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Between-session chasing of losses and wins in an online eCasino

KE ZHANG[1*], JASON D. RIGHTS[2], XIAOLEI DENG[1], TILMAN LESCH[1] and LUKE CLARK[1,3**]

[1] Department of Psychology, Centre for Gambling Research at UBC, University of British Columbia, 2136 West Mall, Vancouver, BC, V6T 1Z4, Canada

[2] The Rights Lab, Department of Psychology, University of British Columbia, 2136 West Mall, Vancouver, BC, V6T 1Z4, Canada

[3] Djavad Mowafaghian Centre for Brain Health, University of British Columbia, 2215 Wesbrook Mall, Vancouver, BC, V6T 1Z3, Canada

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ABSTRACT

Background and aims: This study characterized chasing behaviour as the time to return to an online gambling website after a losing or a winning visit. *Methods:* We analyzed a naturalistic dataset from an eCasino (PlayNow.com, the provincial platform for British Columbia, Canada), comprising 1,909,681 sessions from 15,544 individuals. Analyses distinguished sessions on slot machines, blackjack, roulette, video poker, probability games, or mixed-category sessions. *Results:* Overall, gamblers on most games returned more slowly as a function of the prior loss, and more quickly as a function of the prior win. Loss chasing intensities in blackjack, probability, video poker, and mixed sessions did not differ significantly from slot machines, but roulette was associated with shorter intervals to return ($b = -0.13$, $p < 0.001$). Similarly, win chasing did not vary across slot machines, blackjack, probability games, and video poker, but roulette ($b = -0.08$, $p < 0.001$) and mixed ($b = -0.02$, $p = 0.009$) sessions were associated with shorter intervals. *Discussion and conclusions:* The average behavioural patterns provide limited evidence for loss chasing but clearly indicate win chasing. Although slot machines are commonly considered a high-risk product, roulette in our analyses was associated with the greatest chasing intensities.

KEYWORDS

chasing, online casino, gambling, behavioural marker, addiction

INTRODUCTION

Chasing is widely considered one of the hallmarks of disordered gambling (Lesieur, 1979; Zhang & Clark, 2020). Broadly speaking, it refers to the persistence or escalation of betting in an effort to recover the gambler's debts. From this perspective, chasing is conventionally seen as a response to losing. However, it has also been noted that wins can drive chasing, and exacerbate gambling problems (Delfabbro, King, & Griffiths, 2014; O'Connor & Dickerson, 2003; Young, Wohl, Matheson, Baumann, & Anisman, 2008). Given the house edge (negative expectancy) of commercial gambling products, chasing after wins is likely to increase cumulative losses, as well as providing further opportunity for habit formation (Ferrari, Limbrick-Oldfield, & Clark, 2022). In past work, win chasing was associated with impaired control over gambling (O'Connor & Dickerson, 2003), and high-risk gamblers reported greater gambling desire after wins compared to losses (Young et al., 2008). Hence, examining chasing after wins is also important for understanding the development of gambling problems. In the DSM-5, the chasing item specifically refers to a gambler who "often returns another day to get even" (section 312.31; American Psychiatric Association et al., 2013). Indeed, this 'between-session chasing' is the most frequently endorsed item among the DSM

*Corresponding author.
E-mail: kezhang0904@gmail.com

**Corresponding author.
E-mail: luke.clark@psych.ubc.ca

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items for Gambling Disorder (Sleczka & Romild, 2021; Toce-Gerstein, Gerstein, & Volberg, 2003).

This study primarily aimed to characterize between-session chasing in a large 'behavioural tracking' dataset of online gamblers, examining the time interval between consecutive sessions, as a function of both the amounts lost (loss chasing) and amounts won (win chasing). In light of the close links between chasing and gambling problems, the study also compared chasing intensities across gambling product types, to derive insight into the potential risks associated with different gambling forms.

Most research on between-session chasing to date used retrospective surveys (Gainsbury, Suhonen, & Saastamoinen, 2014; Lesieur, 1979; O'Connor & Dickerson, 2003; Sleczka & Romild, 2021; Temcheff, Paskus, Potenza, & Derevensky, 2016). Temcheff et al. (2016) surveyed 8,674 college women athletes, only the chasing item could distinguish those with and without gambling problems. A Swedish longitudinal survey highlighted that the endorsement of chasing is a stable predictor of the risk of transitioning to more severe gambling problems over 5 years (Sleczka & Romild, 2021). However, self-report measures are subject to a number of biases (Braverman, Tom, & Shaffer, 2014). A small number of studies have examined chasing using field data from (land-based) casinos (Flepp, Meier, & Franck, 2021; Forrest & McHale, 2016; Kainulainen, 2020; Narayanan & Manchanda, 2012; Wardle, Excell, Ireland, Ilic, & Sharman, 2014). Measuring the time interval between visits as an index of chasing, these studies found that gamblers took *longer* to return after a losing session, and shorter intervals to return after winning (Forrest & McHale, 2016; Kainulainen, 2020; Narayanan & Manchanda, 2012). Chasing might also be expressed as increasing the overall bet amount over successive visits. Tracking slot machine engagement in a Swiss casino, a small loss (i.e., below USD 188) did not change the subsequent bet amount, whereas a larger loss *reduced* the subsequent bet amount (Flepp et al., 2021). Thus, the aggregate profile in land-based gambling indicates win chasing, but not loss chasing.

