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Multidimensional Loss Chasing among Online Gamblers: Assessing Optimized Thresholds for the Prediction of Gambling Harm

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Abstract
Loss chasing is a defining clinical criterion for Gambling Disorder. Using actual player records, we investigated the potential for a multidimensional loss chasing concept (based on bet size, betting odds, and time between bets) to predict potential gambling harm among online sports bettors (N=36,331) and daily fantasy sports (DFS) players (N=34,596). Our main focus was whether optimized thresholds (derived from ROC analysis) for loss chasing yielded greater predictive value than both median-derived thresholds and a natural continuous form. Compared to the other tested forms of chasing, optimized thresholds of loss chasing showed the most promise (i.e., positive and statistically significant effects and improved model fit) for two out of three dimensions (i.e., bet size and odds) for one outcome (i.e., loss trajectory) among sports bettors. For these bettors and outcomes, all three loss chasing dimensions predicted the outcome in isolation; however, grouping all three expressions into a single model yielded poor model fit. Loss chasing effects were less apparent (generally non-significant or in the negative direction) for another outcome (i.e., percent change in net loss) and among DFS players. Still, this study demonstrates the promise of a multidimensional concept of loss chasing, and the potential for optimized thresholds to improve prediction of potential harm-related outcomes.

Keywords Gambling · Loss chasing · Chasing losses · Gambling harm · Optimized thresholds

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Introduction

Loss chasing is the tendency for gamblers to amplify their betting in response to losses. Evidence suggests that loss chasing represents a defining marker and/or antecedent of emerging problem gambling (Custer, 1984; Gainsbury et al., 2014; Nigro et al., 2019; Stinchfield et al., 2005; Parke & Parke, 2019; Parke et al., 2016). Recent reviews (e.g., Potenza et al., 2019; Zhang & Clark, 2020) also suggest that loss chasing is a primary risk factor for, and symptom of, problems with gambling. Consistent with this idea, one of the leading etiological frameworks of problem gambling, the Pathways Model (Blaszczynski & Nower, 2002), includes loss chasing as one of the final steps on an at-risk individual's path towards problem gambling—immediately preceding the penultimate step of losing more money than one expects. Finally, loss chasing is listed in the DSM-5 as a clinical criterion for the diagnosis of Gambling Disorder (i.e., "After losing money gambling, often returns another day to get even" the only criterion that is not shared with substance use disorders (Banerjee et al., 2023). As such, chasing one's losses might represent the most distinct marker or risk factor for the development of Gambling Disorder.

Given this importance, there is a growing need for the research community to develop and test operational definitions of loss chasing that can be identified and monitored. A recent scoping review of the loss chasing literature (Banerjee et al., 2023) found that the vast majority of studies have typically measured the concept via self-report, with only eight studies actually measuring and assessing some sort of operational definition of chasing using behavioral tracking (i.e., gambling records) data. Among these eight studies, the review noted some common limitations. One in particular was that most behavioral tracking studies assessed loss chasing within the confines of a "within-session" and "between-session" dichotomy without clear guidance, definition, or agreement, of what constitutes a "gambling session." This issue is particularly notable for gambling outlets that allow individuals to gamble at all times of the day, and thus have no clear means (e.g., opening and closing times) to serve as a demarcation for the beginning and end of sessions. The review's findings also revealed disagreement about the operational definition of "chasing," with many behavioral tracking studies sticking closely to frequency-based measures rooted in the Diagnostic and Statistical Manual of Mental Disorders (DSM) definition (e.g., number of times money was deposited after a loss; Perrot et al., 2018) and intensity-based measures (e.g., increasing stake size after a loss; Auer & Griffiths, 2023; Abe et al., 2021). Importantly, although "chasing" might not represent one distinct gambling behavior, almost all studies considered loss chasing as a single behavioral expression. Even the single study they identified (Chen et al., 2022) that considered multiple behavioral expressions of loss chasing (i.e., "Decisions of when to stop, increase in stake sizes and post- loss speeding," as described in Banerjee et al., 2023), did not measure them in a way that allows for direct comparisons of each expression in terms of its effects on outcomes. Finally, the Banerjee et al. review noted that most investigations of loss chasing were confined to a single gambling environment, meaning that it is unclear whether and to what extent loss chasing effects might differ between products, especially those with different structural designs (e.g., house-based vs. rake-based games, skill-based versus chance-based games). Questions remain in terms of whether: (1) loss chasing can be represented by multiple behavioral expressions rather than a single expression, (2) loss chasing truly fits into a neat "within-session" or "between-session" framework, and (3) loss chasing's effects might differ depending on the gambling environment.

Multidimensional Loss Chasing

In a recent study, Edson et al. (2024) sought to address some of these noted gaps in research. Specifically, Edson and colleagues suggested the need for a multidimensional concept of loss chasing. In a preliminary examination among a population of subscribers to a large European sports betting operator, they examined three different chasing behaviors during bettors' first 30 days of activity: (1) increases in stake size, (2) choosing bets with higher payout odds, and (3) decreases in time between bets, and examined each chasing dimension's effects on mounting losses over subsequent months. Their approach was unique from prior studies in two primary ways. First, for their loss chasing concept, Edson and colleagues proposed a "prior bet" frame of reference for losses, meaning they only considered accelerations in betting behavior to be "loss chasing" in instances where the prior bet was a loss (i.e., total stakes exceeded total winnings), which avoids the subjectivity around what constitutes a gambling "session". Second, they used a standardization procedure, which allowed for direct comparisons between different possible loss chasing behaviors.

Among a cohort of sports bettors, Edson & colleagues found that high levels of loss chasing (i.e., individualized loss chasing scores above the median for a respective metric) were not highly correlated with one another, which suggests that loss chasing might indeed be a multidimensional concept. However, the authors found that only a single dimension—bet size—had a statistically significant and positive effect on their chosen outcome (i.e., increased losses over time — loss trajectory) in bivariate analyses, and this effect disappeared after adjusting for key gambling involvement behaviors (e.g., average stake size), and especially for bettors who generally played at lower stakes.

At least three open questions remain. First, it is unclear how loss chasing should be identified (i.e., distinguishing "high" and "low" value groups by median split versus some other mechanism) for potential harm prediction. Specifically, given the growing utility and importance of Artificial Intelligence (AI; Anderson & Rainie, 2018), do machine-learning processes and related methods (ROC analysis) hold potential to identify more optimized dichotomous thresholds of loss chasing, for the prediction of potential harm? Alternatively, do the raw continuous values of loss chasing hold greater value than dichotomous thresholds for predicting potential harm? Second, is loss chasing associated with diverse outcomes, or are the relationships from Edson & colleagues' study particular to loss trajectory. Third, are loss chasing effects similar or different across gambling environments (e.g., sports betting versus some other gambling product).

The Present Study

In this study, we assessed several research questions that follow from Edson et al. (2024). First, in terms of potential harm prediction, we deternubed whether we could identify an optimized threshold of loss chasing as compared to a simple median cut, and whether either of such discrete thresholds maximize predictive value compared to the raw continuous form of chasing? Second, given the most optimized form of each chasing dimension, we asked if a multidimensional or some sort of unidimensional solution best predicts potential harm.

