138.1]
Percentage discrepancy						
M (*SD*)	1,611.4 (26,652.8)	0.0 (0.0)	222.4 (718.7)	408.6 (786.9)	173.6 (362.4)	11,465.4 (75,907.0)
Mdn [IQR]	100.0 [51.3, 184.9]	0.0 [0.0, 0.0]	106.8 [61.5, 162.1]	103.5 [42.6, 394.2]	84.1 [34.7, 109.0]	110.7 [32.9, 326.4]

Note. Statistics presented: Age = *M* (*SD*); Gender = *N* (%). All monetary values are expressed in $AUD. All percentage discrepancy scores were converted to positive values for ease of interpretation and comparison. M = Mean; SD = Standard deviation; Mdn = Median; IQR = Interquartile range.

We also performed three binomial logistic regression analyses to determine what factors predicted which type of estimation error (underestimation or overestimation) participants would make in their self-reports. For net outcome, we ran two models—one for net losers (i.e., people who lost money over the 30 days) and one for net winners (i.e., people who won money over the 30 days). The third model predicted the type of estimation error when self-reporting bet frequency. We used the following variables as predictors in all three models: age, mean bets per active day, and actual net outcome. The latter two variables were transformed in all models using a cube-root transformation.

As we performed multiple inferential statistical tests, we set alpha (α) at 0.005 for all analyses to reduce the experiment-wise Type-I error rate (Benjamin et al., 2018). An analysis document outlining the full process of processing and analyzing the data is stored on OSF and includes all outcomes produced from the analysis process (https://osf.io/et8ua/).

Results

Accuracy of Self-Reported Values

Among the 514 participants who reported their past 30-day net outcome, only two (0.39%) were perfectly accurate. This number raises to 21 (4.09%) if allowing for a 10% margin of error based on participants' actual net outcome. We selected a 10% margin of error as a reasonable margin that could account for discrepancies caused by customers' rounding and summarizing of their outcomes and bets, but this value is somewhat arbitrary.[2] Participants whose estimate was within 10% of their actual value had a lower actual net outcome (*Mdn* = −$24.25; range = −562.94–535) than the remaining sample (*Mdn* = −$89.12; range = −6,881.16–17,264.99), but this difference was not statistically different using a Wilcoxon rank sum test with continuity correction ($W = 6{,}542$, $p = .041$). They were also more likely to be older (*Mdn* = 45; range = 28–72) than the more inaccurate participants (*Mdn* = 42; range = 18–84), although this difference was also not statistically different ($W = 5912.50$, $p = .27$). The gender distribution for this group (male = 90.48%, female = 9.52%) was not significantly different from the remaining sample (male = 85.19%, female = 7.71%, unknown gender = 7.1%) using a Fisher's exact test ($p = 0.56$).

The most common type of estimation error regarding net outcome was underestimating losses ($N = 333$, 64.79%), followed by underestimating winnings ($N = 66$, 12.84%), overestimating losses ($N = 63$, 12.26%), and overestimating winnings ($N = 50$, 9.73%; see Table 2 for the characteristics of participants who made each estimation error type). Overall, 174 (33.85%) participants self-reported a positive net outcome (they thought they had won money) but actually had a negative net outcome (they lost money), whereas 18 (3.5%) self-reported a negative net outcome but actually had a positive net outcome.

Of the 652 participants who reported their past 30-day gambling frequency, only 17 (2.61%) perfectly recalled the number of bets they had placed. This number raises to 48 (7.36%) if allowing for a 10% margin of error based on participants' actual bet frequency. Participants whose estimate was within 10% of their actual value had a lower actual bet count (*Mdn* = 21.5; range = 1–387) than the remaining sample (*Mdn* = 53.5; range = 1–3,428), and this difference was statistically different according to a Wilcoxon rank sum test with continuity correction ($W = 9898.50$, $p < .001$). They were also more likely to be older (*Mdn* = 43.5; range = 20–74) than the more inaccurate participants (*Mdn* = 42; range = 18–84), although this difference was also not statistically different ($W = 15473.50$, $p = .44$). The gender distribution for this group (male = 93.75%,

[2] In our data analysis document on OSF, we provide rates of accuracy for net outcome and bet frequency based on margins of 5, 10, 20, 30, 40, and 50% for interested readers (access here: https://osf.io/et8ua/). Our data and analysis code are also available for anyone wishing to calculate accuracy levels using alternative margins of error.