This study sought to capture between-session chasing in the online environment, which presents a direct means of linking gamblers' accounts with their behaviour, compared to tracking gamblers in land-based gambling venues (Deng, Lesch, & Clark, 2019). We used a dataset from the PlayNow.com eCasino, the provincial gambling platform in British Columbia (BC), Canada. Across many jurisdictions, online gamblers and land-based gamblers often have different demographic backgrounds (Gainsbury, Wood, Russell, Hing, & Blaszczynski, 2012, 2015). Online gamblers also have a greater risk of disordered gambling than land-based gamblers (e.g., Papineau et al., 2018). In a 2020 prevalence survey in BC, Canada, 24% of online gamblers were classified as high-risk for gambling problems on the Problem Gambling Severity Index (Ipsos & Strategic Science, 2020). Prior studies examining European online gambling datasets have considered the operationalization of chasing behaviour (Auer & Griffiths, 2022; Challet-Bouju et al., 2020; Perrot, Hardouin, Grall-Bronnec, & Challet-Bouju, 2018). Challet-Bouju et al. (2020) and Perrot et al. (2018) inferred chasing from successive money deposits within a short period of time or a deposit within 1 h after placing a bet. Auer and Griffiths (2022) defined five alternative metrics of loss chasing, including an 'across days' chasing measure based on the correlation between the amount lost and the subsequent amount bet, restricted to pairs of consecutive gambling days. In their study, another metric reflecting the percentage of sessions with more than one financial deposit appeared most sensitive to chasing (Auer & Griffiths, 2022). We note these studies did not quantify chasing intensities in relation to winning outcomes.

Our further objective was to examine chasing differences between gambling product categories. Past behavioural tracking studies rarely distinguished games (Forrest & McHale, 2016; Wardle et al., 2014). Some studies have focussed on single gambling products (Flepp et al., 2021; Kainulainen, 2020; Narayanan & Manchanda, 2012), where it is unclear how observed patterns would generalise to other games. Different games vary in their structural characteristics (Griffiths, 1993), in ways that are likely to influence chasing and the potential for disordered gambling. For example, slot machines have a fast and continuous speed of play, and intense audiovisual stimulation, which foster psychological states of immersion (Dixon et al., 2014, 2018; Dowling et al., 2017; Murch & Clark, 2021). In a survey, slot machine gamblers were more likely to "keep playing to try to win back their losses", compared to roulette and blackjack gamblers (Gainsbury et al., 2014). Slot machines were the most popular game type in our dataset, representing 57% of sessions, and they were used as the reference category.

We hypothesized that among online gamblers, the time interval between sessions would decrease as a function of the amount lost in the prior session (*H1: loss chasing*), and would decrease as a function of the amount won in the prior session (*H2: win chasing*). Furthermore, our analyses distinguished game types of slot machines, blackjack, roulette, video poker, and probability games (e.g., pachinko, reactors), and we hypothesized that slot machine sessions would be associated with the shortest between-session intervals, as a function of the amount lost (*H3: loss chasing by game type*) and amount won (*H4: win chasing by game type*) in the prior session.

METHODS

Data overview

The study used a behavioural tracking dataset obtained from the eCasino section of PlayNow.com, the provincial gambling platform for BC, Canada, which is restricted to BC residents. The website requires customers to create a user account, which allows the website to track individual gamblers' bet-by-bet behaviour with timestamps. The dataset was de-identified by the British Columbia Lottery Corporation (BCLC) Data Analytics team by randomly assigning each gambler a unique ID. The dataset spans from 2014-10-01 to 2015-08-31, comprising 527,015,222 individual bets placed by 29,964 gamblers. During the time period under scrutiny, the eCasino contained five game categories, which further comprised 240 specific products: slot machines (n = 195 individual products), roulette (n = 8), blackjack (n = 9), video poker (n = 13), and probability games (n = 15).

Our analysis code is on https://osf.io/dcv65/. We began by aggregating the bet-by-bet data into sessions. We define a session as a period of activity that begins with the first bet and ends with the last bet before the gambler is inactive for 30 min, in which case they are logged off automatically. This time interval reflects the gambler's log-on and log-off periods on the website. During a session, gamblers can play one game type (79% of sessions), or place bets across multiple game categories, termed as "mixed" sessions (21% of sessions). Thus, the aggregated session data comprised six types: slot machines, roulette, blackjack, video poker, probability games, and mixed sessions. Slot machines were the most popular product type in the eCasino (57% of sessions, see Table 1).