Third, we considered whether loss chasing patterns might vary by gambling environment. Specifically, in addition to the sports betting dataset from Edson et al. (2024), we also examined a dataset comprising playing records of daily fantasy sports (DFS) players. Although we do not posit any pre-registered confirmatory hypotheses for gambling environment testing in this article, this study is the first to examine loss chasing and its effects on potential harm among multiple gambling products. Fourth, we considered two separate outcomes, rather than one. These include (1) the outcome from Edson and colleagues' study (loss trajectory), and (2) percent change in net loss from month to month. We also considered a third outcome, voluntary self-exclusion (VSE), a common proxy for gambling harm (Bijker et al., 2023; Håkansson & Henzel, 2020); however, for this study we reserved the VSE outcome for determining optimized cutpoints for loss chasing, as opposed to inferential testing.

All of our research questions, hypotheses, and analyses were preregistered before conducting any of the analyses on the Open Science Framework (OSF; https://osf.io/3w7st/?view_only=0309711d6c2b455ca3c6d99099f136a6*)*. Transparent change documentation for how we constructed machine-learning cutpoints for loss chasing for our DFS cohort (Transparent Change 1), and how we approached the calculation of standard errors for the percent change in net loss outcome (Transparent Change 2) also are available on the study's OSF page (see link above).

Hypotheses

We tested the following confirmatory hypotheses:

Hypothesis 1

Our expectation is that gamblers who exhibit higher levels of loss chasing will present greater risk for potential harm than those who exhibit lower scores. However, there is likely a point of diminishing returns (Mold et al., 2010) whereby higher chasing scores will not necessarily increase one's risk for potential harm. In terms of optimizing such a discrete cutpoint, we believe ROC analysis-informed discretization for prediction (e.g., Liu et al., 2002; Louderback et al., 2021) will hold greater value than a simple (i.e., median) cut. Relatedly, machine learning processes have shown increased promise in gambling research for harnessing analytic power of large player records datasets for the prediction potential harm (Hassanniakalager & Newall, 2022; Murch et al., 2023; Percy et al., 2016). Machine learning, simply put, is a subfield of computer science where predictive models operate without direct user intervention, and attempt to maximize their predictive potential through an iterative process (i.e., trial and error) (Bi et al., 2019). Through this process, machine learning can help to augment ROC analysis by determining the best set of cutpoints (derived from ROC) for maximizing the prediction of potential harm. Therefore, we proposed *Hypothesis 1*: Optimized cutpoints for loss chasing will have greater predictive efficacy (in terms of model fit) of potential harm than median-based cutpoints, which will in turn have greater predictive efficacy than the raw continuous forms of loss chasing, for predicting potential harm (i.e., percent change in net loss and loss trajectory).

Hypothesis 2

As with other social concepts such as inequality (Blesch et al., 2022), and in accordance with the expectations of Edson et al. (2024) in their initial study, we similarly expect that multidimensional models of loss chasing will hold greater utility for prediction than unidimensional models. Therefore, we proposed *Hypothesis 2*: In their best-fitting form, all three proposed dimensions of loss chasing (bet size, betting odds, time between bets) will be positively and significantly associated with potential harm, and a multidimensional model (comprising all three dimensions) will have better model fit than any one unidimensional or bidimensional model.

We do not have specific hypotheses related to differences among the three outcomes tested or the platform under investigation (i.e., sports betting versus DFS).

Method

Data and Participants

For this study, we used two sources of existing data:

February 2015 bwin sports betting subscribers. This dataset includes the betting and transactional records for all individuals who subscribed to bwin's sportsbook platform during February 2015 (N=36,331). These data span between each player's registration date and 2020-07-11. In addition to this main dataset, we also obtained a dataset containing VSE events specific to this cohort. These data span between 2015-02-01 (the earliest date in the sports betting data) and 2020-07-14 (the latest date for which we have VSE data), and contain the VSE event details for any player in the February 2015 registration cohort who self-excluded.

DraftKings DFS subscribers from 2013, *2014*, *and 2015*. This dataset comprises the playing and transactional records for all players who made their first deposit on DraftKings between 2013-08-01 and 2013-09-30 (2013 cohort, N=12,041), and commensurately sized samples of players who first deposited money on DraftKings between 2014-08-01 and 2014-09-30 (2014 cohort, N=12,041) and between 2015-08-01 and 2015-09-30 (2015 cohort, N=12,041). For the purposes of the proposed research, we combined these three groups into a single cohort of DFS players, for a total of 34,596 players (slightly less than the total sum; 1,527 players within the three cohorts deposited money but did not play in any contests). These data span between each player's initial deposit date and 2016-12-31. In addition to this main dataset, we also obtained a dataset also containing VSE outcomes from DraftKings' DFS site specific to these cohorts of players. These data span between 2013-08-01 (the earliest date in the contest data) and 2019-02-04 (the latest date for which we have VSE data), and contain the VSE event details for any player in the 2013, 2014, and 2015 cohorts who self-excluded during that time frame.

Procedures

We received both the sports betting and DFS datasets through a secure File Transfer Protocol. The raw data are at the bet-by-bet level. We summarized both predictor variables and outcome variables as monthly aggregates to avoid excess zero values and ensure a sufficient number of time points for our analyses.

With regards to the 36,331 bettors in the sports betting cohort, we removed 6 bettors from the data whose only betting activity occurred near the very end of the study period, where a complete 30-day monthly period could not be constructed. We retained the remaining 36,325 bettors for constructing and testing optimized loss chasing cutpoints and descriptive analyses of bettor demographics and the variables of interest (i.e., outcome variables and loss chasing metrics). For the main analyses, we divided the cohort of 36,325 into two non-mutually exclusive subgroups based on whether they qualified for one or both of the two main outcomes of interest: loss trajectory (i.e., placed at least one bet during the first 30 days since registration and placed at least one bet on two other 30-day periods; $n=13{,}146$) and percent change in net loss (i.e., placed a bet on at least one set of adjacent 30-day periods; $n=16{,}659$).

With regards to the 34,596 players in the DFS cohort, we removed 2 players whose betting activity likewise occurred near the end of the study period and therefore was not part of a full 30-day monthly period. We retained the remaining 34,594 players for loss chasing threshold optimization and descriptive analyses, and then partitioned this larger group into separate non-mutually-exclusive subgroups representing those who qualified for the loss trajectory outcome ($n=23{,}642$) and the percent change in net loss outcome ($n=26{,}537$).

Ethical Statement

This research complied with ethical research standards. The Cambridge Health Alliance Institutional Review Board determined this study was not human subjects research.

Measures

Dependent Variables

Loss trajectory. For each bettor, and for all their active months (i.e., exclusive 30-day periods with at least one bet) after the first month of play (i.e., first 30 days of activity, where the bettor placed at least one bet), this measure is the value of a linear regression coefficient expressing the relationship between month number and 30-day net loss (Edson et al., 2024).[1] Larger values of loss trajectory represent increasing net losses from month to month.

Percent Change in Net Loss. For each bettor, we considered all adjacent month periods where the bettor was active (i.e., the bettor placed at least one bet during the adjacent months) and assessed whether chasing during Month t predicts percent change in net loss during Month $(t+1)$. We set any instances of percent change in net loss where the corresponding Month t net loss value was zero (i.e., break even) to missing, as the resultant percent change in net loss calculation would otherwise yield a “dividing by zero” error. On a similar note, percent change calculations assume positive values for both Month t and

[1] Edson et al. (2023) constructed loss trajectory using the standardized coefficient between month number and cumulative net loss, whereas we are using the unstandardized coefficient, in order for loss trajectory scores to be more reflective of a bettor’s true “burn rate”. To account for the fact that burn rates are heavily influenced by bettors’ average stakes (the main reason Edson & colleagues used the standardized metric), we controlled for stake per bet and the interaction between stake per bet and loss chasing metrics in all of our models.