Table 3
Self-Reported Betting Frequency Accuracy: Sample Characteristics Overall and by Estimation Type

Variable	Overall, $N = 652$	Accurate recall, $N = 17$	Estimation grouping	
			Underestimated, $N = 454$	Overestimated, $N = 181$
Age	43.3 (15.7)	51.2 (17.9)	43.5 (15.9)	42.1 (14.8)
Gender				
Unknown	45 (6.9%)	0 (0%)	29 (6.4%)	16 (8.8%)
Male	546 (84%)	16 (94%)	376 (83%)	154 (85%)
Female	61 (9.4%)	1 (5.9%)	49 (11%)	11 (6.1%)
Self-reported frequency				
M (*SD*)	57.4 (110.3)	6.3 (6.5)	50.0 (98.0)	80.6 (137.4)
Mdn [IQR]	30.0 [15.0, 60.0]	4.0 [1.0, 10.0]	30.0 [15.0, 50.0]	30.0 [14.0, 100.0]
Actual frequency				
M (*SD*)	115.2 (243.2)	6.3 (6.5)	150.1 (279.9)	37.8 (80.1)
Mdn [IQR]	50.0 [18.0, 128.2]	4.0 [1.0, 10.0]	77.0 [37.0, 163.8]	13.0 [5.0, 34.0]
Absolute discrepancy				
M (*SD*)	−57.8 (220.2)	0.0 (0.0)	−100.1 (245.5)	42.8 (93.0)
Mdn [IQR]	−17.0 [−64.0, 1.0]	0.0 [0.0, 0.0]	−39.0 [−93.0, −15.0]	12.0 [4.0, 34.0]
Percentage discrepancy				
M (*SD*)	215.3 (1,154.4)	0.0 (0.0)	54.4 (22.8)	639.0 (2,137.2)
Mdn [IQR]	57.1 [34.4, 78.6]	0.0 [0.0, 0.0]	55.6 [38.9, 71.4]	73.9 [29.0, 235.2]

Note. Statistics presented: Age = *M* (*SD*); Gender = *N* (%). All percentage discrepancy scores were converted to positive values for ease of interpretation and comparison. M = Mean; SD = Standard deviation; Mdn = Median; IQR = Interquartile range.

female = 2.08%, unknown gender = 4.17%) was not significantly different from the remaining sample (male = 82.95%, female = 9.93%, unknown gender = 7.12%) using a Fisher's exact test ($p = .013$). Substantially, more participants underestimated ($N = 454$, 69.63%) rather than overestimated ($N = 181$, 27.76%) their betting frequency (see Table 3 for the characteristics of participants who made each estimation error type).

Degree of Difference Between Self-Reported and Actual Values

The distribution of participants' self-reported and actual gambling values are visualized in Figure 1. The overall median absolute difference between self-reported and actual net outcome was −$100.20 (range: −$10,218.10 to +4,675.04) and the median percentage difference was 100 (range: 0–599,900). A Wilcoxon-signed rank test with continuity correction determined that the absolute difference between reported and actual values was statistically significant ($V = 105{,}468$, $p < .001$). The overall median absolute difference between self-reported and actual betting frequency was 17 bets (range: −897–3,328) and the median percentage difference was 57.14 bets (range: 0–19,900). The absolute difference between reported and actual bet frequency was statistically significant ($V = 159{,}955$, $p < .001$).

Relationship Between Self-Reported and Actual Values

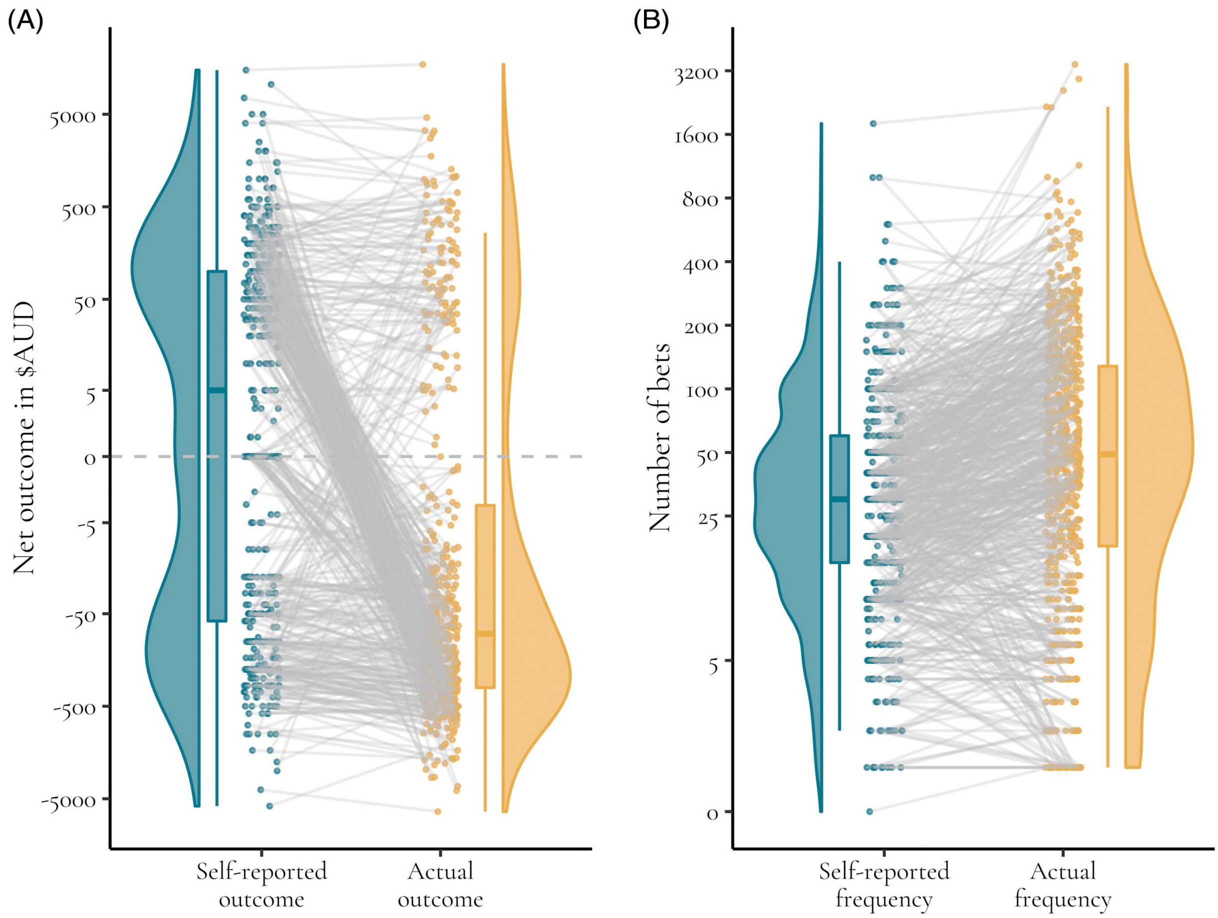
We plotted the relationships between self-reported and actual values for net outcome (Figure 2) and bet frequency (Figure 3) as scatter graphs. Using a Spearman's rank correlation rho, there was a medium, positive, and statistically significant association between self-reported and actual net outcome (rs = 0.25, $p < .001$). The association between self-reported and actual bet frequency was strong, positive, and statistically significant (rs = 0.67, $p < .001$).

