Developing and Validating Lower Risk Online Gambling Thresholds
with Actual Bettor Data from a Major Internet Gambling Operator

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Data Description: The data reported in this manuscript has been used in other published manuscripts. The present study differs from other studies that used these data because it: 1) asked novel, pre-registered research questions related to developing lower risk limits for online gambling using receiver operating characteristic curve analysis, 2) tested existing land-based lower risk gambling limits with online gamblers, 3) examined the generalizability of newly-developed online gambling limits across three datasets, and 4) investigated how these new online gambling limits predicted four outcomes that are proxies for problem gambling.

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Abstract: Objective: To help individuals avoid potential negative consequences associated with their gambling, researchers have developed lower risk limits for time and financial involvement among populations of land-based gamblers. The present study extended these efforts to online gambler populations with prospective longitudinal data.

Method: We used receiver operating characteristic curve analysis and logistic regression models predicting a Brief Biosocial Gambling Screen (BBGS; Gebauer, LaBrie & Shaffer, 2010) to develop lower risk limits for six measures of gambling involvement among subscribers to an online gambling operator. We also tested the utility of these six newly-developed limits and three existing land-based limits for the BBGS outcome and proxies for gambling problems including: (1) voluntary self-limiting, (2) voluntary self-exclusion, (3) closing one's account, and (4) being assigned a flag for potential problem gambling by customer service.

Results: We identified five optimal limits for lower risk online gambling with adequate sensitivity and specificity for predicting BBGS-positive status, and four of those that also predicted at least one proxy outcome in logistic regression models. These four empirically supported gambling limits were: (1) wagering 167.97 Euros or less each month; (2) spending 6.71% or less of annual income on online gambling wagers; (3) losing 26.11 Euros or less on online gambling per month; and (4) demonstrating variability (i.e., standard deviation) in daily amount wagered of 35.14 Euros or less during one's duration active.

Conclusions: Our findings have implications for lower risk gambling limits research and suggest that unique limits might apply to online and land-based gambler populations.

Keywords: gambling, problem gambling, safer gambling thresholds, lower risk gambling limits, internet gambling

Public Health Significance Statement: This study found that gambling online above specific limits is associated with increased likelihood of experiencing gambling-related problems. Public Health guidelines advising gamblers to keep their gambling below certain limits might facilitate safer gambling practices and help reduce the likelihood of emerging gambling-related problems. Individual cases might require more stringent thresholds, and like any behavior with potential for harm, not engaging in gambling at all is the most certain way to prevent gambling problems.

Excessive gambling is an important public health problem that is associated with the accumulation of debt, co-occurring mental health problems, social and occupational harms, and more (Dash et al., 2019; Dickson-Swift, James & Kippen, 2005; Kourgiantakis, Saint-Jacques & Tremblay, 2013; Sundqvist & Rosendahl, 2019). To help people avoid experiencing such negative consequences, researchers have sought to better understand how gambling behaviors could predict gambling-related harm (Currie et al., 2017) and Gambling Disorder (Dowling et al., 2018; Gray et al., 2019). It might be possible to identify lower risk¹ limits based on our understanding of the relationship between specific gambling patterns and harm outcomes that can provide guidance to individuals who choose to gamble. Similar to responsible drinking guidelines for alcohol consumption (e.g., Holman et al., 1996; Rehm & Patra, 2012), scholars have developed guidelines for gambling spending and frequency that reduce or prevent future gambling-related problems (Currie et al., 2006, 2008, 2012, 2017, 2019). Researchers predominantly have tested lower risk gambling thresholds with samples of land-based gamblers in Canada (e.g., Currie et al., 2017). The current study used actual betting records to examine lower risk gambling thresholds (i.e., limits) among online gamblers. We sought to understand whether thresholds specific to online gambling hold added value over land-based thresholds.

To date, only one study about lower risk gambling thresholds has used data from actual gamblers in an online gambling environment (i.e., Brosowski, Meyer & Hayer, 2012), despite

¹ We use the term “lower risk” here and in the rest of the manuscript to refer to levels of gambling activity that are less likely to lead to gambling-related problems, including Gambling Disorder. We realized that there are many potential definitions of “lower risk,” so we used a pre-registered research approach (see Nosek, Ebersole, DeHaven, & Mellor, 2018) to clearly specify our confirmatory hypotheses based on this definition and to guard against ad hoc or post-hoc modification of hypotheses and results. We selected an *a priori* definition of lower risk with a relative risk approach (instead of an absolute risk approach; see Markham, Young & Doran, 2016) that is consistent with the considerable body of literature on lower risk gambling limits (Currie et al., 2006, 2008, 2012, 2017, 2019). However, we want to be entirely clear that “lower risk” does not mean “no risk” or “zero risk,” and that individual gamblers might still be at risk of experiencing gambling-related problems and gambling harm even when staying below land-based or online lower risk limits.