Month ($t+1$) values; in instances where the Month t value is negative (except where the Month ($t+1$) value is zero), this will yield the incorrect sign. Therefore, we reverse coded any values of percent change in net loss (i.e., multiplied by -1) where the corresponding Month t value was negative, and the corresponding Month ($t+1$) value was not equal to zero.

Voluntary Self-exclusion (VSE). For both datasets (DFS and sports betting), we assigned any bettor who elected to voluntarily self-exclude after their first month of play a value of 1, otherwise 0. The DFS VSE data contained 137 VSE events spread across 137 unique players. The sports betting VSE data contained 1,425 VSE events spread across 1,158 unique bettors.

Independent Variables

Loss chasing (continuous). For each person in our sports betting and DFS cohorts, we calculated three loss chasing metrics for every bet made, one for each dimension (i.e., stake size, betting odds, time between bets), following the method proposed by Edson et al. (2024). These calculations are oriented around a z-score. We set any loss chasing scores to zero when: (1) the loss chasing score was less than zero (i.e., de-escalation), or (2) the outcome of the prior bet was a win or break even outcome. We considered each month (i.e., again, 30 day periods of activity) and created individual loss chasing scores for each bettor for each month by dividing the sum of their non-zero z-scores during that month by the number of bets they made during that month.[2]

For time between bets, we created a compound metric, calculating chasing metrics separately for bets separated by at least a day (i.e., 24 h) and bets occurring within the same day, taking the average of the two to determine the time between bets metric's final value. This process helps avoid systematically large standard deviations in this metric. For a detailed description of the raw metric construction, see Edson et al. (2024) and its corresponding study *registration*.

Loss chasing (binary median cutpoint). We started with the continuous loss chasing variables (see above) and then created a binary transformation whereby bettors whose continuous score for the respective loss chasing metric was above the median were assigned to the "high group" and bettors whose score was at or below the median were assigned to the "low group" (see Edson et al., 2024).

Loss chasing (binary ROC-informed cutpoint). Our analytic pipeline for determining optimized cutpoints of loss chasing is illustrated in Fig. 1. We started by following a similar ROC analysis method as employed by Louderback et al. (2021) for determining optimized gambling thresholds in online platforms (Step 1). Using the raw continuous forms of each

[2] Edson et al. (2023) created their bet-invariant metrics by dividing raw loss chasing metrics by the number of losing bets, whereas we are dividing ours by the total number of bets made (both winning bets and losing bets). Edson and colleagues' justification for dividing by the number of losing bets was because only losing bets provide the bettor the opportunity to chase losses. However, their study was only considering loss chasing during the first month of activity. For one of our outcomes (percent change in net loss), we are considering loss chasing during all months of activity. For many bettors, the prior loss that provides an opportunity for chasing might have occurred during a previous month, rather than the present month. Dividing by the number of losing bets in many instances, therefore, might involve raw chasing scores being divided by a zero value (no losing bets that month, where the losing bet that triggered the chasing episode happened during a previous month). For this reason, we feel that bet-invariant loss chasing is better optimized by dividing by the number of total bets, rather than previous bets.

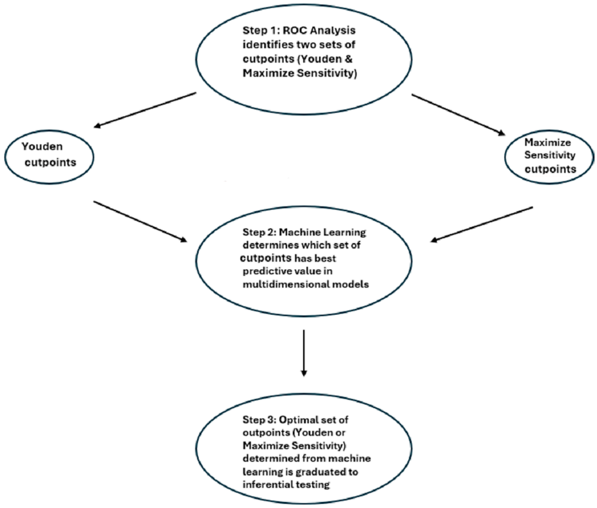

Fig. 1 Analytic pipeline for determining optimized loss chasing cutpoints

loss chasing metric during the first 30 days of activity, we started by estimating, for each DFS player and sports bettor, separate logistic regression models, each containing a single continuous loss chasing metric (bet size, betting odds, time between bets), for each product (sports betting and DSF) predicting the VSE outcome during subsequent months. From these models, we used the coefficient for each metric in each model to test the performance of various cutoffs with ROC analysis (Zhu et al., 2010) using the optimal.cutpoints() function from the R package *OptimalCutpoints* package (López-Ratón, Rodriguez-Álvarez, & Sampedro, 2014). We created two sets of three (i.e., six total) cut-offs for optimizing our ability to discriminate individuals who self-exclude from those who do not self-exclude: (1) a set of three (C_{Y*}: C_{YS}, C_{YO}, and C_{YT} for bet size, betting odds, and time between bets, respectively) that optimize the Area Under the Receiver Operating Characteristic Curve (ROC_AUC) and maximize sensitivity and specificity using Youden's index and (2) another set of three (C_{S*}: C_{SS}, C_{SO}, and C_{ST} for bet size, betting odds, and time between bets, respectively) that optimize ROC_AUC and maximize sensitivity with the constraint that specificity be 0.70 or higher (i.e., to avoid a very high proportion of false positives and thus overly conservative cutoffs).

Next, we used machine learning techniques to determine which set of cutoffs (C_{Y*} or C_{S*}) best predict the VSE outcome (Step 2). Specifically, we tested two competing models, one containing set C_{Y*} binary predictors (C_{YS}, C_{YO}, C_{YT}) and one containing set C_{S*} binary predictors (C_{SS}, C_{SO}, C_{ST}), in terms of their ability to predict VSE using four machine learning algorithms: (1) binary logistic regression, (2) Bayesian networks, (3) neural networks, and (4) random forest models (Percy et al., 2016). We conducted these machine learning processes in Python (version 3.11.3) using the *scikit-learn* package (Pedregosa et al., 2011). For each machine learning algorithm, we used 10-fold cross-validation with 3 repetitions to reduce overfitting (Kim, 2009). We recorded the mean accuracy, mean sensitivity, mean specificity, and ROC_AUC score (i.e., percentage of area under the curve) for each algorithm, and identified the best performing algorithms as those with the largest ROC_AUC score in the testing subset. We used synthetic minority oversampling (SMOTE) in the machine learning models as we expected our data to be unbalanced (see Chawla et al., 2002). In our results, we reported the original and SMOTE estimates for completeness. However, as expected, the data were heavily unbalanced. Therefore, we chose the best performing algorithm based on the SMOTE estimates. This approach ultimately determined the best set of cutoff/critical thresholds (C_{Y*} or C_{S*}) for each loss chasing metric that was moved to inferential testing (Step 3). We conducted these analyses separately for both products/cohorts (DFS and sports betting), thus yielding separate sets of optimal thresholds for each product/cohort. For the DFS cohort, rather than positing a single cutpoint for the machine learning-informed loss chasing binary predictors, we used cutpoints for each cohort and assigned a value of 1 to this variable based on the player's cohort and the respective cutpoint identified for that cohort. For both the sports betting and DFS cohorts, bettors who exceed the critical threshold for a given metric were classified in the "high group" for the respective metric, while all others were classified in the "low group" for the respective metric.