Predicting Inaccuracy of Self-Reported Gambling

Table 4 presents the outcomes from four linear multiple regression models predicting the extent of each net outcome estimation error. The most consistent predictor of greater recall inaccuracy across all estimation error types was participants' actual net outcome. This was particularly the case for participants who actually lost, with smaller loss amounts associated with more inaccuracy when underestimating and—to a greater extent—overestimating losses. Lower actual winning values were also associated with greater inaccuracy among winning bettors, but these effects were not statistically significant at our adjusted α level. We did not include gender as a predictor in these models as there were so few female and unknown gender participants once they were divided across the four estimation error types (see Table 2). Instead, we performed a nonparametric Kruskal–Wallis rank sum test to see whether the percentage discrepancy between self-reported and actual net outcome differed significantly between genders. The difference was the largest for females (*Mdn* = 133.33, range = 6.54–2,000; $N = 40$), followed by males (*Mdn* = 100, range = 0–599,900; $N = 439$), and those with an unknown gender (*Mdn* = 100, range = 23.08–2,129.38; $N = 35$). However, the effect of gender on percentage discrepancy scores was not statistically significant, χ^2 [2, $N = 514$] = 2.43, $p = .30$.

Table 5 presents the outcomes from two linear multiple regression models predicting the extent of each type of estimation error when recalling betting frequency. As with net outcome, the only consistent predictor of greater recall inaccuracy across both estimation error types was participants' actual bet frequency, with higher values associated with greater inaccuracy among underestimators and—to a lesser extent—lower actual values associated with greater inaccuracy among overestimators. Again, we did not include gender as a predictor in the models due to small

Figure 1
Self-Reported and Actual Values for Net Outcome (A) and Betting Frequency (B)



Note. These raincloud figures present a boxplot, density curve, and the raw datapoints for self-reported and actual values, with lines connecting each person's two values. The y-axis on both figures is presented on a log-10 scale as the natural scale for these outcomes is very large and precludes effective visualization. See the online article for the color version of this figure.

cell sizes (see Table 2). We used a nonparametric Kruskal–Wallis rank sum test to see whether the percentage discrepancy between self-reported and actual bet frequency differed significantly between genders. The difference was the largest for those with an unknown gender (Mdn = 68.75, range = 9.09–9,900; N = 45), followed by females (Mdn = 64.29, range = 0–1,900; N = 61), and males (Mdn = 54.95, range = 0–19,900; N = 546). However, the effect of gender on percentage discrepancy was not statistically significant, χ^2 [2, N = 652] = 7.28, p = .03. No statistically significant pairwise differences were observed between gender groups' percentage discrepancy for net outcome or bet frequency as determined using post-hoc Wilcoxon rank sum tests with continuity corrections and Benjamini–Hochberg adjusted p-values.

