Using “Markers of Harm” to

Track Risky Gambling in Two Cohorts of Online Sports Bettors

Please note that this is a non-peer-reviewed pre-print that is currently under review.

William H. B. McAuliffe, Ph.D.^{1*}, williamhbmcauliffe@gmail.com

Eric R. Louderback, Ph.D.¹, elouderback@cha.harvard.edu

Timothy C. Edson, Ph.D.^{1,2}, tedson@cha.harvard.edu

Debi A. LaPlante, Ph.D.^{1,2}, debi_laplante@hms.harvard.edu

Sarah E. Nelson, Ph.D.^{1,2}, sarah_nelson@hms.harvard.edu

¹Division on Addiction, Cambridge Health Alliance, 350 Main Street, Malden, MA, 02148

²Department of Psychiatry, Harvard Medical School, 401 Park Drive, Boston, MA 02215

*= Corresponding author

Declarations of Interest: This research was supported primarily by a research contract between the Division on Addiction and GVC Holdings PLC (hereafter, GVC). GVC is a large international gambling and online gambling operator. GVC had no involvement with the development of our research questions or protocol. They will not see any associated materials (i.e., retrieved studies, charted data, and manuscripts in preparation) while the study is in progress or have any editorial rights to any resulting manuscripts. GVC communication about this work will require approval of the Division on Addiction. GVC is now called Entain (<https://entaingroup.com/>).

The Division on Addiction currently receives funding from EPIC Risk Management; Foundation for Advancing Alcohol Responsibility; Massachusetts Department of Public Health, Bureau of Substance Addiction Services via St. Francis House; Massachusetts Department of Public Health, Office of Problem Gambling Services via Health Resources in Action; MGM Resorts International via the University of Nevada, Las Vegas; National Institutes of Health (National Institute of General Medical Sciences and National Institute on Drug Abuse) via The Healing Lodge of the Seven Nations; Substance Abuse and

Mental Health Services Administration via the Addiction Treatment Center of New England; and Substance Abuse and Mental Health Services Administration via the Gavin Foundation.

During the past 5 years, the Division on Addiction has also received funding from ABMRF/The Foundation for Alcohol Research; Danish Council for Independent Research via Aarhus University Hospital; the David H. Bor Library Fund, Cambridge Health Alliance; DraftKings, Inc.; Fenway Community Health Center, Inc.; Integrated Centre on Addiction Prevention and Treatment of the Tung Wah Group of Hospitals, Hong Kong; Massachusetts Department of Public Health, Bureau of Substance Addiction Services; Massachusetts Gaming Commission, Commonwealth of Massachusetts.

During the past five years, Debi A. LaPlante has served as a paid grant reviewer for the National Center for Responsible Gaming (NCRG; now International Center for Responsible Gaming), received travel funds, speaker honoraria, and a scientific achievement award from the ICRG, has received speaker honoraria and travel support from the National Collegiate Athletic Association, received honoraria funds for preparation of a book chapter from Universite Laval, received publication royalty fees from the American Psychological Association, and received course royalty fees from the Harvard Medical School Department of Continuing Education. Dr. LaPlante is a non-paid member of the New Hampshire Council for Responsible Gambling.

During the past 5 years, Eric R. Louderback has received research funding from a grant issued by the National Science Foundation (NSF), a government agency based in the United States. His research has been financially supported by a Dean's Research Fellowship from the University of Miami College of Arts & Sciences, who also provided funds to present at academic conferences. He has received travel support funds from the Hebrew University of Jerusalem to present research findings.

During the past five years, Sarah E. Nelson has served as a paid grant reviewer for the National Center for Responsible Gaming (NCRG; now International Center for Responsible Gaming [ICRG]), GambleAware, Manitoba Responsible Gaming, Alberta Gambling Research Institute, and the National Institutes of Health (NIH). She has also received travel reimbursement and speaker honoraria from the ICRG and Responsible Gaming Association of New Mexico, travel reimbursement from the American Bar Association, and Foundation for Advancing Alcohol Responsibility. She received honoraria funds for preparation of a book chapter from Universite Laval and publication royalty fees from the American Psychological Association, and received course royalty fees from the Harvard Medical School Department of Continuing Education.

William H. B. McAuliffe and Timothy C. Edson have no funding disclosures to declare.

Abstract

Online gambling poses novel risks for problem gambling, but also unique opportunities to detect and intervene with at-risk users. A consortium of gambling companies recently committed to using nine behavioral "Markers of Harm" that can be calculated with online user data to estimate risk for gambling-related harm. The current study evaluates these markers in two independent samples of sports bettors, collected ten years apart. We find over a two-year period that most users never had high enough overall risk scores to indicate that they would have received an intervention. This observation is partly due to characteristics of our samples that are associated with lower risk for gambling-related harm, but might also be due to overly high risk thresholds or flaws in the design of some markers. Users with higher average risk scores had more intraindividual variability in risk scores. Younger age and male gender were not associated with higher average risk scores. The most active users were more likely than other users to have ever exceeded risk thresholds. Several risk scores significantly predicted proxies of gambling-related harm (e.g., account closure). Overall, the current Markers of Harm system has some correctable limitations that future risk detection systems should consider adopting.

Introduction

Gambling can have a range of negative consequences, both for gamblers themselves (Muggleton et al., 2021) and their close social ties (Goodwin et al., 2017). Many researchers argue that the unfettered access to gambling opportunities that internet platforms afford make them more harmful than land-based gambling venues (Chóliz et al., 2019; Parke & Parke, 2019; Yani-de-Soriano et al., 2012). Indeed, online gamblers more often experience gambling-related harm than gamblers who do not place bets using online platforms (Gainsbury, 2015). The attractiveness of online platforms to gamblers who were already at risk likely explains some of this association (Baggio et al., 2017; Philander & McKay, 2014), but it is probably also partly causal. For instance, Effertz et al. (2018) estimate that the presence of internet gambling in Germany increases the country's healthcare costs by about 27.24 million euros per year. On the other hand, online operators also have many more opportunities to detect and intervene with at-risk gamblers, compared to land-based operators (Wood et al., 2014). In particular, online operators can leverage user data to continuously assess risk for gambling harm (Deng et al., 2019). The current paper examines a recent coordinated effort among industry operators to develop the “Markers of Harm” system, a gambling risk assessment algorithm.

Markers of Harm

Several avenues of research have pointed to the potential of using behavioral markers to accurately identify gamblers for potential harm (Braverman & Shaffer, 2012; Dragicevic et al., 2011). Stemming from such research, the Senet Group, a gambling regulatory body in the United Kingdom (it was recently acquired by the Betting and Game Council; Narayan, 2020), organized a series of meetings among five major United Kingdom gambling operators— 888 Holdings, GVC Holdings (now called Entain), Sky Betting & Gaming, William Hill, and Paddy Power—

to develop an algorithm that would estimate users' risk for gambling harm based on their recent behavior on a given platform. The operators agreed on a minimum of nine "markers of harm" that could be implemented for all platforms. Reports by PricewaterhouseCoopers (PwC & Responsible Gambling Council, 2017) and NatCen (Wardle et al., 2014) informed the markers' development.

Each marker of harm partitions users into four risk threshold categories (i.e., *risk score*; 0 = no-risk, 1 = low-risk, 2 = medium-risk, and 3 = high-risk) based on their *raw score* (i.e., scores on a given marker's original metric). Summing the markers' *risk scores* yields an *overall risk score* ranging from 0-27, which can be updated daily. Entain, for instance, groups overall risk scores into four *overall level categories* (i.e., no-risk = 0-7, Level 1 = 8-9, Level 2 = 10-14, and Level 3 = 15-27). Each overall level category translates to a specific intervention, with a higher level triggering both its own unique intervention and the interventions of the lower level (e.g., a jump in risk score from 1 to 12 will trigger both Level 1 and Level 2 interventions). Level 1 scores trigger an "educational communication" via e-mail; Level 2 scores additionally trigger a 14-day reprieve from marketing for the user; and Level 3 scores additionally trigger a manual review of the user's account by a member of Entain's Player Protection team. Operators intended the distribution of overall level categories to be consonant with PricewaterhouseCooper's report (PwC & Responsible Gambling Council, 2017, p. 18) that 6.3% of active United Kingdom online gamblers self-report that they currently suffer from problem gambling (defined as a sum score of seven or higher on the Problem Gambling Severity Index; Ferris & Wynne, 2001). However, we were not able to find clear documentation about whether Senet Group viewed 6.3% as the target for the percentage of users who are categorized as Level 3 or as Level 1, 2, or 3 combined at any

given time; in practice, Entain tracks the percentage of users who trigger interventions of Level 1 or higher.

The Present Study

We provide an initial evaluation of the Markers of Harm system's first iteration using data from *bwin*, a website that Entain owns. Our analyses test for potential weaknesses in risk detection, such as whether a given marker is (a) too rare or common to identify all and only those at risk for gambling harm (i.e., its prevalence), (b) redundant with other markers (i.e., its intercorrelations), (c) too unstable to differentiate temporary bouts of excessive gambling from a lasting pattern (i.e., its interindividual stability versus its intraindividual change), or (d) only weakly associated with extreme gambling behavior (i.e., most involved bettors), proxies of gambling-related harm (e.g., account closure) and demographic correlates of gambling-related harm (i.e., gender and age). We also ask the same questions of overall score levels across markers.

Although we do intend the present investigation to shed light on the performance of Markers of Harm on an Entain product, our goals are broader, as operators' risk algorithms will likely evolve for years to come. Specifically, we expect that the performance of markers in our study will foretell the likely performance of the same or similar markers on other gambling websites that have similar customer bases (e.g., other European player pools).

Methods

We pre-registered the analysis plan (https://osf.io/x8764/?view_only=cbf23b882ed347028f808b6c4941b553) on the Open Science Framework (OSF), adding two addendums (i.e., Transparent change 1: https://osf.io/ske9h/?view_only=a8d622aa06584829b974d3ceec934ca1 and Transparent change

2: https://osf.io/vxn7u/?view_only=a8d622aa06584829b974d3ceec934ca1) during the research process. Datasets and syntax will either be available by request or posted on a public repository. The [institution blinded for peer-review] IRB evaluated our study plans and confirmed that the study did not qualify as human subjects research because all data were de-identified. Data were transferred via secure FTP from Entain to the [institution blinded for peer review].

Data Sources

The Markers of Harm risk interventions as currently implemented likely affect the behavior of those who trigger them. To investigate the predictive validity of the markers without the confounds of the interventions, we investigated the markers using data collected *before* the risk scoring system was implemented by *bwin* in 2019. In particular, we analyzed sports betting data from *bwin* users who registered in February 2005 and February 2015. The former dataset contains user records from March 2005 through February 2007; the latter dataset contains user records from March 2015 to February 2017. The use of two datasets collected ten years apart allowed us to evaluate the temporal generalizability of our findings.