Control Variables

For all confirmatory analyses, we controlled for average stake size (i.e., stake per bet, which is the total stake divided by total number of bets, for each 30-day period) and an interaction effect between average stake size and any included loss chasing variables. Detailed justifications for these control variables can be found in the study registration and an associated Transparent Change document on this project's OSF page. We report adjusted and unadjusted results for all confirmatory inferential analyses, and consider both for model fit determinations.

Analysis Plan

Here, we describe the entirety of the approach for our planned analyses. Given the wide breadth of these analyses, and to avoid overloading our readers with too much information, we confined many of the results of our planned analyses (including machine learning results and Hypothesis 2 testing results) to an online supplementary materials document. We report quick summaries of these results in the main paper.

Descriptive Analyses

We first examined the distribution of continuous loss chasing variables across bettors/active months. For each dimension of loss chasing (stake size, odds, time between bets), for both cohorts of bettors (DFS and sports betting) we calculated the mean, standard deviation, and five number summary. In a large correlation matrix, we calculated Spearman correlations among the loss chasing variables. We also examined the mean, standard deviation, and five number summary for the distributions of the two continuous outcomes: loss trajectory and percent change in net loss.

Next we calculated a census of the binary machine learning-informed loss chasing variables. Specifically, for each set of loss chasing dimensions (i.e., containing optimized cut points for bet size, betting odds, and time between bets) and for both products/cohorts (DFS and sports betting) we reported the identified cut point thresholds, the specific type of cut that optimized the threshold (i.e., Youden's index or a cut that maximized sensitivity with the constraint that specificity be 0.70 or higher), the best performing machine learning algorithm for each cut (i.e., logistic regression, Bayesian networks, artificial neural networks, and random forest), and the performance statistics of the best-performing algorithm (i.e., mean accuracy, mean sensitivity, mean specificity, and mean ROC_AUC score). We also calculated the mean and standard deviation of the proportion of bettors in the "high group" for each month, for each dimension and across both products. To do this, we constructed a graphic illustrating the relationship between month number and proportion of bettors in each high group, for each loss chasing metric.

Confirmatory Analyses

Hypothesis 1

With the machine-learning informed discrete measures of loss chasing in hand, we compared their predictive efficacy against their corresponding median cutoff discrete measures and the raw continuous measures of loss chasing, for the two main outcomes (i.e., percent change in net loss and loss trajectory). For the loss trajectory outcome, we examined all iterations of loss chasing during Month 1, predicting loss trajectory over subsequent months. For the percent change in net loss outcome, we focused on all adjacent months the bettor was active, using multilevel modeling (Raudenbush & Bryk, 2002) to examine the effects of all iterations of loss chasing during Month *t* predicting percent change in net loss during Month (t+1). We estimated both unadjusted models (i.e., only the respective loss chasing metric as a predictor) and adjusted models (i.e., including stake per bet and an interaction between stake per bet and the respective loss chasing metric). We compared each form of loss chasing (discrete [optimized cutpoint], discrete [median cutpoint], or continuous), including both adjusted and unadjusted models, in terms of model fit (i.e., the Akaike Information Criterion [AIC]; Burnham & Anderson, 2004) to determine which had the best predictive ability, for each chasing dimension, for both outcomes, and separately for DFS players and sports bettors. We omitted the VSE outcome for these analyses, given our use of VSE to determine the critical values of the machine-learning derived cutpoints for loss chasing. Further details of our statistical analyses can be found in the study registration on this project's OSF page.

Percent Change in Net Loss. For the percent change in net loss outcome, we considered loss chasing for each metric for every month of the study period. We used multilevel modeling to assess associations between loss chasing during Month *t* and mounting losses during Month (t+1). We calculated all analyses separately for DFS players and sports bettors. We employed multilevel linear regression, with robust standard errors to mitigate any potential clustering effects (Wang et al., 2015), and other potential assumption violations. We used the lmer() function from the *lme4* package in R (Bates et al., 2015) to estimate multilevel models. For all HLM models, we started by specifying a random intercept, and random slopes for the three loss chasing metrics. In instances where random slopes led to model convergence issues, as a result of overly complex models, we reverted the respective random effect to a fixed effect. Likewise, if a given random slope did not significantly improve model fit (i.e., a decrease in the AIC; Burnham & Anderson, 2004), we reverted it to a fixed effect. We excluded bettor/playing months where: (1) the bettor self-excluded during Month *t* or Month (t+1); or (2) the bettor did not place at least one bet during Month *t* or Month (t+1). The former exclusion was to ensure we were comparing both gambling and losses among individuals who had equal opportunity of time to gamble (i.e., because people who self-exclude have no opportunity to gamble during their exclusion period). The latter exclusion: (1) ensured that low levels of loss chasing during Month t were due in fact to lower levels of chasing rather than simply not playing, (2) helped to avoid excess zeros on the dependent variables, and (3) acted as a buffer against potential serial correlation during extended months of non-activity.

Loss Trajectory. We considered how early loss chasing (i.e., during the first 30 days of activity) for each loss chasing metric relates to subsequent loss trajectory throughout the remainder of the study period, excluding Month 1 (Edson et al., 2024). For this, we calculated all analyses separately for DFS players and sports bettors. We employed OLS linear regression with robust standard errors (Mansournia et al., 2021) to estimate effects. We used the lm() function in base R to estimate the linear models.

Hypothesis 2

With the best fitting form of each chasing dimension (i.e., discrete with machine optimized cutpoints, discrete with median cutpoints, or continuous) in hand for the two outcomes, we proceeded with determining the best combination of dimensions (unidimensional or multidimensional) for predicting the respective outcome. Specifically, we started with the six unidimensional models representing the associations of the three single dimensions of loss chasing (i.e., bet size, betting odds, time between bets) with the two outcomes (i.e., percent change in net loss, loss trajectory). We used stepwise AIC method for variable selection (Yamashita et al., 2007) to determine which combination of the three unidimensional loss chasing metrics best predicted the respective outcome. In instances where the best fitting form for a given dimension was derived from an adjusted model (i.e., including an interaction with stake per bet) from Hypothesis 1, we included stake per bet and the respective interaction in the stepwise AIC process. This process allowed us to determine a best-fitting model.

Planned Sensitivity Analyses

For all confirmatory analyses, we conducted sensitivity analyses where we replaced stake per bet with a new variable: log stake per bet defined as $\log_{10}$(stake per bet). The reasoning for this sensitivity analysis was to determine whether the confounding/interaction effect of bettor stakes on the relationship between loss chasing, loss trajectory, and percent change in net loss is better explained by the general stakes the bettor plays at in terms of orders of magnitude (i.e., are they a \$1 stakes bettor, a \$10 stakes bettor, a \$100 stakes bettor?), rather than their specific stakes.

For the percent change in net loss outcome, we conducted a sensitivity analysis whereby we removed cases that had a zero value (i.e., the bettor played during two adjacent months but their net losses were the same for both months), and for the remainder of cases, we applied a natural log transformation to percent change in net loss and re-estimated the analyses. The reasoning for this sensitivity analysis was due to percent change in net loss being very sensitive to low Month t values (e.g., at or below a value of 1), where such values (depending on their size relative to the Month $[t+1]$ value) can often yield an inflated percent change calculation, in both directions. Log transformation of the outcome tempers this inflation, and in doing so helps to determine whether inflated values might have had a major effect on the main results. We removed zero values of percent change in net loss for this analysis, because they cannot be log transformed.