Predicting Type of Estimation Bias

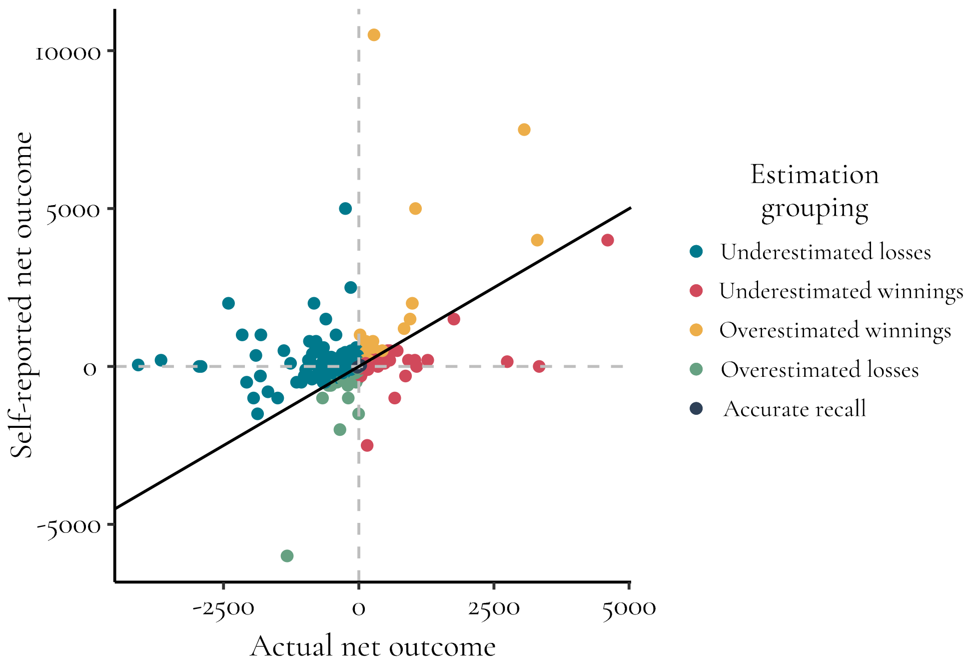
Table 6 presents the outcomes from three logistic regression models predicting which type of estimation error (underestimate/overestimate) participants made based on their demographic (age) and betting characteristics (mean bets per day and actual net outcome). Among net losers (i.e., customers who lost money over the 30-day window), those who lost more money were more likely to underestimate their losses. No variables were significantly predictive of the estimation error type made among net winners (i.e., customers who won money over the 30-day window). In relation to bet frequency, having a higher mean number of bets per active day was associated with underestimating the total number of bets made.

Discussion

The aim of this study was to extend the previous work in this area by (a) determining whether providing instructions on how to calculate net outcome improves recall accuracy, and (b) investigating people's ability to recall their past-month gambling frequency. We found very few participants were able to accurately recall their net outcome or betting frequency, although recall for the latter was better. People were more likely to be favorably biased in their recall (i.e., mentally increasing their funds by underestimating their

Figure 2

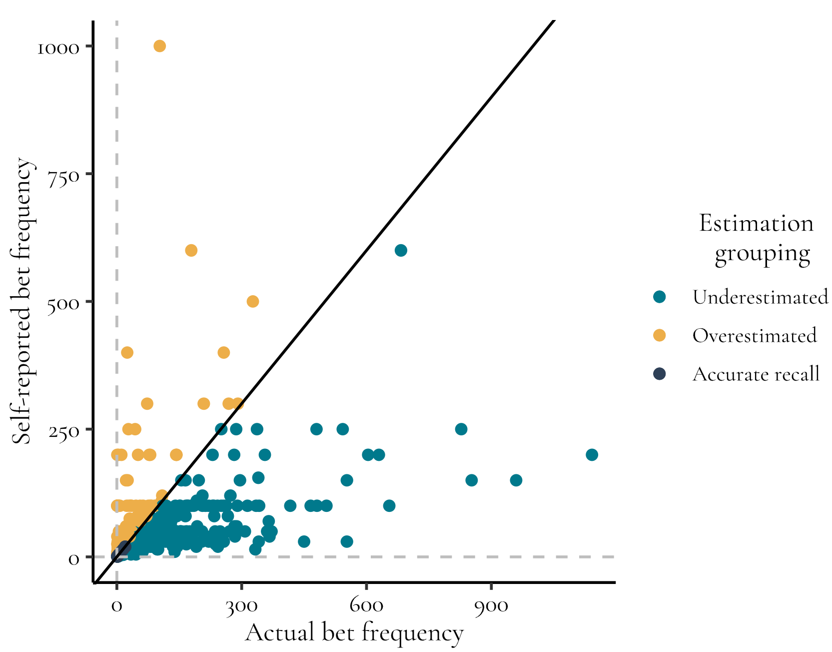
Correlation Between Actual and Self-Reported Net Outcome



Note. This scattergraph shows the relationship between self-reported and actual net outcome. Points are color coded based on the particular estimation error type (or lack of) that each person made. The black line represents perfect accuracy (i.e., recalled outcome and actual outcome are equal). See the online article for the color version of this figure.

Figure 3

Correlation Between Actual and Self-Reported Betting Frequency



Note. This scattergraph shows the relationship between self-reported and actual betting frequency. Points are color coded based on whether the person underestimated or overestimated their number of bets or was accurate in their recall. The black line represents perfect accuracy (i.e., recalled frequency and actual frequency are equal). See the online article for the color version of this figure.