The analysis included gamblers who visited the eCasino more than five times. This represents an arbitrary threshold (although see Finkenwirth, MacDonald, Deng, Lesch, & Clark, 2021; Percy, França, Dragičević, & d'Avila Garcez, 2016), but between-session chasing inherently requires more than one session, and it is challenging to use data from gamblers with low levels of activity in modelling behavioural markers of high-risk gambling. We excluded a further gambler who was an outlier in terms of high bet frequency. The analytical sample included 1,909,681 sessions from 15,544 gamblers.

Table 1. Descriptive statistics of session data by game type

Game	Session count (%)	Gambler count (%)	
Slot machines	1,081,499 (56.63%)	12,285 (79.03%)	
Mixed sessions	412,858 (21.62%)	12,673 (81.53%)	
Probability games	184,933 (9.68%)	5,870 (37.36%)	
Blackjack	141,796 (7.43%)	4,420 (28.44%)	
Video poker	48,691 (2.55%)	1,264 (8.13%)	
Roulette	39,904 (2.09%)	2,402 (15.45%)	
Outcome (Canadian $)			
Game	*Median*	*Mean*	*SD*
Mixed sessions	−35.04	−116.58	874.02
Slot machines	−26.95	−97.58	633.69
Blackjack	−19.96	−104.39	399.74
Video poker	−17.92	−99.68	642.14
Probability games	−12.10	−43.70	784.11
Roulette	−10.00	−79.58	355.21
Time to return (hours)			
Game	*Median*	*Mean*	*SD*
Roulette	144.86	1,111.26	4,193.87
Blackjack	139.93	913.43	3,414.25
Slot machines	127.05	529.91	2,081.96
Mixed sessions	117.51	524.84	2,230.79
Video poker	100.26	435.61	2,057.99
Probability games	86.29	407.46	1,784.55

Note: Gambler count is non-exclusive in game played. For example, the same person can have both slot machine sessions and probability game sessions.

Statistical analysis

Variables. The analysis aimed to measure how prior session outcomes impact the following time to return to the eCasino. The time interval (*Time to Return*, expressed in hours) between the end of the prior session and the start of the next session is the dependent variable. A faster time to return reflects a greater chasing tendency. We applied a natural log transform on *Time to Return* because of its positive skewed nature in distribution, with most gamblers returned in modest time intervals, but some gamblers returned to the eCasino after extremely long intervals. The key predictors were:

- *Game*: game types included slot machines, probability games, blackjack, video poker, roulette, and mixed sessions.
- *Outcome Dummy*: a dummy variable indicated the outcome valence - win or loss, which might lead to differential chasing patterns. A negative net balance refers to a net loss. A positive net balance, which also includes zeros as 'break-even' sessions, refers to a net win. We re-parametrized the model in two ways: we used loss as *Outcome Dummy* reference (loss = 0, win = 1) to interpret loss chasing, and win as *Outcome Dummy* reference (win = 0, loss = 1) to interpret win chasing.
- *Outcome*: the absolute values of net outcome, which is the total paid amount minus the winning amount in a session (see also Leino et al., 2016). Outcome values were standardized with respect to individual gamblers' mean of loss or win amounts; depending on *Outcome Dummy,* a value of zero indicates an average loss (or win) amount for that gambler over the 11-month data. This standardized within person method is in line with our research interest in individual gamblers' responses to the prior outcome when winning or losing more than their personal average.

Additionally, we covaried for other time-related nuisance variables that could impact the timing of a new session:

- *Session Order*: the order of the current session on any given day, included in analyses as a covariate. We tested models that had linear or quadratic effects of raw or (natural) log-transformed session order, and ultimately used a linear effect of log-transformed Session Order as it yielded the best fit via BIC.
- *Start hour*: we anchored time of the day by the session's start time and classify it into the following periods: morning (12:00 AM–8:59 AM), early daytime (9:00 AM–2:59 PM), late daytime (3:00 PM–6:59 PM), night (7:00 PM–11:59 PM).
- *Weekends*: a dummy variable indicating whether the session occurred on a weekday (No = 0) or a weekend (Yes = 1).

- *BC statutory holidays*: a dummy variable indicating whether the session occurred on a holiday (Yes = 1) or not (No = 0).

Analysis. Analyses used R (Version 4.1.1; R Core Team, 2021) and Python (Version 3.6). The data structure is in two-level hierarchical: level 1 contains the variables we introduced earlier, which are clustered by *gambler ID* at level 2. Since there could be random differences in sessional variables between gamblers, we used multilevel linear modelling. An alternative method to analyze time-to-event data is survival analysis, which estimates the probability of a target event occurring. We considered this approach but our dataset comprises multiple events per participant, and our hypothesis refers to the time interval between events, as a continuous dependent variable, which is better suited to the multilevel linear model.