In both datasets, we decided to begin calculating marker scores on March 29th of the first year. This is the first day on which all users had at least 28 full days of betting opportunities, the number of days used for computing most markers. The last day for which we computed markers was March 1st of the third year (i.e., 2007 or 2017). Thus, the study period for both datasets included every day from March 1 (i.e., 2005 or 2015) to February 28 (i.e., 2007 or 2017). The main criterion for inclusion for both samples was having placed at least one sportsbook wager during the study period. Because we only had access to daily summaries of non-sportsbook activity (viz., casino games, bingo, and poker) and the three of the markers required data on individual bets, we excluded users who placed any non-sportsbook wagers

during the study period. The exact sample size fluctuated over the study period based on account closures and reopenings.

February 2005 Registrants

Out of 48,114 total users, 33,248 (2,524 females; $M_{\text{age}} = 30.56$; $SD_{\text{age}} = 10.00$) met inclusion criteria. Of users who met inclusion criteria, 234 did not have markers calculated for the entire study period because their account was never active for more than 27 consecutive days in a row (we chose to not compute markers for users who reopened their account after temporarily closing it until they had been active again for at least 28 days since most markers are based on at least 28 days of potential activity).

February 2015 Registrants

Out of 72,494 total users, 16,087 (1,414 females; $M_{\text{age}} = 30.66$; $SD_{\text{age}} = 10.65$) met inclusion criteria. A smaller percentage of users met inclusion criteria in 2015 than in 2005 because far more users were gambling on events other than sports on *bwin* in 2015 than in 2005, and more users registered without ever gambling during the study period. There were 102 eligible users who did not have markers calculated for the entire study period because their account was never active for more than 27 consecutive days.

Markers of Harm Definitions

Entain computes each marker every day based on the user's activity on the previous day. They do not assign risk scores to users who did not bet on the previous day. We partially mimicked this approach by assigning users who did not bet on the previous day a risk score of zero on all markers. This decision was congruent with our desire for analyses involving risk scores to pertain to users who have had an active account for at least 28 days, rather than users who bet on the previous day only. However, when a user did not bet on the previous day, we did

not automatically decrease their *raw* score to zero. We wanted analyses involving the raw scores to reflect the actual amount of activity users had engaged in during the time window relevant to each marker. As with risk scores, however, analyses involving raw scores did not include users who had reactivated their account until 28 days had passed. We document how we handled practical obstacles to measuring markers in Section 1 of the Supplemental Materials (e.g., quantifying time spent gambling based on wager timestamps). Below, we detail how risk scores are assigned for each marker.

Spend from Norm

The *Spend From Norm* marker measures how much a user deposited on the previous day relative to how much they deposited in the past six months (i.e., 182 days) on “losing days” (i.e., days on which total deposit amount exceeded total withdrawal amount). The logic behind *Spend From Norm* is that a spike in spending may represent the beginning of an unaffordable binge. Obtaining a non-zero risk score for this marker required a net deposit (total deposits minus total withdrawals) of at least 100 British pounds (which we converted into euros as of February 1, 2005 and February 1, 2015 for the 2005-2007 and 2015-2017 samples, respectively) on the previous day and at least one “losing day” in the past six months. Users received a risk score of 1 when yesterday’s net deposit was at least 2.5 times more but less than four times more than the average net deposit on losing days in the past six months; a risk score of 2 when yesterday’s net deposit was at least four times more but less than eight times more than the average net deposit on losing days in the past six months; and a risk score of 3 when yesterday’s net deposit was at least eight times more than the average net deposit on losing days in the past six months.

Frequency of Play

The *Frequency of Play* marker measures time spent placing wagers in the previous week. The *Frequency of Play* marker is intended to measure high absolute levels of involvement. Users received a risk score of 1, 2, or 3 when they spent at least 360 minutes but fewer than 600 minutes, at least 600 minutes but fewer than 900 minutes, or at least 900 minutes, respectively, placing wagers on *bwin* in the past week.

Increase in Frequency of Play

Those who spent at least two more hours wagering on *bwin* in the past seven days than the seven days prior are assessed for *Increase in Frequency of Play*. The *Increase in Frequency of Play* marker represents the ratio of time spent gambling in the past seven days to the average weekly time spent wagering in the 25 weeks before that. The 175 days comprising the 25 weeks are broken up into “financial weeks” of Monday through Sunday. The average includes only financial weeks with activity. A high ratio for this marker can result from a spike in time spent gambling, which may be inconsistent with one’s other obligations. Users received a risk score of 1, 2, or 3 when they spent at least two but less than three, at least three but less than four, and at least four times as much time, respectively, transacting in the past seven days as they did on average during active financial weeks in the 175 days before that.

Late-Night Play

Playing during typical sleeping hours might interfere with performing obligations during the day (Parhami et al., 2012) or result in riskier gambling decisions (Hamel et al., 2021). Receiving a non-zero score on the *Late-Night Play* marker required having gambled between 12:00 AM and 6:00 AM on at least two different days in the past 28 days. Users received a risk score of 1, 2, or 3 when they gambled in total for at least 60 minutes but fewer than 120 minutes,

at least 120 minutes but fewer than 180 minutes, or at least 180 minutes, respectively, on the previous day between 12:00 AM and 6:00 AM.

Deposit Frequency

The *Deposit Frequency* marker tracks the number of days on which a user made a deposit in the past 28 days. Some gamblers report making frequent deposits when they are chasing losses (Parke & Parke, 2019, p. 1345). To receive a non-zero risk score the average deposit in the past 28 days had to be at least 10 British pounds (which we converted into euros as of February 1, 2005 and February 1, 2015 for the 2005-2007 and 2015-2017 samples, respectively). Users received a risk score of 1, 2, or 3 when they made deposits on 12-14, 15-19, or 20 or more of the past 28 days, respectively.

Failed Deposits

The *Failed Deposits* marker indexes the number of days on which a user made an unsuccessful deposit in the past 28 days. We assume most deposits fail due to insufficient funds or typos in providing payment information, but some deposits may be cancelled by users themselves, perhaps because they do not believe that they authorized the transaction, or realized that it would eventually cause an overdraft of their bank account. Users received a risk score of 1, 2, or 3 when they had two, three to four, or five or more days with a failed deposit, respectively, in the past 28 days.

Withdrawal Reversals

The *Withdrawal Reversals* marker measures the proportion of withdrawals from *bwin* that a user cancels. Withdrawal cancellation can occur when an impulse to continue gambling wins out over a desire to save winnings or cut losses (Parke & Parke, 2019). While we assume that most reversals are initiated by users, *bwin* reviews all withdrawal requests and in some cases

unilaterally cancels them. Also, giving users the ability to reverse withdrawals was recently banned in the United Kingdom (Wright, 2020). Thus, *Withdrawal Reversals* is no longer part of the United Kingdom Markers of Harm system, though it remains a part of the system in other countries.

Users received a risk score of 1 when they reversed two to five withdrawals, representing at least 10% but less than 40% of their total initiated withdrawals in the past 28 days, or when they reversed at least six withdrawals, representing at least 10% but less than 20% of their initiated withdrawals in the past 28 days. Users received a risk score of 2 when they reversed two to five withdrawals, representing at least 40% of their initiated withdrawals in the past 28 days, or when they reversed at least six withdrawals, representing at least 20% but less than 40% of their initiated withdrawals in the past 28 days. Users received a risk score of 3 when they reversed at least six withdrawals, representing at least 40% of their initiated withdrawals in the past 28 days.

Multiple Payment Methods

The *Multiple Payment Methods* marker tracks the number of methods a user employs to successfully deposit money in the past 28 days. Different types of payment methods (e.g., e-wallet vs. credit card) and different brands of the same type of payment method (e.g., a Mastercard debit card and a Visa debit card) each count as distinct payment methods. The reasoning behind this marker is that users who run low on cash or credit on one payment method may resort to using a different method to make their next deposit. Users received a risk score of 1, 2, or 3 when they used two, three, or four or more distinct payment methods, respectively, in the past 28 days.

Credit Cards

The Credit Cards marker indicates the number of different credit card types (e.g., Visa, Mastercard) with which a user made a successful deposit in the past 28 days. A body of literature suggests that gambling on credit is associated with unmanageable debt (Swanton & Gainsbury, 2020). The United Kingdom recently banned using credit cards to make deposits to gambling platforms (Pratt, 2020). Consequently, *Credit Cards* is no longer part of the United Kingdom Markers of Harm algorithm, though it remains in other jurisdictions. Users received a risk score of 1, 2, or 3 when they used one, two, or three or more credit cards, respectively, to make deposits in the past 28 days.

Gambling Harm Proxies

A major goal of this study is to assess the relationship between Markers of Harm risk scores and problem gambling severity. However, we lacked a validated problem gambling measure (e.g., problem gambling severity index; PGSI; Ferris & Wynne, 2001). Instead, we relied on the following proxies to assess potential gambling harm.

Account Closure

Voluntary self-exclusion is associated with self-reported problem gambling (Luquiens et al. 2019). Many users close their account because they are experiencing problem gambling, but others close their account for other reasons (e.g., frustration with the operator), and some closures are initiated by *bwin*. We have the information in some but not all cases necessary to know whether account closures were due to problem gambling, so for present purposes we treat all account closures as a single category. We assigned users a “1” if their account was not open at any point during the study period (even if it was later reopened, and even if the closure was initiated in the first February), and a “0” otherwise. The 2005-2007 sample contained 3,813 users

(11.47%) with at least one account closure, while 509 users (3.16%) had at least one account closure in the 2015-2017 sample.

Setting Voluntary Deposit Limits

Voluntary deposit limit-setting is associated with more intensive online gambling involvement (Ivanova et al., 2019; Nelson et al., 2008). Records of decisions to change deposit limits were available for February 2005 registrants, where 834 users (2.51%) who met inclusion criteria had ever lowered their deposit limits. The default deposit limits were 1,000 euros per day and 5,000 euros per month. The option to lower deposit limits was not implemented until November 2005, and thus there are no instances lowering them earlier than that. We gave users a “1” if they had ever lowered the default amount of money that they were allowed to deposit, and a “0” otherwise. Information about voluntary deposit limits was not available for the 2015 sample.

Exceeding Deposit Limits

Exceeding deposit limits is associated with placing more bets per betting day and larger bet amounts (Broda et al., 2008). Data on instances in which users had exceeded their daily or monthly deposit limit (i.e., the default deposit limits, unless they voluntarily changed them) were available for February 2005 registrants. Sixty-six users (0.20%) who met inclusion criteria in that sample had ever exceeded deposit limits. Because default deposit limits for all users were not in place until late September 2005, no instances of exceeding them occurred before this time. We gave users a “1” if they had ever attempted to deposit more than they were allowed to, and a “0” otherwise. Information about exceeding deposit limits was not available for the 2015 sample.

Hypotheses

First, in line with the Senet Group's expectation of categorizing 6% of users as at risk of problem gambling, we hypothesize that, on average, about 6% of the sample on a given day will have an overall risk score of at least 8, the lowest overall risk score that triggers an intervention.