Table 4
Prediction of Inaccuracy When Estimating Net Outcome: Linear Regression Analyses Outcomes

Model and terms	*B* coefficients				*B* with 95% CIs	Statistic	*p*-value	Model fit
	B	*SE*	$CI^{(LB)}$	$CI^{(UB)}$				Adj R^2
Underestimated losses (n = 316)								
Age	0.00	0.00	−0.01	0.01		−0.24	.814	
Bets per active day	0.00	0.01	−0.02	0.01		−0.24	.812	0.04
Actual net outcome	−0.12	0.03	−0.18	−0.06		−3.76	.000	
Overestimated winnings (n = 45)								
Age	−0.03	0.03	−0.08	0.03		−0.93	.357	
Bets per active day	0.23	0.13	−0.04	0.51		1.73	.091	0.15
Actual net outcome	−0.36	0.12	−0.61	−0.11		−2.95	.005	
Underestimated winnings (n = 63)								
Age	0.01	0.01	−0.01	0.04		1.08	.283	
Bets per active day	−0.03	0.03	−0.10	0.04		−0.94	.353	0.06
Actual net outcome	−0.11	0.05	−0.20	−0.01		−2.24	.029	
Overestimated losses (n = 61)								
Age	0.06	0.04	−0.01	0.14		1.73	.088	
Bets per active day	0.05	0.03	0.00	0.11		1.87	.067	0.22
Actual net outcome	−1.03	0.29	−1.62	−0.45		−3.54	.001	

Note. The outcome variable for all models was the percentage discrepancy between self-reported and actual values. For, ease of interpretation, both the percentage discrepancy variable and actual net outcome variable were converted to positive values for losing gamblers. The graphical column visually displays the *B* coefficients and their 95%, confidence intervals (dotted line = 0). Abbreviations: *SE* = Standard error; CI = 95% confidence interval (^{LB} and ^{UB} = lower & upper bounds, respectively).

losses or overestimating their winnings), which is consistent with previous studies (Auer & Griffiths, 2017; Braverman et al., 2014). This finding extended to self-reported betting frequency, where the majority participants underestimated the number of bets they had placed. Self-reported and actual values were correlated, but the discrepancy between these values was often considerable, particularly for participants with favorably biased recall (e.g., those who underestimated losses did so by a median value of AUD $200). The only consistent predictor of the percentage discrepancy between self-reported and actual values was the actual value of interest (net outcome or betting frequency). Lower actual net outcomes were associated with greater inaccuracy among those who underestimated and overestimated their losses. Participants who underestimated their bet count were more likely to have higher actual betting frequencies and those who overestimated had lower actual betting frequencies. Finally, losing more money was associated with underestimating (as opposed to overestimating) net losses among those who actually lost money, and placing more bets per active betting day was associated with underestimating betting frequency.

Comparison With Previous Studies

It is difficult to compare the exact rates of accuracy between our study and the findings of Braverman et al. (2014) and Auer and Griffiths (2017) as these studies defined "accurate recall" using a measure that involved dividing the absolute discrepancy by each person's average bet size, and classifying participants as "accurate" if they scored between −1 and +1 on this measure (i.e., the difference between the self-reported and actual net outcome was

Table 5
Prediction of Inaccuracy When Estimating Bet Frequency: Linear Regression Analyses Outcomes

Model and terms	*B* coefficients				*B* with 95% CIs	Statistic	*p*-value	Model fit
	B	*SE*	$CI^{(LB)}$	$CI^{(UB)}$				Adj R^2
Underestimated bets (n = 439)								
Age	−0.09	0.06	−0.20	0.02		−1.56	.121	
Bets per active day	0.31	0.12	0.08	0.54		2.62	.009	0.24
Actual bet frequency	7.48	1.08	5.35	9.61		6.91	.000	
Overestimated bets (n = 172)								
Age	0.01	0.01	−0.02	0.04		0.74	.458	
Bets per active day	0.10	0.07	−0.03	0.24		1.50	.135	0.17
Actual bet frequency	−1.19	0.22	−1.62	−0.76		−5.49	.000	

Note. The outcome variable for both models was the percentage discrepancy between self-reported and actual values. To best reduce non-linearity, the "Actual bet frequency" variable was log transformed [as opposed to being cubed transformed like other transformed variables included in our linear models (see Data analysis section)] using the log 1*p*() R function in the model predicting underestimation of bets. The graphical column visually displays the *B* coefficients and their 95% confidence intervals (dotted line = 0). Abbreviations: *SE* = Standard error; CI = 95% confidence interval (^{LB} and ^{UB} = lower and upper bounds, respectively).