To test our hypothesis that prior loss and game impacted *Time to Return* to the eCasino, we specified our model as follows, and for simplicity, the model equation does not represent all of dummy codes for all the categorical variables with more than 2 categories:

$$\begin{aligned} Log\left(Time\ to\ Return_{ij}\right) = {} & \beta_{0j} + \beta_{1j}Outcome_{ij} \\ & + \beta_{2j}Outcome\ Dummy_{ij} \\ & + \beta_{3j}Game_{ij} + \beta_{4j}Outcome_{ij} \\ & * Outcome\ Dummy_{ij} \\ & + \beta_{5j}Outcome_{ij} * Game_{ij} \\ & + \beta_{6j}Outcome\ Dummy_{ij} * Game_{ij} \\ & + \beta_{7j}Outcome_{ij} \\ & * Outcome\ Dummy_{ij} * Game_{ij} \\ & + \beta_{8j}BC\ holiday_{ij} + \beta_{9j}Start\ hour_{ij} \\ & + \beta_{10j}Weekend_{ij} \\ & + \beta_{11j}Log\left(Session\ Order_{ij}\right) + e_{ij}, \end{aligned}$$

let i be the last session, j indicates *Gambler ID*. For *Game*, slot machines were set as the reference (slot machines = 0). At level 2 of random factors, the model allowed random intercepts and random slope of $Outcome_{ij} * Outcome\ Dummy_{ij}$ varying by *Gambler ID*, which allowed the degree of win and loss chasing to differ randomly across persons. All other slopes were fixed, as attempting to include more random slopes led to non-converged or improper solutions.

We used the lme4 package in R (Bates, Mächler, Bolker, & Walker, 2015) for modelling. We use $p = 0.01$ as the cut-off alpha level to determine statistical significance given our large data size. Log-transforming the dependent variable makes the model estimates not intuitive for interpretation, thus we transformed estimated coefficients to the percentage of changes using $100 * (e^b - 1)$.

Ethics

The study is an analysis on the de-identified secondary gambling data, which were given to the Centre by the BCLC under a Non-Disclosure Agreement that does not allow data sharing or any reporting of information from individual users. The University of British Columbia's Behavioural Research Ethics Board gave ethical approval to store and analyse the secondary dataset.

RESULTS

Descriptive results

We report medians due to the heavy skewness of the data (Table 1). On average, gamblers lost the most (Median = $-35.04) in mixed sessions. Slot machines – as the most played game category - ranked second (Median = $-26.95). Gamblers lost the least on roulette (Median = $-10.00). In terms of the time to return, gamblers returned the slowest overall after roulette sessions (Median = 144.86 h) and returned the fastest after probability game sessions (Median = 86.29 h). The time to return was intermediate for slot machine sessions (Median = 127.05 h).

Time to return as a function of prior session outcome

Figure 1 shows the time to return as a function of the prior loss and win. The x-axis depicts the standardized loss (win) amount based on the distribution of outcomes for that individual gambler over the data window. Zero constitutes their personal average loss (win) amount, and a positive outcome indicates the gambler lost (won) more than their personal average. A downward slope indicates that gamblers return faster as a function of larger prior loss (win), i.e. chasing, whereas an upward slope indicates that gamblers return slower after larger losses (wins).

After losing the prior session, gamblers returned more slowly across all game types, with the exception of roulette (Table 2). For a standard deviation increase in the prior session net loss, average gamblers playing slot machine sessions were estimated to took 8.59% longer to return to the platform (Table 3a). Compared to slot machines, blackjack ($p = 0.740$), probability games ($p = 0.157$), video poker ($p = 0.103$) on average did not differ significantly in the loss slopes. Mixed sessions on average were marginally faster in comparison to slot machine sessions ($p = 0.015$), but this was not significant at the conservative threshold. For roulette, average gamblers were estimated to return faster overall as a function of the amount lost: a standard deviation increase in the prior loss was estimated to reduce the time to return by approximately 4.78%.[1] The downward slope for roulette was significantly less steep than the upward slope for slot machines ($p < 0.001$), indicating that gamblers in roulette sessions were less sensitive to the prior loss than gamblers in slot machine sessions. The overall model yielded an intraclass correlation coefficient (ICC) of 0.36, a conditional R^2 of 0.39, and a marginal R^2 of 0.05, indicating that fixed and random effects together explained 39% of the variance in time to return, and fixed effect alone explained 5% of the variance.

[1](e^{(outcome + outcome * Roulette)} −1) * 100.