Previous longitudinal studies indicate that people with more severe forms of Gambling Disorder severity are as likely to experience fewer symptoms over time as are people with less severe forms of Gambling Disorder; similarly, people with more severe Gambling Disorder classifications are not more likely than others to experience worsening symptoms over time (LaPlante, Nelson, et al., 2008). Applied to the Markers of Harm, these findings could mean that fluctuations in risk scores over time will be equally common for users who experience different average amounts of risk. Thus, our second hypothesis is that users who have higher average risk scores will not differ in the standard deviations of their average risk scores from users with lower averages. Alternatively, it could be that only users with moderate average risk scores have substantial intraindividual variability because users with low averages almost never engage in risky gambling and users with high averages usually do. We did not pre-register any hypotheses about the overall proportion of variability due to intraindividual differences, but Currie, Hodgins, and Casey (2013) found that over a 14-month period that 63% of the variance in self-reported risk for gambling-related harm is due to interindividual differences. Therefore, one might expect more variance in risk scores to be due to interindividual factors than intraindividual factors.

Third, we hypothesize that men and younger users will more often be categorized as at-risk according to their individual and overall risk scores. Young age and being male are both associated with gambling-related harms (Hing et al., 2016; Kessler et al., 2008).

Fourth, we expect that the most involved bettors will be more likely to ever have received risk scores of 1, 2, or 3 for each marker. We make the same prediction with respect to Levels 1,

2, and 3 overall risk scores. We characterize the most *financially* involved gamblers in two ways: The top 6% of the distribution (i.e., the percentage of users that Senet Group believes might experience gambling harm) in terms of money staked, and the top 1% of that same distribution (in accordance with LaBrie et al., 2007 and LaPlante, Schumann, et al., 2008, who found that the top 1% most involved *bwin* users exhibited unique patterns of betting behavior). High spending on sports wagers is strongly associated with gambling harm (Hing et al., 2019). We also characterize the 1% and 6% most *behaviorally* involved gamblers by total number of bets during the study period.

Fifth, we predict that risk scores will be positively associated with gambling harm proxies (i.e., self-limiting, exceeding limits, and account closure).

Results

All analyses were conducted in R version 4.0.2 (R Core Team, 2020). We used functions in the robustbase (Maechler et al., 2020), car (Fox et al., 2007), Rmpfr (Maechler, 2020), tidyverse (Wickham, 2019), expss (Demin, 2020), data.table (Dowle & Srivivasan, 2019), correlation (Makowski et al., 2020), lmerTest (Kuznetsova et al., 2017), and psych (Revelle, 2019) packages. All regression models employed robust standard errors (Field & Wilcox, 2017), as residual plots from standard linear and logistic regressions revealed assumption violations and outliers. See the OSF page (https://osf.io/au5e2/?view_only=a8d622aa06584829b974d3ceec934ca1) for all scatterplots and residual plots. We used a two-tailed alpha of .05 for each test and emphasized effect sizes over statistical significance.¹

¹ We pre-registered the use of false discovery rate corrections when inferring statistical significance, but we abandoned that plan because we realized we did not have a concrete plan for how we would implement them among the many subsets of tests that we conducted. Furthermore, some models did not converge to proper solutions, which would have affected how many test results factored into the corrections.

Prevalence: Are markers too rare or common to identify all and only those at risk?

Table 1 shows the percentages of users that fell into each risk threshold for each marker on an average day (i.e., *daily average*) and the percentages of users who at some point during the study period met each risk threshold for each marker (i.e., *ever score*). Few users exceeded the no-risk threshold for any marker on an average day in either dataset (e.g., the daily average prevalence of low-risk *Late-Night Play* was zero going out two decimal places). The only partial exception was the low-risk category for *Credit Cards* (1.91% and 0.58% in 2005-2007 and 2015-2017, respectively), where users needed only to have used a single credit card to make a deposit in the past 28 days. Table S2.1 in the Supplementary Materials shows the daily averages after excluding users who had not placed bets on the previous day from the calculation of risk scores on a given day. Although relatively much higher, the percentage of users on a typical day who had at least a low-risk overall score was still below 1%. Overall, our first hypothesis that about 6% of users on an average day would have an overall risk score high enough to trigger an intervention was not supported.

A larger percentage of users had ever fallen into a low-risk, medium-risk, or high-risk category during the study period. *Credit Cards* had the highest prevalence rate for ever having fallen into the low-risk category (36.65% and 12.65% in 2005-2007 and 2015-2017, respectively), but the lowest prevalence for ever having fallen into the high-risk category (close to 0% in both samples). Risk category prevalence rates were higher in 2005-2007 for *Credit Cards*, *Multiple Payment Methods*, *Spend From Norm*, *Frequency of Play*, and *Increase in Frequency of Play*. Low-, medium-, and high-risk Failed Deposit prevalence rates were much

higher in 2015-2017 than in 2005-2007. Less than 1% of users in each dataset had ever had

Level 1, Level 2, or Level 3 overall risk scores.

Table 1

Average Daily Percentages and Overall Percentages of Users Who Fall into a Risk Category

Marker	Daily Average 2005-2007	Daily Average 2015-2017	Ever Score 2005-2007	Ever Score 2015-2017
Spend from Norm				
<i>No-Risk</i>	99.97 (0.01)	99.99 (0.01)	99.30	99.37
<i>Low-Risk</i>	0.01 (0.01)	0.01 (0.01)	4.66	1.97
<i>Medium-Risk</i>	0.01 (0.01)	0.00 (0.01)	3.61	1.70
<i>High- Risk</i>	0.00 (0.00)	0.00 (0.00)	1.56	1.09
Frequency of Play				
<i>No-Risk</i>	99.83 (0.05)	99.93 (0.10)	99.30	99.37
<i>Low-Risk</i>	0.10 (0.04)	0.04 (0.05)	3.87	2.48
<i>Medium-Risk</i>	0.04 (0.01)	0.02 (0.02)	1.70	1.23
<i>High- Risk</i>	0.03 (0.01)	0.02 (0.03)	0.73	0.64
Increased Frequency				
<i>No-Risk</i>	99.84 (0.10)	99.93 (0.08)	99.30	99.36
<i>Low-Risk</i>	0.05 (0.03)	0.02 (0.02)	5.01	2.74
<i>Medium-Risk</i>	0.03 (0.02)	0.01 (0.02)	5.13	2.58
<i>High- Risk</i>	0.08 (0.05)	0.04 (0.05)	9.16	4.78
Late-Night Play				
<i>No-Risk</i>	100 (0.01)	99.99 (0.01)	99.30	99.37
<i>Low-Risk</i>	0.00 (0.01)	0.01 (0.01)	0.76	1.20
<i>Medium-Risk</i>	0.00 (0.00)	0.00 (0.00)	0.17	0.32
<i>High- Risk</i>	0.00 (0.00)	0.00 (0.00)	0.05	0.10
Deposit Frequency				
<i>No-Risk</i>	99.87 (0.03)	99.85 (0.07)	99.30	99.37
<i>Low-Risk</i>	0.06 (0.02)	0.06 (0.04)	1.99	2.15
<i>Medium-Risk</i>	0.05 (0.01)	0.05 (0.03)	1.11	1.32
<i>High- Risk</i>	0.02 (0.01)	0.04 (0.01)	0.37	0.50
Failed Deposits				
<i>No-Risk</i>	100 (0.00)	99.76 (0.18)	99.30	99.35
<i>Low-Risk</i>	0.00 (0.00)	0.12 (0.09)	0.03	8.22
<i>Medium-Risk</i>	0.00 (0.00)	0.07 (0.06)	0.00	4.04
<i>High- Risk</i>	0.00 (0.00)	0.05 (0.04)	0.00	1.49

Withdrawal Reversals				
<i>No-Risk</i>	99.98 (0.01)	99.97 (0.02)	99.30	99.36
<i>Low-Risk</i>	0.00 (0.00)	0.01 (0.01)	0.08	0.42
<i>Medium-Risk</i>	0.02 (0.01)	0.02 (0.01)	1.66	0.96
<i>High- Risk</i>	0.00 (0.00)	0.01 (0.00)	0.03	0.19
Multiple Methods				
<i>No-Risk</i>	99.72 (0.10)	99.83 (0.09)	99.30	99.36
<i>Low-Risk</i>	0.25 (0.09)	0.15 (0.08)	7.80	4.87
<i>Medium-Risk</i>	0.02 (0.01)	0.02 (0.01)	0.80	0.53
<i>High- Risk</i>	0.00 (0.00)	0.00 (0.00)	0.13	0.06
Credit Cards				
<i>No-Risk</i>	98.04 (0.82)	99.42 (0.30)	99.29	99.37
<i>Low-Risk</i>	1.91 (0.81)	0.58 (0.30)	36.65	12.65
<i>Medium-Risk</i>	0.05 (0.02)	0.01 (0.01)	1.30	0.24
<i>High- Risk</i>	0.00 (0.00)	0.00 (0.00)	0.00	0.00
Overall Level				
<i>No-Risk</i>	99.99 (0.00)	99.98 (0.01)	99.30	99.37
<i>Low-Risk</i>	0.00 (0.00)	0.01 (0.01)	0.53	0.77
<i>Medium-Risk</i>	0.00 (0.00)	0.01 (0.01)	0.13	0.32
<i>High- Risk</i>	0.00 (0.00)	0.00 (0.00)	0.00	0.01

Note. Standard deviations are in parentheses. Less than 100% of users ever had no-risk scores because some users were either never active long enough to receive a marker score or were only eligible to receive one on a small number of days.

Table 2 shows the daily averages and average maximum raw score for each individual marker, as well as for the overall score. The average maximum score suggests that the average user does not even occasionally engage in excessive gambling behavior as defined by the markers of harm.

Users who only engage in sports betting may represent a lower-risk group (Brosowski et al., 2020; LaPlante et al., 2014), potentially explaining why we observed such low rates of exceeding risk thresholds. In a planned sensitivity analysis using an expanded sample, we computed the prevalence rates of all users across all gambling types, not just sports, for the six markers that we could calculate without having access to bet-level data (see Table S2.2).

Although relatively higher, the daily prevalence of low-risk, medium-risk, and high-risk categories combined remained at less than 1%, except for *Credit Cards*, where the low-risk category average was 2.76%.