Table 6
Prediction of Bias Type When Estimating Net Outcome: Logistic Regression Analyses Outcomes

Term	*B* coefficient				*B* with 95% CIs	Statistic	*p*-value
	B	*SE*	$CI^{(LB)}$	$CI^{(UB)}$			
Net losers' model; predicting underestimation of losses (*n* = 396)							
Age	0.00	0.01	−0.02	0.02		0.19	.85
Bets per active day	0.22	0.31	−0.37	0.85		0.72	.47
Actual net outcome	−0.37	0.08	−0.54	−0.23		−4.74	.00
Net winners' model; predicting overestimation of winnings (*n* = 116)							
Age	0.00	0.01	−0.03	0.02		−0.13	.90
Bets per active day	−0.26	0.39	−1.06	0.50		−0.67	.50
Actual net outcome	−0.10	0.06	−0.24	0.01		−1.67	.10
Bet frequency model; predicting underestimation of betting (*n* = 635)							
Age	0.00	0.01	−0.01	0.01		−0.08	.93
Bets per active day	1.98	0.24	1.53	2.46		8.31	.00
Actual net outcome	0.03	0.02	−0.01	0.07		1.48	.14

Note. *SE* = standard error; CI = 95% confidence intervals (^{LB} and ^{UB} = lower and upper bounds, respectively). The graphical column visually displays the *B* coefficients and their 95% confidence intervals

within one average bet size). We were not provided with participants' wager amounts and were therefore unable to calculate their average bet size. Instead, we chose to standardize each participant's absolute discrepancy between their self-reported and actual net outcome by dividing it by their actual net outcome and producing a percentage discrepancy score, thus providing an indication of the extent to which they were (in)accurate relative to their actual outcome. We found only two (0.39%) participants were perfectly accurate in recalling their past-month net outcome but, using percentage discrepancy scores, 21 (4.09%) were within a 10% margin of their actual net outcome. By contrast, Braverman et al. (2014) found 13% and 7% of participants' self-reported outcomes were within one average bet size of their actual past three-month and 12-month outcomes, respectively. Auer and Griffiths (2017) found 74% of their participants' self-reported outcomes were within one average bet size of their actual past-month outcome. Using percentage discrepancy scores as our primary outcome in our multiple regression analyses may explain why we found smaller losses and win amounts were associated with greater inaccuracy of self-reports, whereas Braverman et al. (2014) and Auer and Griffiths (2017) found the obverse.[3]

To more directly compare the results found here and those of previous studies (Auer & Griffiths, 2017; Braverman et al., 2014), Figure 4 displays the only variable that has been consistently reported in all studies, namely the overall median absolute discrepancy between self-reported and actual net outcome. As can be seen, the discrepancy found in the present study is considerably larger than in previous investigations. This is contrary to our expectations as, unlike previous studies, we provided participants with brief instructions and examples of how to calculate their net outcome. In addition, we only asked participants to recall their past-month outcomes, and not the greater time periods of three and 12 months studied by Braverman et al. (2014). The larger discrepancy here could be the result of the Australia having a high national minimum wage and one of the highest per-capita gambling expenditure rates in the world (Queensland Government Statistician's Office., 2021); though a further replication study in Australia would be required to confirm whether the substantial discrepancy here is typical of Australian gamblers (Heirene, 2020). The difference in result could also be in part due to the different online gambling platforms used by customers, which include different gambling activities and likely a varied presentation of outcomes to customers.

Limitations

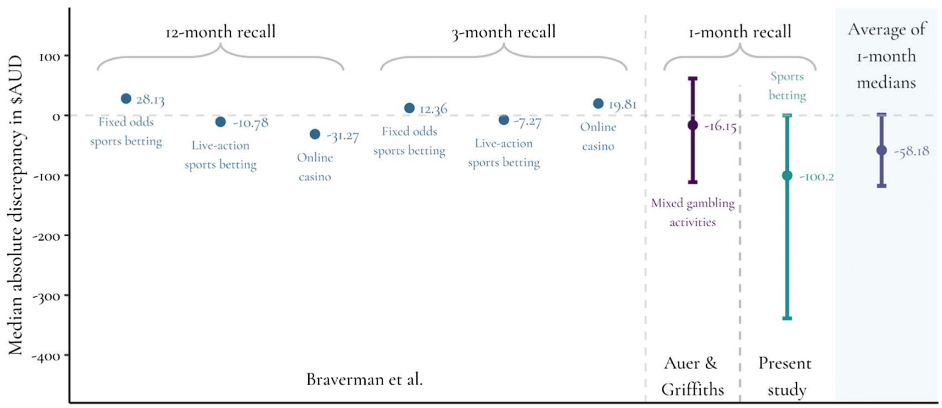
Our findings and their generalizability are limited in several ways. First, as discussed above, we were not provided with participants' betting amounts and were therefore unable to calculate the standardized measure of bias computed by Braverman et al. (2014) and Auer and Griffiths (2017) that would have allowed direct comparisons with their findings. Second, only 1.885% of the customers sent the study recruitment email started the survey and even fewer completed the requisite questions. Thus, the final sample represents only a small, self-selected proportion of the wagering site's customers. However, briefly comparing the characteristics of the 652 customers included in our analyses with the 102 excluded due to lack of responses or not having gambled in the previous 30 days, the former were more likely to be male ($p < .001$, Chi-square test) and had a higher number of bets ($p < .001$), betting days ($p < .001$), and bets per day ($p < .001$) in the past 30 days than excluded customers (Wilcoxon-signed rank tests). The differences in net outcome ($p = .382$) and age ($p = .874$) between the samples were not statistically different (Wilcoxon-signed rank tests).[4] While we did not have access to the details of all 40,000 customers invited to take part, the comparison with the smaller number of customers who opened the survey but were not included in analyses suggests that the sample used in this study may comprise more regular gamblers and urges caution in applying our findings to more infrequent bettors.