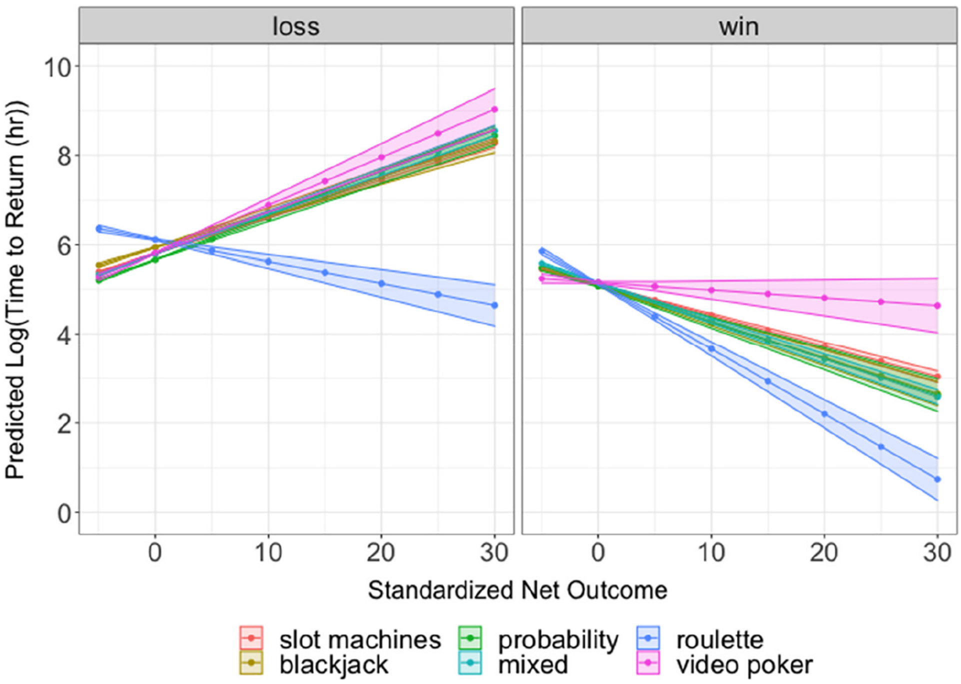

Fig. 1. Between-session chasing by game type
Note: The shaded area is standard errors.

Table 2. Summary of between-session across game types

	Time to return (hours)	
	Loss chasing	Win chasing
Slot machines	✗	✓
Mixed sessions	✗	✓*
Roulette	✓*	✓*
Blackjack	✗	✓
Probability games	✗	✓
Video poker	✗	✓

Note: '✓' indicates a numerical effect in the direction of chasing; '✗' indicates a directional absence of chasing under the measurement. '*' indicates a significant difference ($p < 0.01$) in chasing relative to slot machines as the reference category.

For the analyses of win chasing, average gamblers were estimated to return faster as a function of the prior amount won across all game types, thus indicating a propensity for win chasing (see Fig. 1, Table 3b). For a standard deviation increase in the prior win, average slot machine gamblers were estimated to take 6.68% less time to return. The rates of win chasing differed by game types: for mixed sessions and roulette, the slope for win chasing was on average significantly steeper than for slot machines (mixed, $p = 0.009$; roulette, $p < 0.001$). For mixed sessions, a one standard deviation increase was associated with an average 8.23% shorter time to return, and for roulette, an average 13.59% shorter time to return. Blackjack ($p = 0.222$), probability ($p = 0.324$), and video poker ($p = 0.012$) sessions on average did not differ significantly from slot machine sessions.

DISCUSSION

The DSM-5 operationalizes chasing as often returning to the casino another day (American Psychiatric Association et al., 2013), termed between-session chasing. As a diagnostic criterion, it is arguably the only behaviourally-observable item used in the identification of Gambling Disorder, and it is considered a defining hallmark of problematic gambling (Gainsbury et al., 2014). By analyzing timestamped online gambling data, our analyses refine the understanding of between-session chasing by measuring the time taken for gamblers to return to the platform after winning or losing sessions, across a number of different gambling products. Overall, the fixed factors alone, which included outcome and game type, as well as the time-related nuisance variables, only explained a small portion (5%) of the variance in the time to return. In combination with the level 2 random factors that allowed the degree of win and loss chasing to differ randomly across subjects, 39% of the variance in the time to return was explained. This moderate effect highlights the high degree of individual variation in chasing behaviours. On an aggregate level, we saw that gamblers on most game types returned more *slowly* after losing sessions, and returned more quickly after winning sessions. These findings are consistent with previous research that measured the interval between sessions for land-based casinos, betting shops, and online horse-racing games (Forrest & McHale, 2016; Kainulainen, 2020; Narayanan & Manchanda, 2012). In our data, roulette was a notable exception: this game had the longest intervals between sessions overall, but was the only game to show loss chasing as a function of greater