Results

Cohort Demographics

The full sports betting cohort (N=36,325) was mostly male (90.8%), with a mean age of 29.8 (SD=10.3) and a median age of 27 (min=14, 25% = 22, 75% = 35, max=95). Most bettors were from Germany (34.9%), followed by Spain (15.8%), Great Britain (13.9%) and France (10.1%), while the remaining 25.3% of bettors were from other countries. Among the full DFS cohort (N=34,594), we had available information on player age for 11,304 players. Among these players, the average age was 33.8 (SD=9.9), and the median age was 32 (min=15, 25% = 27, 75% = 39, max=82).

ROC Analysis Cutpoints and Machine Learning

For both the sports betting and DFS cohorts, Youden's index cutpoints (identified in ROC analysis) yielded the best-optimized cutpoints. In machine learning discrimination analyses, SMOTE-balance estimates outperformed unbalanced estimates, however even the best classifiers still yielded poor/fair discrimination with modest to low AUC scores, specificity and accuracy, and very low recall (sensitivity). The best performing machine learning classifier (in terms of maximizing AUC, and based on the point estimate) was logistic regression for the sports betting cohort (AUC: 0.602) and Bayesian networks for the DFS cohort (AUC: 0.701). The full machine learning results, including the identified cutpoints, can be found in the supplementary materials (Sect. 1).

Descriptive Results

Continuous Loss Chasing Measures

Among the full sports betting cohort, and across all of these players active months during the study period for these bettors (N=213,680), the mean value for the monthly (i.e., bet invariant) bet size loss chasing metric was 0.6 (SD=10.6; NOTE: values in this section represent standardized 'loss chasing units'), while the median value was 0.1 (min=0, 25% = 0, 75% = 0.4, max=2292.2). The mean value for monthly odds loss chasing was 2.4 (SD=319.9), and the median value was 0.02 (min=0, 25% = 0, 75% = 0.3, max=121547.4). The mean value for monthly time between bets loss chasing for this cohort was 0.3 (SD=24.8), and the median value was 0.2 (min=0, 25% = 0.04, 75% = 0.3, max=8501.7).

Among the full DFS cohort, across all playing months (N=285,171), the mean monthly bet size loss chasing metric was 0.3 (SD=1.0), while median value was 0.1 (min=0, 25% = 0, 75% = 0.3, max=197.4). The mean monthly odds loss chasing metric was 62.1 (SD=3883.2), while the median value was 0 (min=0, 25% = 0, 75% = 0.4, max=980391.2).

Table 1 Spearman correlations between continuous loss chasing metrics

	Bet size	Odds	Time between bets
Bet size	-	0.29	0.36
Odds	0.07	-	0.30
Time between bets	0.18	0.33	-

Note: Correlations below the diagonal are for the sports betting cohort and correlations above the diagonal are for the DFS cohort. All correlations are statistically significant at $p < 0.05$

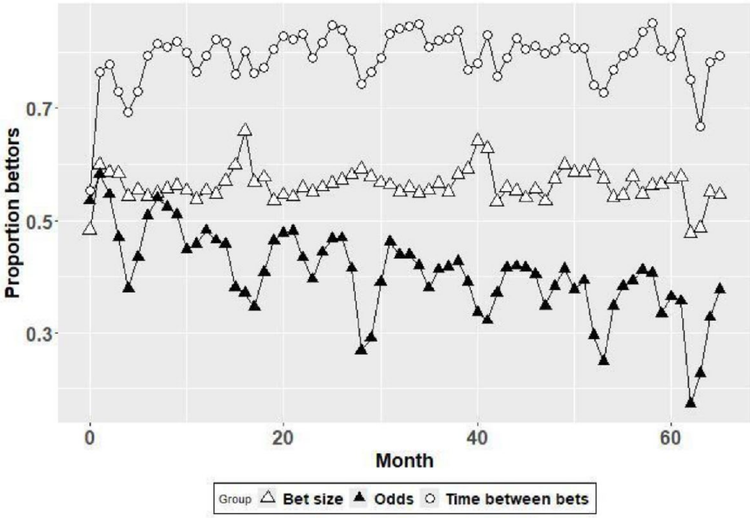

Fig. 2 Monthly proportion of bettors exceeding optimized loss chasing cutpoints, sports betting cohort

Finally, the mean monthly time between bets loss chasing metric was 0.3 (SD = 10.0) and the median was 0.2 (min = 0, 25% = 0.2, 75% = 0.3, max = 3521.2).

Spearman correlations between the three continuous bet-invariant loss chasing metrics, for both the full sports betting cohort and the full DFS cohort, are shown in Table 1. None of the loss chasing metrics were strongly correlated across either cohort. With regards to the ROC-informed loss chasing metrics, a graphical illustration of the percentage of individuals who exceeded those thresholds, for the sports betting and DFS cohorts, is shown in Figs. 2 and 3, respectively. As shown in Fig. 2, similar proportions of sports bettors exceeded the thresholds across all three dimensions (all hovering around 50%) during the first month (i.e., month 0), however the proportions for the three dimensional thresholds quickly diverge over subsequent months, with the proportion of time between bets threshold exceeders increasing (to around 80%), the percentage of those exceeding bet size threshold remaining roughly the same (50%), and the percentage of those exceeding the odds threshold decreasing (below 50%) by the final months. The DFS cohort follows a similar trend, with slightly less than half of DFS players exceeding any of the three loss chasing dimensional thresholds at the beginning of the study period. Over time we see similar levels of divergence, with the percentage exceeding the odds threshold dipping to less than a half, the percentage exceeding the bet size threshold remaining a little over 50%, and the percentage exceeding the time between bets threshold rising to nearly 100%, by the final month of the study period.

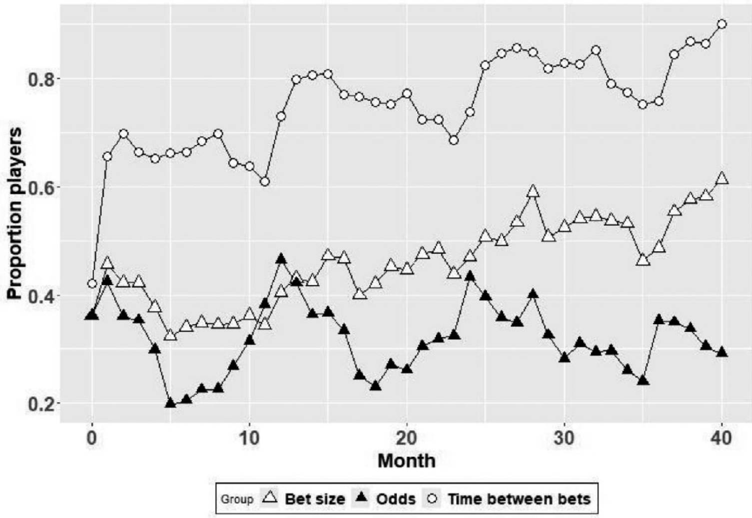

Fig. 3 Monthly proportion of bettors exceeding optimized loss chasing cutpoints, DFS cohort

Outcomes

For the subgroup of the sports betting cohort with valid loss trajectory values ($n=13{,}146$), the mean value for loss trajectory was 32.2 (SD = 246.0), while the median was 10.0 (min = -6273.5, 25% = 2.7, 75% = 28.1, max = 11168.5). For the DFS subgroup ($n=23{,}642$), the mean value for loss trajectory was 11.1 (SD = 1962.0), while the median value was 10.6 (min = -287822.8, 25% = 3.1, 75% = 29.4, max = 17768.1). For the subgroup of sports bettors with valid percent percent change in net loss values ($n=127{,}790$), the mean value was −1.1 (SD = 10344.5), while the median value was −1.1 (min = -1915080.0, 25% = -76.5, 75% = 138.5, max = 533455.6). For the subgroup of DFS players ($n=197{,}393$), the mean value was 87.0 (SD = 10184.5), while the median value was −14.9 (min = -2850471.0, 25% = -79.83871.0, 75% = 138.3, max = 1544500.0).