[3] We are confident in this assumption as we originally used participants' absolute discrepancy scores as the outcome variable in our regression models predicting self-report inaccuracy and found the same as Braverman et al. (2014) and Auer and Griffiths (2017)—greater loss and win amounts were consistently associated with greater levels of self-report inaccuracy.

[4] See subsection of our analysis document on OSF titled "Representativeness of our sample" (https://osf.io/et8ua/) for a more detailed comparison of the two groups.

Figure 4

Cross-Study Comparison of Absolute Median Discrepancy Between Self-Reported and Actual Net Outcome



Note. This figure displays, for comparative purposes, the median absolute discrepancy between self-reported and actual net outcome values found in Braverman et al. (2014), Auer and Griffiths (2017), and the present study. We also computed and present the unweighted average one-month median discrepancy based on the outcomes from Auer and Griffiths and the present study. The error bars for Auer and Griffiths' and the present study's median values represent the interquartile range (i.e., 25th and 75th percentiles). The error bars for the average one-month median discrepancy represent the standard deviation. The values from previous studies were converted from the original currencies (Euro and NOK) to AUD using an online digital currency converter (https://www.xe.com/currencyconverter/) on 2021/06/21. See the online article for the color version of this figure.

A further limitation of the study is that the sample comprised only Australian sports and race wagering customers and may therefore not generalize to people from other countries and those engaging in other forms of gambling, including cash-based gambling. Relatedly, we focused only on people's gambling with one site, and many online gamblers report holding accounts across multiple sites simultaneously (Gainsbury et al., 2015; U.K. Gambling Commission, 2020). As a result, outcomes from one site may be less relevant to consumers than their overall, across-site outcomes. Lastly, the account data provided by the site did not include indicators of race or ethnicity and so we were unable to determine the extent to which our findings generalize along these factors.

Implications and Future Research

This was the first study (to the authors' knowledge) to explore self-report accuracy in the gambling context outside of Europe and our results advance the understanding of this topic in several ways. First, our findings indicate that providing guidance on how to calculate one's net outcome does not improve the accuracy of peoples self-reported outcomes. It may be unrealistic to expect customers to learn to calculate their own net outcome so quickly and based on only brief guidance. However, we did not directly compare self-reported outcomes made with and without the added guidance within this study and thus further research in needed to clarify the value of providing this type of instruction and how it should be presented.

The findings support the importance of providing gambling customers with regular activity statements that clearly demonstrate their wins, losses, and net outcomes to improve individual's understanding of these such that they are making informed decisions about their future bets based on past outcomes and available funds (Behavioural Economics Team of the Australian Government [BETA], 2020). Existing research suggests including graphic illustrations in activity statements may be useful in assisting individuals to keep track of wins, losses, and net outcomes (BETA, 2020). Activity statements should be provided by default to customers at regular periods given that most will unlikely voluntarily access this information (Heirene et al., 2021) and they should include clear statements of net outcomes rather than a list of all activity, although a detailed breakdown of all bets should also be available to customers.

The discrepancy between self-reported and actual net outcome observed in this study was considerably larger than found in previous studies (Auer & Griffiths, 2017; Braverman et al., 2014), suggesting recall inaccuracy may be more problematic in terms of biasing people's decision making than previously thought. Of note, Braverman et al. (2014) found the size of the discrepancy between self-reported and actual values was more consistently associated with self-reported problem gambling than the type of estimation bias (e.g., overestimating winnings) someone displayed. We did not have access to problem gambling scores but found the extent of recall inaccuracy was not associated with our measure of betting intensity (i.e., bets per day). However, this is only a proxy measure of risky gambling and is not sufficiently indicative of problem gambling in isolation. Our findings are concerning with regard to gambling harms—most people who gamble online lose substantially more money than they think they do and may be unknowingly spending outside of their means.

This was also the first study (to the authors' knowledge) to explore the accuracy of self-reported betting frequency. People appear to be better able to recall the number of bets they have placed (7.36% accurate within a 10% margin) than their net outcome (4.09% accurate within a 10% margin), although recall remains poor. This finding supports our contention that poor recall of gambling outcomes may be in part due to the difficulty and variability associated with calculating net outcome. This may suggest that betting operators be required to provide greater transparency over outcomes for customers using clear terminology about net outcomes with consideration of each person's chosen bet size. The potential loss and win should be clearly stated for customers before a bet is made and after the outcome is provided to increase accurate understanding of outcomes. Overall, gambling sites need to improve the ways in which they are communicating their customers' (potential) outcomes to them so that they are supported to make informed decisions about their gambling.