Table 2

Means, Standard Deviations, and Medians of Markers on their Original Metric

Marker	Daily Average 2005-2007	Daily Average 2015-2017	Average Maximum 2005-2007	Average Maximum 2015-2017
Spend From Norm	0.01 (0.00), 0.01	0.01 (0.00), 0.01	1.28 (3.37), 0.40	0.83 (3.02), 0.00
Frequency of Play	4.87 (1.64), 4.44	2.29 (2.16), 1.67	70.78 (160.27), 23	46.59 (168.62), 6.17
Increase Frequency	0.20 (0.09), 0.18	0.11 (0.10), 0.08	6.79 (13.11), 4	7.40 (158.40), 1.38
Late-Night Play	0.04 (0.02), 0.04	0.04 (0.04), 0.02	4.71 (12.28), 2	4.45 (15.37), 0
Deposit Frequency	0.27 (0.07), 0.26	0.20 (0.11), 0.17	2.07 (2.85), 1	1.80 (3.08), 1
Failed Deposits	0.00 (0.00), 0.00	0.04 (0.03), 0.03	0.01 (0.11), 0	0.59 (1.38), 0
Withdrawal Reversals	0.00 (0.00), 0.00	0.00 (0.00), 0.00	0.11 (0.31), 0	0.03 (0.15), 0
Multiple Methods	0.04 (0.02), 0.04	0.08 (0.05), 0.07	0.93 (0.53), 1	0.69 (0.59), 1
Credit Cards	0.04 (0.02), 0.04	0.02 (0.01), 0.02	0.40 (0.52), 0	0.16 (0.37), 0
Overall Score	0.03 (0.01), 0.03	0.02 (0.01), 0.02	0.91 (1.46), 0	0.57 (1.43), 0

Note. The format of each cell is: Mean (Standard Deviation), Median. Possible ranges: *Spend from Norm*, 0- depends on deposit limits; *Frequency of Play*, 0-10,080; *Increase Frequency*, 0- ~10,080; *Late-Night Play*, 0-360; *Deposit Frequency*, 0-28; *Failed Deposits*, 0-28; *Withdrawal Reversals*, 0-1; *Multiple Methods*, 0-51 in 2015-2017 and 0-44 in 2005-2007 dataset, based on the payment types actually used; *Credit Cards*, 0-4 in 2015-2017 and 0-6 in the 2005-2007 dataset, based on the payment types actually used; *Overall Score*, 0-27.

Intercorrelations: Are markers redundant with other markers?

Table 3 shows the Spearman correlation matrix of average daily risk scores. Magnitudes ranged from .01 (*Credit Cards* and *Failed Deposits*) to .60 (*Frequency of Play* and *Increase in Frequency of Play*) in the 2005-2007 samples, and .04 (*Late-Night Play* and *Credit Cards*) to .62 (*Frequency of Play* and *Increase in Frequency of Play*) in the 2015-2017 sample. Correlation

magnitudes were generally similar across datasets (mean = .18, SD = .14 in the 2005-2007 sample; mean = .25, SD = .13 in the 2015-2017 sample). One exception is that *Failed Deposits* exhibited stronger correlations in the 2015-2017 dataset than in the 2005-2007 dataset, where its correlations with other markers were very small.

Table 3

Correlation Matrix of Daily Average Individual Risk Scores Across the Study Period

Marker	Spend Norm	Frequency Play	Increase Frequency	Late Night	Deposit Frequency	Failed Deposits	Withdrawal Reversals	Multiple Methods	Credit Cards
Spend Norm	--	.23	.29	.17	.41	.32	.25	.22	.14
Frequency Play	.30	--	.62	.56	.29	.24	.19	.14	.07
Increase Frequency	.32	.60	--	.42	.32	.32	.21	.21	.13
Late-Night	.17	.39	.27	--	.20	.16	.11	.12	.04
Deposit Frequency	.36	.34	.30	.21	--	.40	.34	.29	.14
Failed Deposits	.04	.04	.03	.05	.03	--	.25	.38	.20
Withdrawal Reversals	.10	.07	.07	.04	.08	.11	--	.20	.07
Multiple Methods	.33	.28	.32	.15	.30	.04	.08	--	.23
Credit Cards	.23	.11	.16	.06	.13	.01	.08	.19	--

Note. We used spearman correlations to avoid parametric assumptions. Data from 2015 registrants are above the diagonal; data from 2005 registrants are below the diagonal. All correlations are highly statistically significant (i.e., $p < .001$).

Table S2.3 in the Supplemental Materials contains the Spearman correlation matrix of average daily raw scores. Raw marker intercorrelations are generally higher than their risk score

counterparts (mean = .40, SD = .29, range = .07 - .99 in the 2005-2007 sample; mean = .47, SD = .25, range = .06 - .99 in the 2015-2017 sample). Some of the apparent independence among markers in Table 3 is probably due to risk thresholds eliminating risk-relevant information (see Bollen & Barb, 1981). Some subsets of markers' raw scores were strongly correlated, such as *Deposit Frequency*, *Spend From Norm*, and *Multiple Payment Methods* (correlations ranged from .83 to .99 across both samples) and *Frequency in Play* and *Increase in Frequency of Play* ($\rho = .88$ in 2005-2007 and $\rho = .92$ in 2015-2017).

Table S2.4 in the Supplemental Materials contains the correlation matrix of maximum risk scores. We used polychoric correlations here because risk scores only take on four different values but represent a continuum of harm severity. Correlations in this table are generally about twice as large as their Table 3 counterparts (mean = .49, SD = .19, range = .20. - .90 in the 2005-2007 sample; mean = .56, SD = .18, range = .19. - .91 in the 2015-2017 sample). Table S2.5—the Spearman correlation matrix of maximum raw scores—in the Supplemental Materials paints a similar though less extreme picture (mean = .31, SD = .23, range = .04. - .76 in the 2005-2007 sample; mean = .41, SD = .22, range = .05. - .89 in the 2015-2017 sample).

Interindividual Stability and Intraindividual Change: Are markers too unstable to differentiate temporary from lasting patterns?

See Table 4 for the intraclass correlations (ICCs) of daily average risk scores and overall levels. Most random intercept models did not converge, likely due to the low prevalence rate of markers suppressing intraindividual variation. The same was true of random intercept models using raw marker scores (see Table S2.6 in the Supplementary Materials). However, the results from other optimizers (i.e., estimation methods) had identical ICCs, even when they too had convergence issues. Different optimizers yielding the same results can indicate that system

warnings of non-convergence issues represent false positives, in which case results can still be meaningfully interpreted (Bates et al., 2012). For risk scores on individual markers, ICCs ranged from .007 to .433 across both samples. Overall levels had an ICC of .085 in 2005-2007, and .184 in 2015-2017. Although there are stable interindividual differences in risk scores, the majority of variance in all cases occurs within persons.

Table 4

Interpersonal Variability in Average Marker Risk Scores

Markers	ICC 2005-2007	ICC 2015-2017
Spend From Norm	.007‡	.009‡
Frequency of Play	.313	.178
Increased Frequency	.041‡	.025‡
Late-Night Play	.019‡	.031‡
Deposit Frequency	.383	.433
Failed Deposits	.064‡	.225 [†]
Withdrawal Reversals	.037‡	.354
Multiple Methods	.215‡	.260
Credit Cards	.235‡	.269‡
Overall Level	.085‡	.184‡

Note. ICC = intraclass correlation from random-intercept model using REML estimation.

In some cases few or no optimizers converged to a proper solution, but ICCs across optimizers were identical or very similar, suggesting that the convergence warnings could be false positives.

[†] = Standard REML estimation did not converge or had separation issues, but at least one other optimizer did not.

‡ = No optimizer converged without separation issues.

Because most users never exceeded no-risk thresholds, we decided to examine how often those who had ever exceeded one for a given marker were in the low-risk, medium-risk, and high-risk category (see Table S2.7 in the Supplementary Materials). The median number of days

in a low-, medium-, or high-risk category was between one and 13 days for each subset of users, depending on the marker and the sample. However, the higher means and maximum values reveal that there were users who spent many if not most of the days they had an active account above a marker's no-risk threshold.

To test whether average risk was related to intraindividual variability in risk, we fit a linear regression of risk score standard deviation on risk score average using robust maximum likelihood (see Table 5). Higher averages were associated with higher intraindividual variation for both individual markers (range = 1.13 - 6.40 in the 2005-2007 sample; range = 0.49 - 4.71 in the 2015-2017 sample) and overall level scores ($b = 2.72$ in 2005-2007 and $b = 1.83$ in 2015-2017); most of these associations were statistically significant. Table S2.8 shows the same regressions, but using raw averages instead. All effects here were positive and statistically significant. Our second hypothesis that average risk scores would not predict the magnitude of intraindividual variation in risk scores was falsified.

The positive regression coefficients may be artifacts of range restriction, outliers, or non-linear functional forms. For example, Figure 1 shows an inverted-U relationship between risk scores averages and standard deviations for 2015-2017 *Credit Cards*. In Figure 2, 2005-2007 *Deposit Frequency* shows a strong, positive relationship when averages and standard deviations are low, a weaker relationship as values increase, and many outliers.

Table 5

Robust Regression of Risk Score Standard Deviations on Risk Score Averages

Marker	2005-2007		2015-2017	
	<i>B</i> [95% CI]	<i>p</i>	<i>B</i> [95% CI]	<i>p</i>
Spend From Norm	6.40 [5.29, 7.51]	< .001	3.53 [1.67, 5.40]	<.001
Frequency of Play	1.31 [1.09, 1.53]	<.001	1.63 [0.87, 2.40]	<.001
Increase Frequency	3.50 [2.84, 4.17]	<.001	1.27 [0.36, 2.18]	<.001
Late-Night Play	6.28 [NA, NA]	NA	4.71 [2.78, 6.64]	<.001
Deposit Frequency	1.13 [0.91, 1.35]	<.001	0.96 [0.59, 1.33]	<.001
Failed Deposits	4.51 [NA, NA]	NA	1.25 [0.70, 1.79]	<.001
Withdrawal Reversals	3.30 [1.71, 4.90]	.001	0.49 [-0.16, 1.13]	.138
Multiple Methods	1.69 [1.55, 1.84]	<.001	0.97 [0.37, 1.58]	.002
Credit Cards	1.26 [1.19, 1.33]	<.001	1.23 [1.07, 1.39]	<.001
Overall Level	2.72 [1.58, 3.89]	<.001	1.83 [0.93, 2.73]	<.001

Note. NA = Failure in model convergence resulted in no standard error estimate. Robust linear regression would not converge, so standard regression results are reported instead.

Figure 1.

Average and Standard Deviation of Credit Cards Risk Scores, 2015-2017

Figure 2.

Average and Standard Deviation of Deposit Frequency Risk Scores, 2015-2017

Most two-lines tests of the effect of average risk scores on standard deviations in risk scores did not converge, presumably due to a lack of sufficient variability in each variable to estimate multiple regression coefficients (see Table 6). Table S2.9 in the Supplementary Materials shows results from the same models, but using raw scores instead of risk scores. Those that did converge generally returned statistically significant effects, with both coefficients positive in sign but the first regression coefficient being much larger than the second regression coefficient. These results suggest that average risk is positively associated with intraindividual variability, but that the relationship is much more pronounced at the lower end of the distribution. No statistically significant evidence of U-shaped relationships replicated across both samples.