Hypothesis 1

Loss trajectory. The main regression analyses comparing the various forms of loss chasing predicting loss trajectory, for both the sports betting and DFS cohorts, are shown in Table 2. Table 2 presents both the adjusted effects (i.e., controlling for stake per bet and an interaction between stake per bet and the respective loss chasing effect) and unadjusted effects.

Concerning the sports betting cohort (i.e., the left columns of Table 2), for two out of three dimensions of loss chasing (bet size and odds), models using the ROC cutpoints (unadjusted) had the lowest AIC values, and therefore best model fit, relative to the other models. For time between bets, the adjusted median cut was the best fitting form. For all three forms, the median and ROC cuts were very close to one another in terms of both their effects on loss trajectory, and model fit. Although the unadjusted effects yielded improved model fit, it is important to note that only the bet size metric of loss chasing was robust (i.e., remained statistically significant and positive) in adjusted models. The odds and time between bets

Table 2 Linear regression results, loss chasing predicting loss trajectory

Loss Chasing Metric	Effect	Sports betting				DFS			
		Estimate	Std. Error	p-value	AIC	Estimate	Std. Error	p-value	AIC
Bet Size (median cut)	Adjusted	19.2	8.3	0.02	182046	-96.9	108.0	0.37	**425220**
Bet Size (Opt cut)		16.8	7.9	0.03	182043	-81.9	100.0	0.41	425227
Bet Size (continuous)		-0.1	0.0	0.03	182065	-22.7	24.9	0.36	425368
Bet Size (median cut)	Unadjusted	19.1	4.0	0.00	182042	26.7	29.3	0.36	425592
Bet Size (Opt cut)		19.7	3.9	0.00	**182042**	24.2	23.0	0.29	425592
Bet Size (continuous)		0.0	0.0	0.02	182062	-1.0	6.0	0.87	425593
Odds (median cut)	Adjusted	11.5	7.7	0.13	182059	-95.0	96.4	0.32	**425193**
Odds (Opt cut)		12.1	7.6	0.11	182058	-79.5	80.6	0.32	425253
Odds (continuous)		0.0	0.1	0.42	182064	0.0	0.0	0.25	425370
Odds (median cut)	Unadjusted	11.2	4.9	0.02	182056	38.6	32.7	0.24	425590
Odds (Opt cut)		12.0	4.7	0.01	**182055**	34.9	22.1	0.11	425591
Odds (continuous)		0.0	0.0	0.83	182062	0.0	0.0	0.56	425593
TBB (median cut)	Adjusted	19.9	8.4	0.02	**182045**	-86.2	82.9	0.30	**425241**
TBB (Opt cut)		11.2	7.7	0.15	182056	-86.2	93.9	0.36	425242
TBB (continuous)		0.0	0.1	0.89	182065	-1.0	1.1	0.33	425370
TBB (median cut)	Unadjusted	14.1	4.3	0.00	182051	37.3	20.2	0.06	425591
TBB (Opt cut)		13.2	5.0	0.01	182055	39.3	25.5	0.12	425590
TBB (continuous)		0.0	0.0	0.36	182062	0.1	0.07	0.25	425593

NOTE: We considered p-values less than 0.05 to be statistically significant; Lowest AIC across metrics, both adjusted and unadjusted, are in bold; Opt = Optimized threshold (ROC analysis)

metrics were not statistically significant in adjusted models. Continuous effects of loss chasing, across all models, were nonexistent (i.e., marginal estimated effect and poorer model fit).

Concerning the DFS cohort (i.e., the right columns of Table 2), all three models comprising the median cutpoint (adjusted for stake per bet and its interaction) had the lowest AIC values relative to the other unadjusted and adjusted models for the respective dimension. In these instances and in several others, loss chasing predicted loss trajectory negatively, meaning greater chasing during month 1 was associated with decreased loss trajectory during the remaining months. In contrast to the sports betting results, all of the loss chasing predictors across both adjusted and unadjusted models (including in the best fitting models)

Table 3 Multilevel linear regression results, loss chasing predicting percent change in net loss

Loss Chasing Metric	Effect	Sports betting				DFS			
		Estimate	Std. Error	*t*	AIC	Estimate	Std. Error	*t*	AIC
Bet Size (median cut)	Adjusted	178.4	91.3	1.95	2719373	-99.7	49.3	2.02	4203250
Bet Size (Opt cut)		281.0	135.3	2.08	**2708518**	-55.6	52.2	1.07	4202519
Bet Size (continuous)		-0.3	6.0	0.05	2725287	-52.2	31.8	1.64	4203505
Bet Size (median cut)	Unadjusted	40.1	89.7	0.45	2719617	-95.6	47.9	2.00	4203248
Bet Size (Opt cut)		92.0	129.5	0.71	2708987	-49.6	50.8	0.98	**4202518**
Bet Size (continuous)		-0.2	4.2	0.05	2725281	-59.7	33.1	1.80	4203498
Odds (median cut)	Adjusted	-203.7	59.6	3.42	2725265	-88.9	52.0	1.71	4202364
Odds (Opt cut)		-211.9	64.7	3.28	**2724592**	-29.0	50.0	0.58	4203154
Odds (continuous)		-0.1	0.7	0.11	2725293	0.0	0.0	0.02	4203532
Odds (median cut)	Unadjusted	-193.2	58.2	3.32	2725265	-78.2	50.9	1.54	**4202363**
Odds (Opt cut)		-188.7	57.9	3.26	2725265	-30.1	48.7	0.62	4203151
Odds (continuous)		-0.1	0.6	0.12	2725285	0.0	0.0	0.05	4203516
TBB (median cut)	Adjusted	-8.1	66.9	0.12	2724326	-64.6	49.3	1.31	4203306
TBB (Opt cut)		260.3	187.3	1.39	**2716509**	-87.2	59.8	1.46	4203475
TBB (continuous)		-23.2	214.7	0.11	2723853	-0.1	2.9	0.02	4203507
TBB (median cut)	Unadjusted	-66.2	65.0	1.02	2724362	-62.8	48.2	1.30	**4203304**
TBB (Opt cut)		-124.7	126.7	0.98	2717253	-86.3	58.5	1.48	4203473
TBB (continuous)		-319.1	208.7	1.53	2723962	-0.1	2.2	0.04	4203504

NOTE: We considered t scores greater than or equal to 1.96 to be statistically significant; Lowest AIC across metrics, both adjusted and unadjusted, are in bold; Opt=Optimized threshold (ROC analysis)

for DFS players were not statistically significant. The continuous effects of loss chasing, as with the sports betting cohort, were nonexistent.