Our findings further question the use of self-reported outcomes in gambling research and indicate that self-reported gambling frequency is also often inaccurate. Similar outcomes have been observed for self-reported alcohol (Northcote & Livingston, 2011, November–December) and drug use (Ashrafi et al., 2018) but, unlike with substance use, objective measures of gambling involvement and expenditure are available via online account data, loyalty card data, and information collected by financial institutions (e.g., Heirene et al., 2021; Muggleton et al., 2021). The results of gambling studies predicated on self-report should be interpreted cautiously. This has major implications for the gambling field from the understanding of gambling harms to evidence of intervention and policy impact. Self-report surveys are often used in government-commissioned research to understand the prevalence of gambling and related harms in a region (e.g., Tajin et al., 2021; U.K. Gambling Commission, 2018, 2020), and outcomes from these studies are used to recommend local policies and practices (e.g., Wardle et al., 2019). Such surveys are also regularly used to evaluate the impact of strategies that aim to reduce or prevent gambling harms, such as self-exclusion (e.g., Hing et al., 2015) and precommitment schemes (see Blaszczynski et al., 2014). If, as suggested here, 50% of people are more than 100% inaccurate in their estimations of their recent gambling outcomes, then comparing self-reported outcomes between intervention and control samples or preintervention and postintervention is unlikely to produce reliable information about the effectiveness of an intervention.

There is a need to replicate gambling studies relying on self-reports using objective expenditure and frequency data to ensure the veracity of our understanding of gambling related phenomena. The data sources mentioned above—online gambling account data, loyalty card data, and information collected by financial institutions—can provide reliable expenditure data and the hosting organizations should be encouraged to make their anonymized data available for research purposes. Currently, only online gambling expenditure can be reliably tracked. The increasing move toward cashless gambling payments (Gainsbury & Blaszczynski, 2020; Taskinson, 2020) will assist with overcoming the major limitation of these data sources—namely, the absence of information about cash expenditure. There has also been increased interest in the extent to which financial institutions can add a valuable source of gambling-related data due to the ability to track expenditure across multiple types of gambling (e.g., online and casino). Swanton et al. (2019) have suggested that financial institutions could take a more active role in informing customers about their gambling expenditure, and our findings support the value of this strategy.

Finally, our findings support previous studies (Auer & Griffiths, 2017; Braverman et al., 2014) in showing that demographic characteristics, namely age and gender, are not associated with self-report inaccuracy in this context. Indeed, none of the variables in our regression models—other than the actual values for net outcome and frequency—were predictive of inaccurate self-reports and our models were, overall, poor at explaining variability in the outcomes. Future research should explore the predictive value of other characteristics hypothesized to be associated with self-report accuracy, such as the presence of mood and substance disorders (Braverman et al., 2014).

Conclusions

This study aimed to test whether people can accurately recall their past gambling outcomes and behavior. Our findings call into question the reliability of self-reported gambling expenditure and frequency and support the value of using actual betting data to study gambling-related phenomena. Further, findings suggest governments and gambling operators should not presume that individuals are making informed choices about their betting based on an accurate understanding of their outcomes.

Analysis Code and *R* Packages Used

We used R [Version 4.0.2; R Core Team (2020)] and the R-packages *beepr* [Version 1.3; Bååth (2018)], *dplyr* [Version 1.0.6; Wickham et al. (2020)], *english* [Version 1.2.5; Fox et al. (2020)], *extrafont* [Version 0.17; Winston (2014); Chang (2012)], *extrafontdb* [Version 1.0; Chang (2012)], *ggplot2* [Version 3.3.3; Wickham (2016)], *KableExtra* (Zhu, 2020), *papaja* [Version 0.1.0.9997; Aust and Barth (2020)], *patchwork* [Version 1.1.1; Pedersen (2020)], *performance* [Version 0.7.0; Lüdecke et al. (2020)], *raincloudplots* [Version 0.2.0; Allen et al. (2021)], *stringr* [Version 1.4.0; Wickham (2019); Wickham (2019)], *tibble* [Version 3.1.3; Müller and Wickham (2020)], *tidyr* [Version 1.1.3; Wickham (2020)], and *tidyverse* [Version 1.3.0; Wickham et al. (2019)] for our analyses. The full list of packages used is included in our analysis scripts.

All analysis scripts and datasets can be accessed on our OSF project page (https://osf.io/8vjeh/). This manuscript (including all findings, tables, and figures) were developed entirely in R using an RMarkdown script and the *papaja* package. We have developed a guide on how to independently reproduce our results and this manuscript using the data and analysis scripts available online (see https://osf.io/9zr3k/; please contact the corresponding author with any questions about this process: robert.heirene@sydney.edu.au; robheirene@gmail.com).

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