We formally examined the possibility of non-linear relationships using Simonsohn's (2018) "two lines" test, which provides more statistical power than polynomial regressions to detect U-shaped relationships. The two-lines test provides evidence for a U-shaped relationship when both of its regression coefficients are statistically significant and of opposite sign. It was not designed to detect other non-linear effects, though one could interpret statistically significant regression coefficients of the same sign but differing magnitude as consistent with an exponential or logarithmic relationship.

Table 6

U-shaped effect of Daily Marker Risk Score Averages on Daily Marker Risk Score Standard Deviations

Marker	2005-2007						2015-2017					
	<i>B1</i>	<i>Z</i>	<i>p</i>	<i>B2</i>	<i>Z</i>	<i>p</i>	<i>B1</i>	<i>Z</i>	<i>p</i>	<i>B2</i>	<i>Z</i>	<i>p</i>
Spend From Norm	NC						NC					
Frequency of Play	NC						NC					
Increase Frequency	23.68	68.33	<.001	2.16	8.10	<.001	NC					
Late-Night Play	15.15	83.13	<.001	2.51	7.96	<.001	NC					
Deposit Frequency	NC						NC					
Failed Deposits	NC						NC					
Withdrawal Reversals	NC						NC					
Multiple Methods	NC						NC					
Credit Cards	5.57	287.54	<.001	0.53	18.72	<.001	21.00	112.71	<.001	0.79	12.44	<.001
Overall Level	NC						NC					

Notes. NC = The model did not converge. Tests are based on the two-lines test, which assumes one sign change in the functional form. The statistical significance of both regression coefficients provides evidence of a U-shaped relationship, provided the coefficients are of opposing signs. (However, in some cases, the scatterplot appears U-shaped, even though the coefficients are merely of very different magnitude, rather than of a different sign.) B1 = Unstandardized regression coefficient for before the direction change; B2 = Unstandardized regression coefficient for after the direction change. *p*-values are based on robust standard errors.

Demographics: Are markers associated with common correlates of gambling harm?

Age

See Table 7 for linear effects of age on daily average risk scores. In a few cases the maximum likelihood estimator did not converge. In the models that did converge, age either had no significant effect on average risk scores or had a significant *positive* effect but the coefficient

value was 0 to two decimal places. Thus, we find little support for our fourth hypothesis that *younger* users would show elevated average risk scores.

We re-ran the models using two-lines tests to check for U-shaped relationships between age and average risk scores (Table S2.10). No U-shaped relationships were statistically significant in both samples. All coefficients were indistinguishable from zero to two decimal places.

Table 7

Robust Regression of Daily Marker Averages on Age

Marker/Overall Risk	2005-2007		2015-2017	
	<i>B</i> [95% CI]	<i>p</i>	<i>B</i> [95% CI]	<i>p</i>
Spend From Norm	0.00 [0.00, 0.00]	.001	0.00 [0.00, 0.00]	.917
Frequency of Play	0.00 [0.00, 0.00]	<.001	0.00 [0.00, 0.00]	<.001
Increase Frequency	0.00 [0.00, 0.00]	<.001	0.00 [0.00, 0.00]	<.001
Late-Night Play	0.00 [NA, NA]	NA	0.00 [0.00, 0.00]	.006
Deposit Frequency	0.00 [0.00, 0.00]	<.001	0.00 [0.00, 0.00]	.004
Failed Deposits	0.00 [NA, NA]	NA	0.00 [0.00, 0.00]	.022
Withdrawal Reversals	0.00 [0.00, 0.00]	.532	0.00 [0.00, 0.00]	.391
Multiple Methods	0.00 [0.00, 0.00]	.001	0.00 [0.00, 0.00]	.021
Credit Cards	0.00 [0.00, 0.00]	<.001	0.00 [0.00, 0.00]	<.001
Overall Level	0.00 [0.00, 0.00]	.031	0.00 [0.00, 0.00]	.212

Note. NA = Model failed to converge properly.

Gender

We used robust maximum likelihood to estimate the effect of gender on average risk scores, with females as the reference category (see Table 8). Out of the 20 models we ran, three

did not converge. Among those that did, most effects were non-significant. The few significant effects were all positive, indicating that males were at higher risk (e.g., *Credit Cards*, 2015-2017). However, none of the regression coefficients were larger than 0.01. There is minimal support at best for our fourth hypothesis that males would have higher average risk scores.

Table 8

Robust Regression of Daily Marker Averages on Gender

Marker/Overall Risk	2005-2007		2015-2017	
	<i>B</i> [95% CI]	<i>p</i>	<i>B</i> [95% CI]	<i>p</i>
Spend From Norm	0.00 [0.00, 0.00]	.073	0.00 [0.00, 0.00]	.373
Frequency of Play	0.00 [0.00, 0.00]	.274	-0.00 [-0.00, 0.00]	.172
Increase Frequency	-0.00 [-0.00, 0.00]	.763	-0.00 [-0.00, 0.00]	.628
Late-Night Play	NA [NA, NA]	NA	0.00 [NA, NA]	NA
Deposit Frequency	-0.00 [-0.00, 0.00]	.314	-0.00 [-0.00, 0.00]	.723
Failed Deposits	0.00 [NA, NA]	NA	0.00 [-0.00, 0.00]	.461
Withdrawal Reversals	0.00 [0.00, 0.00]	.033	0.00 [0.00, 0.00]	.087
Multiple Methods	0.00 [-0.00, 0.00]	.920	0.00 [-0.00, 0.00]	.706
Credit Cards	0.01 [0.01, 0.01]	<.001	0.00 [0.00, 0.00]	.009
Overall Level	0.00 [0.00, 0.00]	.023	0.00 [0.00, 0.00]	.154

Note. The reference category is female.

Most-Involved Bettors: Are markers associated with extreme betting behavior?

From March 2005 to February 2007, the 6% ($n = 1,995$) most behaviorally involved bettors all placed more than 1,133 wagers, and the top 1% ($n = 333$) all placed more than 4,590. The top 6% most financially involved bettors each spent more than 6,878.78 euros on wagers, and the top 1% each spent more than 44,974.12 euros. From March 2015- February 2017, the 6% ($n = 967$) most behaviorally involved bettors placed at least 472 wagers, and the top 1% ($n = 161$) placed at least 2,094. The top 6% most financially involved bettors each spent more than

4,205.65 euros on wagers, and the top 1% each spent more than 30,089.19 euros. Figures S3.1-S3.4 in the Supplemental Materials provide centile plots of bets placed and money spent.

See Table 9 for polychoric correlations between being a top 6% or top 1% user in terms of spending or number of bets and the highest risk score during the study period. The strong positive associations across both samples (range = .29-.87 for individual markers; range = .71-.81 for overall level) support our third hypothesis: the most intensely involved users are more likely to have, at some point, reached overall levels of risk not attained by less involved users. Effect size magnitudes did not differ greatly across samples, Top 1% vs. Top 6% of users, or number of bets vs. amount of money wagered.

Associations with Gambling Harm Proxies

See Table 10 for binary logistic regression models using daily average risk scores to predict account closure, lowering deposit limits, and exceeding deposit limits using robust M-estimation. We observed quasi-complete separation in some cases (i.e., some users had a predicted probability of 1) due to the relative rarity of the gambling harm proxies. Separation problems in robust models typically also occurred for their corresponding standard logistic regression models. Firth's penalized logistic regression models (which can alleviate separation problems; Mansournia et al., 2018) returned similar numerical results to their robust counterparts.

Table 9

Associations Between Being a “Most-Involved” User and Highest Marker and Overall Risk Scores

Marker/ Overall Score	Top 1% Total Bets 2005-2007	Top 1% Total Bets 2015-2017	Top 6% Total Bets 2005-2007	Top 6% Total Bets 2015-2017	Top 1% Wagered 2005-2007	Top 1% Wagered 2015-2017	Top 6% Wagered 2005-2007	Top 6% Wagered 2015-2017
Spend Norm	.56	.50	.60	.59	.68	.70	.77	.77
Frequency Play	.79	.84	.83	.87	.75	.79	.77	.82
Increase Frequency	.71	.77	.77	.84	.69	.73	.72	.77
Late-Night Play	.72	.80	.76	.81	.68	.68	.68	.75
Deposit Frequency	.67	.70	.73	.76	.72	.67	.44	.78
Failed Deposits	.44	.60	.29	.63	.54	.61	.44	.64
Withdrawal Reversals	.29	.52	.28	.58	.30	.66	.36	.65
Multiple Methods	.58	.47	.62	.51	.62	.49	.64	.51
Credit Cards	.31	.32	.32	.38	.32	.29	.39	.32
Overall Level	.71	.77	.78	.78	.73	.75	.81	.79

Note. We used polychoric correlations because all variables are categorical. All correlations are highly statistically significant (i.e., $p < .001$).

Table 10

Robust Regression of Gambling Harm Proxies on Average Marker and Overall Risk Scores

Gambling Harm Proxy	Exceeding Limits		Reduce Deposit Limits		Account Closure			
Dataset	2005-2007						2015-2017	
Marker/Overall Risk	<i>b</i> [95% CI]	<i>p</i>	<i>b</i> [95% CI]	<i>p</i>	<i>b</i> [95% CI]	<i>p</i>	<i>b</i> [95% CI]	<i>p</i>
Spend From Norm	17.21 [-6.43, 40.86]	.154	14.02 [3.48, 24.56]	.009	155.02 [†] [141.99, 168.04]	<.001	116.35 [†] [102.41, 148.92]	<.001
Frequency of Play	1.68 [-0.43, 3.80]	.118	1.16 [0.20, 2.12]	.017	13.93 [12.11, 15.75]	<.001	4.24 [2.06, 6.43]	<.001
Increase Frequency	3.12 [-0.53, 6.77]	.094	2.81 [1.07, 4.55]	.002	18.25 [16.80, 19.70]	<.001	22.96 [†] [18.48, 27.44]	<.001
Late-Night Play	23.77 [-82.36, 129.91]	.661	22.52 [-9.73, 54.76]	.171	223.31 [171.65, 274.96]	<.001	28.70 [2.70, 54.70]	.031
Deposit Frequency	1.34 [-0.91, 3.59]	.244	1.36 [0.62, 2.09]	<.001	13.12 [11.29, 14.96]	<.001	5.62 [4.40, 6.85]	<.001
Failed Deposits	NA [NA, NA]	NA	NA [NA, NA]	NA	140.11 [18.37, 261.84]	.024	6.11 [4.98, 7.24]	<.001
Withdrawal Reversals	3.43 [-13.87, 20.73)]	.697	3.32 [0.12, 6668.75]	.234	23.81 [18.57, 29.04]	<.001	28.23 [†] [22.02, 34.44]	<.001
Multiple Methods	3.87 [0.48, 7.28]	.023	3.43 [2.19, 4.66]	<.001	13.35 [11.93, 14.76]	<.001	5.56 [3.93, 7.19]	<.001
Credit Cards	2.74 [1.04, 4.45]	.002	2.10 [1.47, 2.74]	<.001	3.24 [2.89, 3.59]	<.001	4.05 [3.00, 5.10]	<.001
Overall Level	4.80 [-43.70, 53.30]	.846	6.09 [-5.53, 17.71]	.304	213.75 [†] [167.08, 260.43]	<.001	24.40 [16.29, 32.51]	<.001

Note. [†] = Separation violation. Regression coefficients are on their original log odds scale because the odds ratios were often extremely large. NA = Model did not converge. Confidence intervals of robust estimates do not necessarily correspond with *p*-values.