Percent change in net loss. The main regression results for percent change in net loss, for both the sports betting and DFS cohorts, are shown in Table 3. Concerning the sports betting cohort (the left columns of Table 3), for all dimensions of loss chasing, models comprising the optimized cutpoint (adjusted for stake per bet and its interaction) had the lowest values of AIC. For bet size dimension, this effect was strong and statistically significant (i.e., $t > 1.96$) in the positive direction. For the odds dimension, the effect was strong and statistically significant in the negative direction. For time between bets, the effect was strong and in the positive direction, but not statistically significant. As with loss trajectory, continuous effects of loss chasing were nonexistent.

Concerning the DFS cohort (the right side of Table 3), models comprising the optimized cutpoint for bet size loss chasing (unadjusted), the median cut for odds loss chasing (unadjusted) and the median cut for time between bets loss chasing (unadjusted) had the lowest values of AIC. None of these effects were statistically significant and all were in the negative direction.

Hypothesis 2

Taking the best fitting forms of loss chasing across all dimensions (bet size, odds, time between bets) and across both products (sports betting, DFS), we entered them into a stepwise AIC process to determine the combination(s) of dimensions that yield a betting fitting model. For all dimensions and across both products, none of the stepwise AIC processes yielded a best fitting model containing all three dimensions of loss chasing, where each dimension was a positive and significant predictor of loss chasing. In an unplanned exploratory analysis, we determined that high multicollinearity between loss chasing predictors was likely not a contributing factor to these results (i.e., variance inflation factors were very small). Interested readers can find the full results of Hypothesis 2 testing in our supplementary materials (Sect. 2).

Planned Sensitivity Analyses

Detailed results from planned sensitivity analyses are available in our supplementary materials (Sect. 3). In our first sensitivity analysis (i.e., revised adjusted models where we transformed the stake per bet covariate by its common logarithm; Supplementary Tables 3 and 4), the effects of loss chasing (across each product, dimension, and for every form) were either not statistically significant and/or were in the negative direction. In the second sensitivity analysis (i.e., natural log transforming percent change in net loss; Supplementary Table 5) the effect of loss chasing was small (i.e., between 1.00 and − 1.00) and in the negative direction in most instances. Importantly, for the adjusted model for bet size loss chasing predicting percent change in net loss for sports bettors (i.e., the only effect on percent change in net loss that was positive and statistically significant in the main analysis) became a negative effect in this sensitivity analysis.

Discussion

For this study, we assessed the efficacy of machine-learning informed cutpoints for multidimensional loss chasing (Edson et al., 2024), in terms of its prediction of two novel potential harm outcomes: loss trajectory and percent change in net loss. For all three dimensions of loss chasing (bet size, odds, time between bets), we compared the predictive value of optimized cutpoints (i.e., using ROC analysis to determine two candidate sets of cutpoints, Youden and Maximize Sensitivity, and machine learning analysis to determine which of the two sets of cupoints best predicted VSE) against median cutpoints and the natural continuous form of each dimension. With the best fitting forms in hand, we used a model fit procedure (stepwise AIC) to determine whether a unidimensional or some combination of dimensions (i.e., a multidimensional model) best predicted each outcome. We conducted these analyses separately for a large cohort of sports bettors (N=36,331) and a large cohort of DFS players (N=34,596), to determine whether findings were similar across platforms, or idiosyncratic.

The operational definition of loss chasing we assessed is grounded in a z-score calculation expressing the relationship between a bettors' current behavior on the respective metric (i.e., bet size, odds, time between bets) and their running mean and standard deviation on the respective metric. It is important to keep in mind that loss chasing assessed in this way deviates from the traditional DSM definition of chasing (i.e., returns another day to get even), which infers a specific motivation (get even) for the continuation of a behavior. Such a definition cannot easily be assessed with actual gambling records, especially without continual access to self-reported data on motivation. As such, we follow others (e.g., Auer & Griffiths, 2023; Edson et al., 2024) with a definition of chasing rooted in amplification of betting behavior, and with no specific motivation attached to it, except that said amplification follows losses.

Another major point to keep in mind is that our operational definition of chasing might be specific to individualized betting experiences. For example, a bettor who starts low on a respective behavior (e.g., low stakes) and amplifies their behavior over time after losses will likely yield higher chasing scores than an individual who starts high (with an initially large bet after a loss, moderates their stakes, and then slowly increases stakes after more losses). In addition to assessing their associations with potential gambling harm, researchers should continue to assess how these metrics perform and adapt to betting trends — specifically, how might specific betting trends affect their values or lead to important differences? Although this was not the focus of the present study, it represents an important direction for future research into the development of tractable loss chasing definitions.

Hypothesis Tests

With these points in mind, one of the major goals of this study (Hypothesis 1) was to determine the "most optimized form" of loss chasing for the prediction of potential harm. We sought to determine whether discrete cutpoints of loss chasing (ROC-informed and median cuts) lead to improved predictiveness of potential gambling harm compared to the natural continuous form. Among the two discrete cutpoints, we also sought to determine which is better optimized to predict the two outcomes, with the expectation that ROC analysis would lead to better results than simple median cuts. Limiting this synthesis to sports bettors and loss trajectory (the only area where we consistently observed significant findings), discrete loss chasing generally had greater predictive power (i.e., strong and significant positive effects) compared to the raw continuous form of loss chasing, which were virtually nonexistent in all confirmatory analyses. This result suggests that loss chasing for some bettors above a certain level, with respect to their typical pattern of play, increases their risk for potential harm (mounting losses), but chasing anywhere above that level might not necessarily make things materially worse. In terms of identifying a critical threshold of chasing, results also showed that ROC analysis-informed optimized cutpoints performed slightly better than median cutpoints for two out of three dimensions (bet size and odds). For the time between bets dimension, the median cutpoint slightly edged out optimized cutpoints in terms of both its effect and model fit, but not by much. More generally, the optimized learning cuts and median cuts tended to mirror each other both in terms of effects and overall model fit. Thus, with the caveat that we are basing this conclusion on a single cohort and outcome, and that optimized thresholds only yielded marginal improvements over a median cut for only two out of three of dimensions, Hypothesis 1 was mostly supported for sports betting.

Edson et al. (2024) was the first to suggest that loss chasing is likely a multidimensional concept. A secondary goal of this study (Hypothesis 2) was therefore to test, first, whether all three forms of loss chasing were significant predictors of potential harm in some capacity, and second, whether a single multidimensional model (containing all three dimensions: bet size, odds, time between bets, in their optimized form) held improved prediction over any one unidimensional model. After graduating the best fitting forms to stepwise AIC, this process did not yield a multidimensional model where all three forms jointly predicted either loss trajectory or percent change in net loss. Thus, Hypothesis 2 was not supported. For one product (online sports betting) and outcome (loss trajectory) loss chasing appears to be multidimensional insofar as all three dimensions have positive predictive value; however, they do not appear to work well together as joint predictors of potential harm. Their effects might need to be considered independently.

It was also notable that, even in univariate analysis, loss chasing effects did not hold up in a series of sensitivity analyses. In particular, all loss chasing effects predicting loss trajectory among sports bettors (including the bet size metric, which was robust to specific stakes in main analyses) were non-significant in a sensitivity analysis that considered bettors' general stakes (i.e., log of stake per bet) rather than specific stakes (i.e., the natural form of stake per bet). These findings could suggest that while unique predictors of gambling harm, such as loss chasing, are important, their effects will tend to be washed out by other relevant predictors, such as general involvement. Indeed, putting chasing behavior aside, you would likely be hard pressed to find gamblers with significant problems who gamble infrequently and/or at lower stakes. For this reason, and to reduce the noise of general gambling involvement, future research in this area should consider innovative analytic strategies such as splitting off high and low involvement players from one another based on some threshold, and conducting analyses of unique risk factors such as loss chasing within subgroups.