Table 3. Between-session chasing regression results

a: the reference of loss

Term	estimate	std.error	statistic	df	*p value*	conf.low	conf.high	transformed estimate
(Intercept)	5.78	0.01	568.55	18,612.91	<0.001	5.76	5.80	32,420.96
Outcome	0.08	0.00	24.61	10,311.00	<0.001	0.08	0.09	8.59
Outcome Dummy (Win = 1)	−0.70	0.00	−198.74	1,881,406.20	<0.001	−0.70	−0.69	−50.23
Blackjack	0.14	0.01	13.15	1,204,495.17	<0.001	0.12	0.16	14.52
Probability	−0.14	0.01	−21.90	1,799,009.01	<0.001	−0.15	−0.13	−13.13
Mixed	−0.01	0.00	−2.48	1,894,476.10	0.013	−0.02	0.00	−1.03
Roulette	0.31	0.02	19.09	1,212,709.45	0.000	0.28	0.34	35.96
Video poker	0.01	0.01	0.54	1,583,210.18	0.586	−0.02	0.04	0.82
Outcome * Outcome Dummy (Win = 1)	−0.15	0.00	−30.51	7,102.44	<0.001	−0.16	−0.14	−14.06
Outcome * Game (Loss chasing by Game)								
Blackjack	0.00	0.01	−0.33	36,217.27	0.740	−0.02	0.01	−0.30
Probability	0.01	0.01	1.42	166,567.99	0.157	0.00	0.02	1.02
Mixed	0.01	0.00	2.44	190,163.82	0.015	0.00	0.02	0.97
Roulette	−0.13	0.02	−8.41	67,375.14	<0.001	−0.16	−0.10	−12.31
Video poker	0.02	0.02	1.63	51,664.05	0.103	−0.01	0.05	2.51
Outcome Dummy (Win = 1) * Game								
Blackjack	−0.15	0.01	−16.18	1,896,136.80	<0.001	−0.17	−0.14	−14.36
Probability	0.10	0.01	10.58	1,545,180.88	<0.001	0.08	0.12	10.72
Mixed	0.06	0.01	8.59	1,885,785.52	<0.001	0.04	0.07	5.88
Roulette	−0.29	0.02	−16.55	1,837,680.26	<0.001	−0.33	−0.26	−25.50
Video poker	0.04	0.02	2.69	1,845,311.57	0.007	0.01	0.07	4.42
Outcome * Outcome Dummy (Win = 1) * Game								
Blackjack	−0.01	0.01	−0.71	14,101.80	0.477	−0.03	0.02	−0.90
Probability	−0.02	0.01	−1.60	19,349.36	0.109	−0.05	0.01	−2.24
Mixed	−0.03	0.01	−3.60	30,746.84	<0.001	−0.04	−0.01	−2.60
Roulette	0.05	0.02	2.53	27,129.20	0.011	0.01	0.10	5.59
Video poker	0.03	0.02	1.12	9,090.02	0.261	−0.02	0.07	2.74
Time nuisance								
BC holidays (Yes = 1)	0.04690	0.01	7.27	1,889,227.59	<0.001	0.03	0.06	4.80
Early daytime 9am–2pm	−0.08159	0.00	−22.45	1,895,871.95	<0.001	−0.09	−0.07	−7.84
Late daytime 3pm–6pm	0.02936	0.00	7.73	1,897,520.24	<0.001	0.02	0.04	2.98
Night	0.52839	0.00	140.19	1,900,153.44	<0.001	0.52	0.54	69.62
Weekend (Yes = 1)	0.04741	0.00	18.78	1,892,680.48	<0.001	0.04	0.05	4.86
Log(Session count)	−0.22919	0.00	−93.33	1,897,962.69	<0.001	−0.23	−0.22	−20.48

b: the reference of win

Term	**estimate**	**std.error**	**statistic**	**df**	***p value***	**conf.low**	**conf.high**	**transformed estimate**
(Intercept)	5.09	0.01	485.57	20,924.79	<0.001	5.07	5.11	16,084.84
Outcome	−0.07	0.00	−16.07	6,344.69	<0.001	−0.08	−0.06	−6.68
Outcome Dummy (Loss = 1)	0.70	0.00	198.74	1,881,406.18	<0.001	0.69	0.70	100.93
Blackjack	−0.02	0.01	−1.79	1,262,439.64	0.073	−0.04	0.00	−1.92
Probability	−0.04	0.01	−4.11	1,396,047.74	<0.001	−0.06	−0.02	−3.82
Mixed	0.05	0.01	7.45	1,886,143.90	<0.001	0.03	0.06	4.79
Roulette	0.01	0.02	0.75	1,305,816.86	0.452	−0.02	0.05	1.29
Video poker	0.05	0.02	2.86	1,691,066.32	<0.001	0.02	0.09	5.27
Outcome * Outcome Dummy (Loss = 1)	0.15	0.00	30.51	7,102.47	<0.001	0.14	0.16	16.36
Outcome * Game (Win chasing by Game)								
Blackjack	−0.01	0.01	−1.22	9,578.00	0.222	−0.03	0.01	−1.20
Probability	−0.01	0.01	−0.99	15,655.75	0.324	−0.04	0.01	−1.24
Mixed	−0.02	0.01	−2.63	23,893.85	0.009	−0.03	0.00	−1.66
Roulette	−0.08	0.02	−4.75	14,347.93	<0.001	−0.11	−0.05	−7.40
Video poker	0.05	0.02	2.51	7,325.55	0.012	0.01	0.09	5.32