Most binary logistic regression models, even those without quasi-complete separation, yielded extremely large, positive regression coefficients and extremely wide confidence intervals. These estimates were statistically significant for account closure in all cases in both samples. The effects were statistically significant for most but not all models predicting lowering deposit limits, and were only significant in two of 10 cases for exceeding deposit limits. Given the rarity of these latter outcomes, especially exceeding deposit limits, these null results are perhaps unsurprising. Average overall level score had a regression coefficient larger than that of any individual marker for Account Closure in 2005-2007, but not for the other outcomes.

In an unplanned attempt to obtain more interpretable results, we computed the counts and percentages of ever having fallen into a given risk category based on experiencing each gambling harm proxy (see Table 11). In support of the markers' validity, the percentage of users who fell into a certain risk category was higher for those who had experienced a certain gambling harm proxy than those who had not. Exceptions sometimes occurred in cases where counts were extremely low (e.g., Account Closure, 2015-2017 and Overall Level 3) and when counts were unusually high (e.g., Account Closure, 2005-2007 and *Credit Cards*, Ever Low-Risk).

Table 11

Counts and Percentages of Gambling Harm Proxies Based on Ever Falling Into A Risk Category

Marker	Exceeded Limit 2005-2007		Lowered Limit 2005-2007		Account Closure 2005-2007		Account Closure 2015-2017	
	No	Yes	No	Yes	No	Yes	No	Yes
Spend from Norm								
<i>Ever Low-Risk</i>	1,526	24	1,463	87	1,157	393	272	45
	4.60%	36.36%	4.51%	10.43%	10.31%	10.31%	1.75%	8.84%
<i>Ever Medium-Risk</i>	1,179	20	1,128	71	871	328	224	49
	3.55%	30.30%	3.48%	8.51%	2.96%	8.60%	1.44%	9.63%
<i>Ever High-Risk</i>	508	11	496	23	392	127	160	15
	1.53%	16.67%	1.53%	2.76%	1.33%	3.33%	1.03%	2.95%

Frequency of Play	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	1,271	15	1,202	84	897	389	366	33
	3.83%	22.73%	3.71%	10.07%	3.05%	10.20%	2.35%	6.48%
<i>Ever Medium-Risk</i>	557	8	515	50	356	209	185	14
	1.68%	12.12%	1.59%	6.00%	1.21%	5.48%	1.19%	2.75%
<i>Ever High-Risk</i>	239	4	222	21	140	103	97	6
	0.72%	6.06%	0.68%	2.52%	0.48%	2.70%	0.62%	1.18%
Increased Frequency	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	1,647	20	1,569	98	1,228	439	399	41
	4.96%	30.30%	4.84%	11.75%	4.17%	11.51%	2.56%	8.06%
<i>Ever Medium-Risk</i>	1,680	24	1,599	105	1,264	440	373	42
	5.06%	36.36%	4.93%	12.59%	4.29%	11.54%	2.39%	8.25%
<i>Ever High-Risk</i>	3,018	29	2,884	163	2,421	626	711	58
	9.10%	43.94%	8.90%	19.54%	8.22%	16.41%	4.56%	11.39%
Late-Night Play	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	248	6	225	29	168	86	180	13
	0.75%	9.09%	0.69%	3.48%	0.57%	2.26%	1.16%	2.55%
<i>Ever Medium-Risk</i>	56	1	50	7	28	29	49	3
	0.17%	1.52%	0.15%	0.84%	0.10%	0.76%	0.31%	0.59%
<i>Ever High-Risk</i>	15	0	13	2	7	8	15	1
	0.05%	0.00%	0.04%	0.24%	0.02%	0.21%	0.10%	0.19%
Deposit Frequency	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	649	14	598	65	390	273	283	63
	1.96%	21.21%	1.84%	7.79%	1.32%	7.16%	1.82%	12.38%
<i>Ever Medium-Risk</i>	359	9	324	44	195	173	165	47
	1.08%	13.64%	1.00%	5.28%	0.66%	4.54%	1.06%	9.23%
<i>Ever High-Risk</i>	118	4	107	15	52	70	63	17
	0.36%	6.06%	0.33%	1.80%	0.18%	1.84%	0.40%	3.34%
Failed Deposits	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	11	0	11	0	6	5	1,213	109
	0.03%	0.00%	0.03%	0.00%	0.02%	0.13%	7.79%	21.41%
<i>Ever Medium-Risk</i>	1	0	1	0	0	1	576	74
	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	3.70%	14.54%
<i>Ever High-Risk</i>	0	0	0	0	0	0	193	47
	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.24%	9.23%
Withdrawal Reversals	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	26	0	25	1	11	15	50	17
	0.08%	0.00%	0.08%	0.12%	0.04%	0.39%	0.32%	3.34%
<i>Ever Medium-Risk</i>	548	3	526	25	449	102	127	27
	1.65%	4.55%	1.62%	3.00%	1.53%	2.68%	0.82%	5.30%

<i>Ever High-Risk</i>	9 0.03%	0 0.00%	8 0.02%	1 0.12%	6 0.02%	3 0.08%	18 0.12%	13 2.55%
Multiple Methods	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	2,570 7.75%	24 36.36%	2,440 7.53%	154 18.47%	2,012 6.84%	582 15.26%	717 4.60%	67 13.16%
<i>Ever Medium-Risk</i>	262 0.79%	3 4.55%	240 0.74%	25 3.00%	145 0.49%	120 3.15%	75 0.48%	10 1.96%
<i>Ever High-Risk</i>	43 0.13%	1 1.52%	36 0.11%	8 0.96%	16 0.05%	28 0.73%	9 0.06%	0 0.00%
Credit Cards	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Low-Risk</i>	12,139 36.58%	48 72.72%	11,808 36.43%	379 45.44%	10,972 37.28%	1,215 31.86%	1,939 12.45%	96 18.86%
<i>Ever Medium-Risk</i>	429 1.29%	3 4.55%	410 1.26%	22 2.64%	335 1.14%	97 2.54%	37 0.24%	2 0.39%
<i>Ever High-Risk</i>	1 0.00%	0 0.00%	1 0.00%	0 0.00%	0 0.00%	1 0.03%	0 0.00%	0 0.00%
Overall Level	No	Yes	No	Yes	No	Yes	No	Yes
<i>Ever Level 1</i>	169 0.51%	6 9.09%	156 0.48%	19 2.28%	83 0.28%	92 2.41%	96 0.62%	28 5.50%
<i>Ever Level 2</i>	43 0.13%	0 0.00%	37 0.11%	6 0.72%	16 0.05%	27 0.71%	38 0.24%	13 2.55%
<i>Ever Level 3</i>	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	1 0.01%	0 0.00%

Note. The counts and percentages represent how many and what share of people, respectively, who did (Yes) or did not (No) experience a gambling harm proxy ever fall into a given risk category.

Discussion

With the cooperation of five gambling operators, The Senet Group created the Markers of Harm system to enable operators to identify and intervene with at-risk users. Each of the nine markers that comprise the system have cut-offs for low, medium, and high risk; summing their risk scores together yields an overall risk score, for which there are cut-offs to trigger interventions of varying magnitudes. We used two datasets from *bwin*'s online sportsbook (one covering 2005-2007, and another covering 2015-2017) to evaluate the markers' prevalence,

intercorrelations, inter- and intraindividual stability, and correlations with extreme betting activity, demographic variables, and gambling harm proxies.

Prevalence: Are markers too rare or common to identify all and only those at risk?

Contrary to our first hypothesis that about 6% of users would have an overall score high enough to trigger an intervention on an average day, the actual percentage hovered just above zero. There are several possible explanations for this finding. First, our prevalence rates were based on all users who had *active accounts*. In contrast, Entain computes markers for users who *placed bets on the previous day only*. When we calculated daily averages for users who were active on the previous day only, the daily average prevalence was much higher, though still well below 6%.

Second, to account for the fact that even at-risk bettors may not wager on any one day, Entain aims to have a sufficiently high percentage of users who qualify for a Level 1, Level 2, or Level 3 intervention at least once in the past month *among users who have been active in the previous month*. The fact that we computed prevalence rates for *everyone* in the registration cohort who met inclusion criteria resulted in low prevalence rates. This is because engagement with *bwin* declines for most users over time. Indeed, betting activity among *bwin* sports bettors who registered in February 2005 peaked during the first month immediately following registration on the website, after which it sharply dropped for about six months, and plateaued thereafter (LaPlante, Schumann, et al., 2008, pgs. 2403-2405). The main exception to this trend was the 1% most-involved users in terms of financial and behavioral involvement in live-action betting (i.e., wagering on an ongoing sports event), whose activity was persistently high over the 18 months of observation (pgs. 2408-2409). Our low prevalence rates were driven by users whose interest in *bwin* is short-lived but do not bother to close their account. In contrast,

computing markers for recently active users only would increase prevalence rates, driven by a relatively small number of persistent users who evince higher risk scores. Calculating “ever” circumvented this issue to some extent. “Ever” calculations were much higher than the daily average rates, but the “ever” rates of an entire registration cohort — even over two years — is still unlikely to yield rates as high as the monthly “ever” rate among users who are still actively betting.

Third, our figures apply only to users who bet exclusively at sportsbooks. People who engage in fewer types of gambling activities experience gambling-related harm less often than those who engage with a wide variety of gambling opportunities (Brosowski et al., 2020; LaPlante et al., 2014). Also, online sports bettors experience gambling-related harm less often relative to online casino bettors (Conolly et al., 2018, p.73). The fact that prevalence rates were higher for the markers we could calculate for all users, including those who played casino, poker, or other games during the study period is consistent with this observation.

Finally, prevalence rates might be low due to the design of the markers themselves. One issue is whether risk thresholds are set too high. For instance, *Late-Night Play* requires users to gamble for at least 60 minutes between 12AM and 6AM on a single night to qualify for a low-risk score. This happens infrequently among sports bettors. Game-specific thresholds may be necessary to adequately capture risk for users who prefer sports betting. A second issue is whether the raw scores measure risk as precisely as they could. For example, markers that capture one’s usual amount of involvement (i.e., *Spend From Norm* and *Increases in Frequency in Play*) do not account for the variance of those averages. This means that intraindividual outlier values could produce artificially inflated averages, making it difficult for users to exceed risk

thresholds. Future research should reconsider both where risk thresholds are placed and the definitions of some markers.

Intercorrelations: Are markers redundant with other markers?