Loss Chasing Effects Were Idiosyncratic

For one of the two cohorts we examined (sports bettors) and one of the two outcomes we assessed (loss trajectory), all three dimensions of loss chasing (bet size, odds, and time between bets) shared strong and significant positive relationships. Notably, these findings contrast with those of Edson et al. (2024) who assessed the relationship between loss chasing and loss trajectory among this same sports betting cohort, but found that only one dimension (bet size) had a significant and positive effect. It is important to note that Edson and colleagues controlled for more potential confounders in addition to average stake size during bettors' first month of activity (e.g., number of bets, variability in stake size), and made some different methodological choices from the current work (e.g., they standardized coefficient for loss trajectory while we left it unstandardized). Any one of these design choices, or several of them, could explain these conflicting findings.

Building on Edson and colleagues' original study, ours extended their methodology to include another type of gambling cohort (DFS players) and outcome (percent change in net loss). Surprisingly, we did not find loss chasing to be associated with increased losses (i.e., positive changes in loss trajectory or percent change in net loss) for the DFS cohort. In fact, for DFS players loss chasing was often associated with significant negative effects, especially for percent change net loss. Moreover, with a single exception (i.e., the optimized cut of the bet size loss chasing metric for sports bettors), the effect of loss chasing on percent change in net loss was either non-significant or significant in the negative direction. With regards to the aforementioned exception, this significant positive effect became a non-significant negative effect in sensitivity analysis, after we log transformed percent change in net loss. Therefore, we interpret the single significant finding we observed for this outcome with caution. At this time, we can only confidently conclude that loss chasing had a positive effect on one of the two outcomes we assessed (loss trajectory) and for only one of the two cohorts/products we assessed (sports betting).

The exact reasons for why loss chasing was idiosyncratic to loss trajectory and sports betting are unclear. However, we can speculate on some potential reasons. Regarding the specificity to loss trajectory, it is possible that the positive relationships we observed reflect a broader association between first-month gambling behaviors and longer-term outcomes more generally (Braverman & Shaffer, 2012). In contrast, with regards to percent change in net loss, it is possible that gambling behaviors observed during any given month of activity might not share a strong relationship with what happens the next month. It is further possible that the most acute negative results of loss chasing (i.e., a spike in accumulated mounting losses) happen fairly quickly (i.e., within the same month as the chasing), as opposed to the next month when natural adaptation might have occurred as a result of those acute losses (Edson & LaPlante, 2020; LaPlante et al., 2008). This is an assertion worth further exploring.

Regarding the specificity of loss chasing to the sports betting cohort, one possible explanation is that the mechanics of DFS do not lend themselves as easily to behaviors such as loss chasing. Here, it should be noted that for the DFS cohort and percent change in net loss outcome specifically, in many instances we observed a negative relationship between this outcome and the several expressions of loss chasing. We interpret this to mean that greater loss chasing was associated with better performance the next month for DFS players, which could mean net winning for some players and more modest losses for others. This surprising finding could be attributable to the higher degree of skill that DFS requires relative to sports betting (Das & Kumar, 2024). Specifically, while many sports bettors might attribute poor performance to bad luck, and so double down to try and "recoup their losses", DFS players might react to poor performance with a change in strategy, a deceleration in activity, or withdrawal from the activity altogether. Further scrutiny of the playing records data could glean further insight into this possibility.

Limitations and Future Directions

This study has several limitations. First, while a major strength of this study was its inclusion of two types of cohorts (sports betting and DFS), we only examined bettors/players from single operators/platforms within these products. The data does not capture these individuals' gambling on other products and operators. Researchers should consider pooling data from multiple operators and re-testing the hypotheses posited in this study.

Second, the machine learning algorithms resulted in poor classification. Notably, even after performing synthetic minority oversampling (SMOTE), machine learning classification remained relatively poor, with only modestly improved AUC in SMOTE balanced models. This result could mean that SMOTE was not effectively balancing the data. It is also possible that combining all three loss chasing metrics into single algorithms resulted in poor predictive accuracy, especially given the later results from testing Hypothesis 2 (i.e., unidimensional models were often better fitting than multidimensional models). Future research in this area could identify optimized cutpoints using more parsimonious machine learning models, using datasets that have a higher base rate of self-exclusion or some other relevant outcome (e.g., Problem Gambling Severity Index; Delfabbro et al., 2021), or by confining the analytic sample to more involved bettors. Alternatively, researchers could consider using percentile rankings, such as the 80th percentile based on traditional Pareto principle (Tom et al., 2014), instead of machine learning.

Third, some of the thresholds we chose for this study (e.g., constraining specificity to 0.7 in Maximize Sensitivity thresholds and choosing the median as a baseline threshold in inferential analysis) can be considered somewhat arbitrary. Other researchers conducting this type of research might select different thresholds and arrive at different conclusions from ours.

Fourth, one of the potential harm outcomes, loss trajectory, was constructed by modeling the linear trends of time and net losses, which for some bettors might have been based on very few (i.e., a minimum of two) datapoints, meaning this outcome should be considered a proxy of mounting losses, rather than some sort of absolute measure. Future research could attempt to create more accurate trends by limiting to more highly involved bettors and introducing squared or quadratic effects.

Fifth, all of the outcomes we assessed in this study (VSE, loss trajectory, and percent change in net loss) exist as proxies of "potential harm." Indeed, some bettors might not self-exclude due to gambling problems, while those experiencing mounting losses might be doing so within their financial limits.

Finally, the operational definition of chasing we used for this study only considered losses from the previous bets (i.e., we set any z-scores to zero when the previous bet was a win or break even). Future research in this area should consider tweaking the calculation of loss chasing to account for cumulative losses over a greater period (e.g., setting z-scores to zero when the bettor's cumulative performance the previous day, week, month, or entire time on the gambling site was positive or break even). Future research should also consider comparing the effects of loss chasing to that of (1) win chasing (Zhang et al., 2024; i.e., by reversing the coding scheme whereby z-scores are set to zero when previous bet[s] were losses, rather than wins) and (2) general betting escalation (i.e., not coercing any positive z-scores to zero). Such comparisons should be confined to more involved bettors, who are more likely to have a greater variety of previous wins and losses in order to create variation on these metrics.

Conclusion

Like many concepts in science, the definition and operationalization of loss chasing is evolving, and its potential multidimensionality represents yet another measurement approach for this concept. In this study, we observed that ROC analysis techniques hold potential to optimize at least two dimensions of loss chasing (bet size, odds) for at least one outcome (loss trajectory) among sports bettors. However, loss chasing dimensions appear to have better predictive value when considered in isolation and independently from one another. Moreover, the effects of loss chasing appear to be less pronounced for a related potential harm outcome (percent change in net loss) and DFS players. We emphasize that this study represents a first step in this line of investigation. Future research should investigate the importance of loss chasing in other cohorts and samples of gamblers, based on player record data, self-report data, and payments transaction data (see Ghaharian et al., 2023). Only via rigorous testing and comparisons across diverse groups will the validity, reliability, and generalizability of loss chasing measures be identified, which would then be better able to inform evidence-based prevention and treatment modalities to addressing this key criterion in the development of Gambling Disorder.

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