(continued)

Table 3. Continued

b: the reference of win								
Term	**estimate**	**std.error**	**statistic**	**df**	***p value***	**conf.low**	**conf.high**	**transformed estimate**
Outcome Dummy (Loss = 1) * Game								
Blackjack	0.15	0.01	16.18	1,896,136.83	<0.001	0.14	0.17	16.76
Probability	−0.10	0.01	−10.58	1,545,183.59	<0.001	−0.12	−0.08	−9.68
Mixed	−0.06	0.01	−8.59	1,885,785.57	<0.001	−0.07	−0.04	−5.55
Roulette	0.29	0.02	16.55	1,837,680.76	<0.001	0.26	0.33	34.23
Video poker	−0.04	0.02	−2.69	1,845,312.00	0.007	−0.07	−0.01	−4.23
Outcome * Outcome Dummy (Loss = 1) * Game								
Blackjack	0.01	0.01	0.71	14,101.90	0.477	−0.02	0.03	0.91
Probability	0.02	0.01	1.60	19,349.58	0.109	−0.01	0.05	2.29
Mixed	0.03	0.01	3.60	30,747.18	<0.001	0.01	0.04	2.67
Roulette	−0.05	0.02	−2.53	27,129.38	0.011	−0.10	−0.01	−5.30
Video poker	−0.03	0.02	−1.12	9,090.11	0.261	−0.07	0.02	−2.66
Time nuisance								
BC holidays (Yes = 1)	0.05	0.01	7.27	1,889,227.57	<0.001	0.03	0.06	4.80
Early daytime 9am–2pm	−0.08	0.00	−22.45	1,895,871.93	<0.001	−0.09	−0.07	−7.84
Late daytime 3pm–6pm	0.03	0.00	7.73	1,897,520.23	<0.001	0.02	0.04	2.98
Night	0.53	0.00	140.19	1,900,153.43	<0.001	0.52	0.54	69.62
Weekend (Yes = 1)	0.05	0.00	18.78	1,892,680.47	<0.001	0.04	0.05	4.86
Log(Session count)	−0.23	0.00	−93.33	1,897,962.67	<0.001	−0.23	−0.22	−20.48
Conditional *R*-squared	0.39							
Marginal *R*-squared	0.05							

Note: panel (a) as losses as the reference level, and panel (b) has wins as the reference level.

amounts lost, as well as significantly steeper slopes (in comparison to slot machines) for both loss and win chasing.

In sharp contrast to loss chasing, win chasing – defined as a faster time to return as a function of the previous amount won – was a consistent pattern here across all game types. In a previous field study from Swiss land-based casinos, windfall wins carried over to increase the amount bet on the subsequent casino visit (Rüdisser, Flepp, & Franck, 2017). One possible explanation for these win chasing patterns is the so-called house money effect (Thaler & Johnson, 1990), which describes increased risk-taking because windfalls are not yet internalized as the gamblers' own funds; any loss of such windfalls would not hurt as much as the loss of one's own funds (Peng, Miao, & Xiao, 2013). As a cognitive explanation, one might expect such effects to be short-lived, whereas we observe between-session chasing of wins over the order of days, by which time the win should have been internalized as one's own. In our view, this may point to other explanations, such as a wealth effect, by which an increase in personal wealth enables larger spending in the future (Mehra, 2001). In the context of gambling sessions, prior wins increase financial resources to allow a faster time to return.

In contrast, we did not observe faster return times after losing sessions for most game types. With a greater loss, gamblers took *longer* to return to the website, indicating an absence of loss chasing in the aggregate data. In the break-even effect, individuals typically increase risk-taking when losing in an effort to recover their losses, but this should *only* occur when the losses are recoverable (Thaler & Johnson, 1990). In our data, the time intervals to return did not get faster with increasing amounts lost (except for roulette, discussed below), and this might be because further risk-taking did not offer the potential to break-even. We note that this explanation requires significant cognitive processing, to calculate the current difference from one's reference point (e.g., their starting account balance (Imas, 2016)), and the possible impact of a large win to offset that difference. Alternatively, longer return times after losing could be driven by financial constraints: significant losses may simply deplete financial resources to continue gambling (i.e. the converse of the 'wealth effect' described above for win chasing). Times to return may also be exogenously influenced by financial factors such as the next payday (Dahan, 2019). In future research, these explanations could be disambiguated by merging gambling data with banking information (Muggleton et al., 2021): for example, if the longer return times are due to insufficient funds, gamblers may be more likely deposit funds into their gambling account following pay days, which would be visible in the banking data.