Intercorrelations among daily average risk scores on individual markers varied widely, but generally hovered between .10 and .40. However, these correlations were attenuated relative to correlations among average raw scores, some subsets of which showed evidence of redundancy (e.g., intercorrelations as high as .99). Also, average risk score correlations were about half the size of maximum risk score correlations. This implies that the highest level of risk that a user has ever exhibited has informational value over and above the level of risk that they usually exhibit.

The ideal magnitude of marker intercorrelations is a complex matter. Markers that correlate too strongly are redundant. If markers vary in how strongly they correlate with other markers, the result may be accidental overweighting of certain types of risky behavior in the computation of overall risk scores. On the other hand, using markers that vary too independently might result in overlooking at-risk users who have elevated scores on many markers over a long period, but do not have a high overall score on any one day.

One solution to these trade-offs would be to combine subsets of highly overlapping markers together, and then aggregate across subsets to generate an overall risk score. Users could receive a subset score equal to the highest risk score within the subset, reducing the likelihood that a certain type of excessive behavior goes overlooked. For instance, the correlations among daily average raw scores of *Deposit Frequency*, *Spend From Norm*, and *Multiple Payment Methods* ranged from .83 to .99 across both samples, suggesting that they could be aggregated together without losing unique information about risk. This approach would also prevent

simultaneously exceeding risk thresholds on highly correlated markers from being sufficient to receive a high overall risk score.

Interindividual Stability and Intraindividual Change: Are markers too unstable to differentiate temporary from lasting patterns?

Random intercept models suggest that 9-18% of variability in overall level scores is accounted for by stable between-person variance. In no case did more than 50% of variability in risk scores for an individual marker owe to interindividual influences. We tentatively conclude that most variation in risk scores is due to intraindividual factors. However, we are not able to determine what proportion of intraindividual variance reflects systematic sources of variance (e.g., using a new credit card method because other credit cards are maxed out) versus unsystematic sources of variance (e.g., arbitrary choices about which credit card to use). Systematic intraindividual variance represents real change in risk for gambling-related harm, whereas unsystematic variance represents transient, risk-irrelevant factors. So the fact that most of the variation in risk scores is intraindividual does not imply that most risk score variation tracks actual changes in risk. It also does not imply that the majority of systematic variance in risk scores is due to systematic intraindividual change. Future research could use latent variable methods that partial out unsystematic variance to estimate what proportion of systematic variance in risk scores is due to interindividual versus intraindividual factors (see Steyer et al., 2015).

Because the Markers of Harm are designed to measure whether users are *currently* at risk of harm, less stable markers could be more valid insofar as they are more sensitive to the ebbs and flows of risk. But since individual differences in gambling-related harm are fairly stable (Currie et al., 2013), unstable markers might fail to distinguish between users who are

occasionally at risk from those who are chronically at risk, the latter of which could be in greater need of intervention. One way to address this issue could be to trigger more intensive interventions when users exceed a threshold several times during a short period.

We observed statistically significant, positive associations between the means and standard deviations of average risk scores for most markers. The regression coefficients (ranging from 0.49 to 6.40) extrapolate beyond the low averages and standard deviations exhibited by most users. Very low intraindividual variation among low-risk users is the primary reason for the positive associations. These results are inconsistent with our hypothesis that there would be no relationship between average risk scores and standard deviations of average risk scores. This hypothesis was based on longitudinal studies using survey measures of problem gambling (LaPlante, Nelson, et al., 2008). A recent longitudinal survey study found an inverted-U relationship (Sleczka & Romild, 2021), such that low- and moderate-risk gamblers show more variability in their symptom severity relative to problem gamblers and non-risky gamblers. This is consistent with some of our two-lines tests on raw scores suggesting that positive associations between means and standard deviations level off or reverse directions at higher average risk levels.

Demographics: Are markers associated with common correlates of harm?

Our hypothesis that male gender and younger age would be positively related to average risk scores was not supported. Effect sizes were trivially small for the few markers that had statistically significant associations. The failure of markers to capture age and gender differences in problem gambling reported in survey studies could be regarded as evidence against their validity, but could also indicate that these demographic associations do not hold in the *bwin* sports betting population, which skews younger and male.

Most-Involved Bettors: Are markers associated with extreme betting behavior?

We observed strong associations between highest risk score during the study period and being a Top 6% or Top 1% user in terms of number of bets or money wagered. This dovetails with evidence that elevated gambling engagement is a strong predictor of problem gambling (Baggio et al., 2017; Hing et al., 2019). On the other hand, the markers could lack discriminant validity in that elevated involvement is not necessarily harmful for those with more money or leisure time. An important avenue for future research would involve observing how much the association between gambling involvement and marker scores shrinks after statistically controlling for a direct measure of gambling-related harm.

Proxies of Gambling-Related Harm: Are markers associated with proxies of harm?

Additional support for the markers' validity comes from the fact that almost all risk scores were positively associated with all three gambling harm proxies, though these associations were not always statistically significant. When tabulating these associations in terms of counts and percentages, positive relationships failed to hold only when exceeding a certain risk threshold was very rare or very common.

Limitations

Our investigation was confined to *bwin* users, which prevents us from generalizing our results to other gambling websites that use the Markers of Harm system. We also excluded users who played bingo or casino games during the study periods because we did not have information on how much time users spent on these activities. A sensitivity analysis showed that this exclusion attenuated our estimates of the highest risk scores users had ever obtained, but did not have a large effect on daily average risk scores. However, it is possible that users spend more time playing casino and bingo games, leaving open the possibility that the average daily

prevalence of non-zero risk scores on *Late-Night Play*, *Frequency of Play*, and *Increase in Frequency of Play* is higher among the general *bwin* population.

Our proxies for gambling harm circumvented problems with questionnaire measures such as self-selection into surveys, low response rates, response styles, and comprehension failures (Shaffer et al., 2010). On the other hand, there are always potential innocuous explanations for concerning behaviors: Some people self-exclude to avoid exposure to gambling advertisements (Håkansson & Henzel, 2020), those who lower deposit limits may be particularly conscientious about managing their money, and some users may be able to afford losing the money that they tried to deposit when they accidentally exceeded their deposit limit. Conversely, at-risk users might be reluctant to close their account or limit their ability to make large deposits.

Complementing behavioral measures of gambling harm with questionnaire measures would help triangulate how strongly a given marker predicts problem gambling.

Future Directions

Overall risk levels did not reliably outperform all individual markers in the magnitude of its relationships with gambling harm proxies, perhaps indicating that the procedure for computing them needs improvement. One weakness of the current system is that it gives each marker equal weight in the overall risk score, even though some markers have stronger associations with proxies of gambling harm than others. Similarly, identical overall scores composed of different profiles of individual marker scores are treated as though they designate identical risk. This is suboptimal because the same threshold does not necessarily reflect the same degree of risk across markers. Machine learning or item response theory models could be used to discover a weighting procedure that optimizes the prediction of a specific outcome or a latent risk factor, respectively (Embretson & Reise, 2013; Percy, 2016). Relatedly, many risk

thresholds are somewhat arbitrary. Receiver Operating Characteristic curves could help determine which thresholds maximize predictive accuracy, sensitivity, and specificity (e.g., Currie, et al., 2017; Louderback et al., 2021).

Future research should also identify potential additions to the Markers of Harm system that would have incremental validity. The PricewaterhouseCooper report (PwC & Responsible Gambling Council, 2017) identified over 60 valid markers of problem gambling. The academic literature contains others still (Adami et al., 2013; Braverman & Shaffer, 2012; Gray et al., 2012; Haeusler, 2016; Kyonka & Schutte, 2018). Hopefully, the need to replace *Credit Cards* and *Withdrawal Reversals* in the United Kingdom algorithm because of new regulations will generate thoughtful discussion about what new markers should be introduced.

Conclusion

We found that the Markers of Harm system currently implemented at Entain yields low estimates of at-risk sports gamblers on *bwin*, though they may be in line with actual prevalence rates among irregular users who wager on sports events only. Markers are positively associated with elevated gambling involvement and proxies of gambling-related harm. Ways to improve the system include recalibrating risk thresholds to ensure that they trigger interventions for a sufficiently high percentage of users, developing an aggregation procedure that optimizes the precision of overall risk scores, and adding markers that tap underrepresented dimensions of risk. Automated risk algorithms represent the frontier of consumer protection in the gambling industry, but routine evaluation is necessary to ensure their continued improvement.

References

- Baggio, S., Dupuis, M., Berchtold, A., Spilka, S., Simon, O., & Studer, J. (2017). Is gambling involvement a confounding variable for the relationship between Internet gambling and gambling problem severity? *Computers in Human Behavior*, 71, 148-152.
- Bates, D., Maechler, M., Bolker, B., Walker, S., Christensen, R. H. B., Singmann, H., ... & Scheipl, F. (2012). Package 'lme4'. *CRAN. R Foundation for Statistical Computing, Vienna, Austria*. <https://rdrr.io/cran/lme4/man/convergence.html>
- Bollen, K. A., & Barb, K. H. (1981). Pearson's r and coarsely categorized measures. *American Sociological Review*, 232-239.
- Braverman, J., & Shaffer, H. J. (2012). How do gamblers start gambling: Identifying behavioural markers for high-risk internet gambling. *The European Journal of Public Health*, 22(2), 273-278.
- Broda, A., LaPlante, D. A., Nelson, S. E., LaBrie, R. A., Bosworth, L. B., & Shaffer, H. J. (2008). Virtual harm reduction efforts for Internet gambling: effects of deposit limits on actual Internet sports gambling behavior. *Harm Reduction Journal*, 5(1), 27.
- Brosowski, T., Olason, D. T., Turowski, T., & Hayer, T. (2020). The Gambling Consumption Mediation Model (GCMM): A multiple mediation approach to estimate the association of particular game types with problem gambling. *Journal of Gambling Studies*, 1-34.
- Chóliz, M., Marcos, M., & Lázaro-Mateo, J. (2019). The risk of online gambling: A study of gambling disorder prevalence rates in Spain. *International Journal of Mental Health and Addiction*, 1-14.
- Conolly, A., Davies, B., Fuller, L., Heinze, N., & Wardel, H. (2018). Gambling behavior in

- Great Britain in 2016. Birmingham: Gambling Commission.
- <http://www.gamblingcommission.gov.uk/PDF/survey-data/Gambling-behaviour-in-Great-Britain-2016.pdf>
- Currie, S. R., Hodgins, D. C., & Casey, D. M. (2013). Validity of the problem gambling severity index interpretive categories. *Journal of Gambling Studies*, 29(2), 311-327.
- Currie, S. R., Hodgins, D. C., Casey, D. M., el-Guebaly, N., Smith, G. J., Williams, R. J., & Schopflocher, D. P. (2017). Deriving low-risk gambling limits from longitudinal data collected in two independent Canadian studies. *Addiction*, 112(11), 2011-2020.
- Dragicevic, S., Tsogas, G., & Kudic, A. (2011). Analysis of casino online gambling data in relation to behavioural risk markers for high-risk gambling and player protection. *International Gambling Studies*, 11(3), 377-391.
- Deng, X., Lesch, T., & Clark, L. (2019). Applying data science to behavioral analysis of online gambling. *Current Addiction Reports*, 6(3), 159-164.
- Dowle, M. & Srinivasan, A. (2019). data.table: Extension of `data.frame`. R package version 1.12.8. <https://CRAN.R-project.org/package=data.table>
- Demin, G. (2020). expss: Tables, Labels and Some Useful Functions from Spreadsheets and 'SPSS' Statistics. R package version 0.10.6. <https://CRAN.R-project.org/package=expss>
- Effertz, T., Bischof, A., Rumpf, H. J., Meyer, C., & John, U. (2018). The effect of online gambling on gambling problems and resulting economic health costs in Germany. *The European Journal of Health Economics*, 19(7), 967-978.
- Embretson, S. E., & Reise, S. P. (2013). *Item response theory*. Psychology Press.
- Ferris, J. A., & Wynne, H. J. (2001). *The Canadian problem gambling index* (pp. 1-59). Ottawa,

ON: Canadian Centre on Substance Abuse.