Slot machines are considered to have among the highest risk potential for any form of gambling (Meyer, Fiebig, Häfeli, & Mörsen, 2011). Accordingly, we expected slot machine sessions to be associated with the shortest times to return. Overall, we found little support for this hypothesis: times to return did not differ significantly between blackjack, probability, video poker, and slot machines. Notably, roulette displayed shorter times to return than slot machines, as a function of both losses and wins, and roulette was the only game type where time to return decreases as a function of the prior amount lost. This apparent uniqueness of roulette should be considered in the context of roulette having the longest overall times to return of any product type, as well as a smaller net loss than other games (Table 1). These differences may render roulette gamblers more sensitive to the moderation by prior outcome, such that each unit of loss would result in larger change in time to return. In terms of structural characteristics, we note that these effects pertain to online roulette, and this is a faster game than land-based (i.e. casino) roulette, and is also accompanied by more intense audiovisual feedback. There is limited research considering the specific product risk associated with online roulette, or indeed for any individual types of eCasino products. It is possible that online gamblers who prefer roulette may display distinct psychological characteristics; for example, Bonnaire, Bungener, and Varescon (2009) reported that gamblers who preferred table games, including roulette, showed lower levels of depression and alexithymia compared to gamblers who preferred slot machines and racetrack gambling. Our findings for roulette arose from exploratory analyses, and as our predictions were of intensified chasing on slot machines, these findings for online roulette clearly warrant replication. Nevertheless, they do provide evidence for an overarching hypothesis that chasing tendencies differ by product category, which is relevant to developing algorithms for detecting high-risk gambling from behavioural data (Edson et al., 2023; Ghaharian, Abarbanel, Kraus, Singh, & Bernhard, 2023). We also recognize that gamblers at risk for gambling problems typically engage with a range of product types (LaPlante, Nelson, & Gray, 2014) such that future work in this area should give attention to both the expressions of chasing on specific gambling products, but also the characteristics of gamblers who chase.

In this study, we quantified the DSM-5 criterion for chasing – the tendency to return another day ("to get even") – as the time interval between successive online gambling sessions. Previous research (Auer & Griffiths, 2022; Challet-Bouju et al., 2020; Perrot et al., 2018) has focused on increased spending or deposits over time as expressions of chasing. Our study operationalizes the diagnostic item for gambling disorder to derive a concrete behavioural indicator for high-risk gambling. This approach further allows for the characterization of chasing after wins and losses, showing how between-session chasing varies by session outcome.

A number of limitations should be noted. Our data back to 2014–2015 and the online gambling landscape has continued to evolve since that time. We lack demographic descriptives for this de-identified dataset. As with most analyses of behavioural tracking data, it is possible that customers within our dataset held accounts on other gambling platforms (The Behavioural Insights Team, 2021), and visits to other websites would not be represented in our time to return variable. Mitigating this limitation, PlayNow is the only licensed online gambling website in BC, compared to other jurisdictions with many licensed operators. Second, sessions were defined based on a cut-off of 30 min of inactivity on the website, which is somewhat arbitrary. For example, a gambler may sporadically play over the course of a day, with breaks of an hour or longer; should this be classified as one session or several? In principle, the same issue can arise in land-based casinos, e.g., when visiting the bar or ATM. Another limitation is that our analyses focus on time to return as a specific expression of between-session chasing, which may alternatively be measured in the bet volume over successive sessions (Auer & Griffiths, 2022; Flepp et al., 2021). Further behavioural markers exist to characterize *within*-session chasing tendencies (Chen, Doekemeijer, Noël, & Verbruggen, 2022; O'Connor & Dickerson, 2003). We are exploring these alternative expressions in ongoing research, which also incorporates self-exclusion data (Deng, Lesch, & Clark, 2021; Finkenwirth et al., 2021) as a marker of disordered gambling. Lastly, as noted by a reviewer, mixed sessions represent an interesting instance of a multiple (or chained) reinforcement schedule (Saini, Miller, & Fisher, 2016) controlled by the participant. Even single-category sessions could still involve the gambler switching between specific games, such as different slot machines. The product categories, and within-category products, will vary in structural characteristics, some of which are highly relevant to chasing; for example higher volatility games are associated with longer losing streaks, which may prompt switching products (Delfabbro, King, & Parke, 2023). Future research may drill down further on these session characteristics, viewed from the perspective of operant behaviour.

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