- Field, A. P., & Wilcox, R. R. (2017). Robust statistical methods: A primer for clinical psychology and experimental psychopathology researchers. *Behaviour Research and Therapy*, 98, 19–38.
- Fox, J., Friendly, G. G., Graves, S., Heiberger, R., Monette, G., Nilsson, H., ... & Suggests, M. A. S. S. (2007). The car package. *R Foundation for Statistical Computing*.
- Gainsbury, S. M. (2015). Online gambling addiction: the relationship between internet gambling and disordered gambling. *Current Addiction Reports*, 2(2), 185-193.
- Goodwin, B. C., Browne, M., Rockloff, M., & Rose, J. (2017). A typical problem gambler affects six others. *International Gambling Studies*, 17(2), 276-289.
- Gray, H. M., LaPlante, D. A., & Shaffer, H. J. (2012). Behavioral characteristics of Internet gamblers who trigger corporate responsible gambling interventions. *Psychology of Addictive Behaviors*, 26(3), 527-535.
- Håkansson, A., & Henzel, V. (2020). Who chooses to enroll in a new national gambling self-exclusion system? A general population survey in Sweden. *Harm Reduction Journal*, 17(1), 1-12.
- Hamel, A., Bastien, C., Jacques, C., Moreau, A., & Giroux, I. (2021). Sleep or play online Poker?: Gambling behaviors and tilt symptoms while sleep deprived. *Frontiers in Psychiatry*, 11, 1540.
- Hing, N., Russell, A., Tolchard, B., & Nower, L. (2016). Risk factors for gambling problems: An analysis by gender. *Journal of Gambling Studies*, 32(2), 511-534.
- Hing, N., Russell, A. M., Thomas, A., & Jenkinson, R. (2019). Hey big spender: An ecological

- momentary assessment of sports and race betting expenditure by gambler characteristics. *Journal of Gambling Issues*, (42).
- Ivanova, E., Magnusson, K., & Carlbring, P. (2019). Deposit limit prompt in online gambling for reducing gambling intensity: A randomized controlled trial. *Frontiers in Psychology*, 10, 639.
- Kessler, R. C., Hwang, I., LaBrie, R., Petukhova, M., Sampson, N. A., Winters, K. C., & Shaffer, H. J. (2008). DSM-IV pathological gambling in the National Comorbidity Survey Replication. *Psychological Medicine*, 38(9), 1351-1360.
- Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: tests in linear mixed effects models. *Journal of Statistical Software*, 82(13).
- LaBrie, R. A., LaPlante, D. A., Nelson, S. E., Schumann, A., & Shaffer, H. J. (2007). Assessing the playing field: A prospective longitudinal study of internet sports gambling behavior. *Journal of Gambling Studies*, 23(3), 347-362.
- LaPlante, D. A., Nelson, S. E., & Gray, H. M. (2014). Breadth and depth involvement: Understanding Internet gambling involvement and its relationship to gambling problems. *Psychology of Addictive Behaviors*, 28(2), 396–403.
- LaPlante, D. A., Nelson, S. E., LaBrie, R. A., & Shaffer, H. J. (2008). Stability and progression of disordered gambling: Lessons from longitudinal studies. *The Canadian Journal of Psychiatry*, 53(1), 52-60.
- LaPlante, D. A., Schumann, A., LaBrie, R. A., & Shaffer, H. J. (2008). Population trends in Internet sports gambling. *Computers in Human Behavior*, 24(5), 2399-2414.
- Louderback, E. R., LaPlante, D. A., Currie, S. R., & Nelson, S. E. (2021). Developing and

- validating lower risk online gambling thresholds with actual bettor data from a major Internet gambling operator. *Psychology of Addictive Behaviors*.
<https://doi.org/10.1037/adb0000628>
- Luquiens, A., Vendryes, D., Aubin, H. J., Benyamina, A., Gaiffas, S., & Bacry, E. (2018). Description and assessment of trustability of motives for self-exclusion reported by online poker gamblers in a cohort using account-based gambling data. *BMJ open*, 8(12).
- Makowski, D., Ben-Shachar, M. S., Patil, I. & Lüdecke, D. (2020). *Methods for Correlation Analysis*. CRAN.
- Maechler, M., Rousseeuw, P., Croux, C., Todorov, V., Ruckstuhl, A., Salibian-Barrera, M., ... & Maechler, M. M. (2020). Package ‘robustbase’. *Basic Robust Statistics*.
- Mächler, M. (2015). Arbitrarily Accurate Computation with R: The Rmpfr Package. version 0.8-1. <https://CRAN.R-project.org/package=Rmpfr>
- Mansournia, M. A., Geroldinger, A., Greenland, S., & Heinze, G. (2018). Separation in logistic regression: causes, consequences, and control. *American Journal of Epidemiology*, 187(4), 864-870.
- Muggleton, N., Parpart, P., Newall, P., Leake, D., Gathergood, J., & Stewart, N. (2021). The association between gambling and financial, social and health outcomes in big financial data. *Nature Human Behaviour*, 1-8.
- Narayan, N. (2020, April 08). BGC to take over assets and responsibilities of SENET GROUP. Retrieved March 12, 2021, from <https://europeangaming.eu/portal/latest-news/2020/04/08/68038/bgc-to-take-over-assets-and-responsibilities-of-senet-group/>
- Nelson, S. E., Edson, T., Louderback, E. R., Tom, M., Grossman, A., & LaPlante, D. (2020).

- Changes to the playing field: A contemporary study of actual online sports betting.
<https://doi.org/10.31234/osf.io/tc8ps>
- Nelson, S. E., LaPlante, D. A., Peller, A. J., Schumann, A., LaBrie, R. A., & Shaffer, H. J. (2008). Real limits in the virtual world: Self-limiting behavior of Internet gamblers. *Journal of Gambling Studies*, 24(4), 463-477.
- Parhami, I., Siani, A., Rosenthal, R. J., Lin, S., Collard, M., & Fong, T. W. (2012). Sleep and gambling severity in a community sample of gamblers. *Journal of Addictive Diseases*, 31(1), 67-79.
- Parke, A., & Parke, J. (2019). Transformation of sports betting into a rapid and continuous gambling activity: A grounded theoretical investigation of problem sports betting in online settings. *International Journal of Mental Health and Addiction*, 17(6), 1340-1359.
- Percy, C., França, M., Dragičević, S., & d'Avila Garcez, A. (2016). Predicting online gambling self-exclusion: an analysis of the performance of supervised machine learning models. *International Gambling Studies*, 16(2), 193-210.
- Philander, K. S., & MacKay, T. L. (2014). Online gambling participation and problem gambling severity: is there a causal relationship? *International Gambling Studies*, 14(2), 214-227.
- Pratt, K. (2020, April 14). UK Bans Use Of Credit Cards To Pay For Gambling. Retrieved May 14, 2020, from <https://www.forbes.com/sites/advisoruk/2020/04/14/uk-bans-use-of-credit-cards-to-pay-for-gambling/#5b27de46190c>
- PwC & Responsible Gambling Council. (2017). Remote gambling research: Interim report on Phase 2. London: Gamble Aware. https://about.gambleaware.org/media/1549/gamble-aware_remote-gambling-research_phase-2_pwc-report_august-2017-final.pdf
- R Core Team (2020). R: A language and environment for statistical computing (Version 4.0. 0).

R Foundation for Statistical Computing.

Revelle, W. (2019) psych: Procedures for Personality and Psychological Research,

Northwestern University, Evanston, Illinois, USA,

<https://CRAN.R-project.org/package=psych> Version = 1.9.12.

Sleczka, P., & Romild, U. (2021). On the stability and the progression of gambling problems:

longitudinal relations between different problems related to gambling. *Addiction*, 116(1), 116-125.

Shaffer, H. J., Peller, A. J., LaPlante, D. A., Nelson, S. E., & LaBrie, R. A. (2010). Toward a

paradigm shift in Internet gambling research: From opinion and self-report to actual behavior. *Addiction Research & Theory*, 18(3), 270-283.

Simonsohn, U. (2018). Two lines: A valid alternative to the invalid testing of U-shaped

relationships with quadratic regressions. *Advances in Methods and Practices in Psychological Science*, 1(4), 538-555.

Steyer, R., Mayer, A., Geiser, C., & Cole, D. A. (2015). A theory of states and traits—Revised.

Annual Review of Clinical Psychology, 11, 71-98.

Swanton, T. B., & Gainsbury, S. M. (2020). Gambling-related consumer credit use and debt

problems: a brief review. *Current Opinion in Behavioral Sciences*, 31, 21-31.

Wardle, H., Parke, J., & Excell, D. (2014). Machines research programme: Report 1—theoretical

markers of harm for machine play in a bookmaker's: a rapid scoping review. *Responsible Gambling Trust*.

<https://about.gambleaware.org/media/1169/report-1-theoretical-markers-of-harm-for-machine-play-in-a-bookmakers-a-rapid-scoping-review.pdf>

Wickham et al., (2019). Welcome to the tidyverse. *Journal of Open Source Software*,

4(43), 1686, <https://doi.org/10.21105/joss.01686>

- Wood, R. T., Shorter, G. W., & Griffiths, M. D. (2014). Rating the suitability of responsible gambling features for specific game types: A resource for optimizing responsible gambling strategy. *International Journal of Mental Health and Addiction*, 12(1), 94-112.
- Wright, M. (2020, November, 9). Withdrawal reversals to be blocked on all gambling sites. Retrieved February 2, 2021, from <https://onlinebingo.co.uk/news/withdrawal-reversals-blocked>
- Yani-de-Soriano, M., Javed, U., & Yousafzai, S. (2012). Can an industry be socially responsible if its products harm consumers? The case of online gambling. *Journal of Business Ethics*, 110(4), 481-497.