the recent growth of internet gambling opportunities and considerable body of research on online gambling (Adami et al., 2013; Braverman et al., 2013; Dragicevic, Tsogas & Kudic, 2011; Gray, LaPlante and Shaffer, 2012; Ivanova, Magnusson, & Carlbring, 2019; LaPlante et al., 2009; LaPlante, Nelson and Gray, 2014; Nelson et al., 2008; Philander, 2014; Shaffer et al., 2010). Data from actual online gambling records can provide unique insights into gambling behavior as it more validly measures financial and time engagement metrics on a given platform for gamblers than do self-report measures (Braverman, Tom & Shaffer, 2014). The present study used actual player data records from bwin Interactive Entertainment, AG (bwin) and survey data from their subscribers to develop and test lower risk gambling thresholds for online gambling. We developed these lower risk limits by following a pre-registered research and analysis plan (see Mellor & Nosek, 2018 and Nosek et al., 2018 for discussions of the benefits of pre-registration) using the Brief Biosocial Gambling Screen (BBGS; Gebauer, LaBrie & Shaffer, 2010) as the primary outcome, and then tested the limits' utility for predicting proxies for gambling harm including (1) voluntary self-limiting, (2) voluntary self-exclusion, (3) account closure, and (4) being assigned a flag for potential problem gambling by customer service.

Lower Risk Gambling Thresholds

A considerable body of literature has focused on developing, validating, and testing lower risk gambling guidelines based on population samples (Currie et al., 2006, 2008, 2012, 2017, 2019). The key results suggest that researchers can develop empirically-based lower risk limits for gambling that minimize the likelihood of gambling-related harm using self-reported data from surveys of population-based samples. For example, the latest study on these lower risk thresholds used retrospective longitudinal data and showed that gambling more than eight times per month, spending more than \$75 Canadian dollars on gambling, or spending more than 1.7%

of one's yearly household income on gambling makes one more likely to have experienced gambling-related harm (Currie et al., 2017). Although these studies included individuals who engaged in both land-based and internet forms of gambling, they did not examine online gambling specifically and the samples were relatively small.

The one study that did use actual data from online gambling subscriber records to examine lower risk gambling limits (i.e., Brosowski et al., 2012) found that internet gamblers who exceeded Currie's (2006) modified land-based thresholds (i.e., more than 21 active days or more than 400 Euros in amount wagered during a 214 day period), were more likely to have closed their account for gambling problems. Other authors have argued that evidence-based guidelines for responsible gambling are important and could be used to reduce the potential for harm among individual gamblers. Brosowski et al. (2015) found that lower risk gambling thresholds could be developed for a population of German gamblers based on cross-sectional, self-reported survey data. Hing and colleagues (2019) suggested that stakeholders develop evidence-based standards for safer gambling practices among ordinary gamblers and high-risk populations, but they do not fully develop specific limits for financial involvement in gambling. In one of the largest studies of gambling expenditures and gambling-related harm using survey data from four countries (i.e., Australia, Canada, Finland and Norway), Markham et al. (2016) found that the expenditure-gambling harm relationship was linear or r-shaped (i.e., steadily increasing harm across all levels of financial involvement in gambling). Importantly, their findings differ from those of Currie et al. (2017), who found the risk curves for gambling expenditures and gambling-related harm were j-shaped (i.e., little to no chance of harm at lower levels of financial involvement in gambling, but escalating chance after a turning point).

In response to the line of research developing lower risk gambling limits, critics have raised concerns regarding potential limitations (see Abbott, 2017), notably that the limits might not apply equally to different populations and that there has been reliance on mostly retrospective study designs to develop such limits. Other critics of safer gambling limits (see Cunningham, 2006) have suggested that methodological limitations could be present in studies of such limits, due to (1) operationalization decisions for measuring frequency of gambling and (2) sampling bias resulting from missing data in the survey that was used to create the initial limits. We address these limitations by expanding the scope of lower risk gambling guidelines to actual players in an online gambling context in the European Union using prospective longitudinal data.

Internet Gambling Research

Internet gambling research using player records almost exclusively has utilized data from European gambling operators. This body of literature has examined actual subscriber data to determine how play behaviors could influence the risk of developing gambling problems or screening positive for a Gambling Disorder (Deng, Lesch & Clark, 2019; LaBrie et al., 2007; LaBrie et al., 2008; Luquiens et al., 2019). LaBrie et al.'s (2007) major findings suggest that most online sports gamblers on the bwin platform wager a small to moderate amount of money per month, place bets a few days per month, and tend to have small to moderate losses over their duration of internet gambling. They also identified a small percentage (i.e. 1-3%) of internet sports gamblers who exhibit very high levels of financial and time involvement, with very high amounts for total amount wagered and amount lost (i.e., 10,000s or 100,000s of Euros). Overall, these studies reveal the insights into gambling behavior that can be gleaned when using

prospective data from actual gambling records, as opposed to self-reported gambling behavior which can be biased in either direction (see Braverman, Tom & Shaffer, 2014).

Importance of Developing Lower Risk Gambling Limits for Internet Gamblers

An important gap in research and intervention on internet gambling is the absence of lower risk thresholds for online gamblers. Moreover, there is no existing literature to our knowledge that extends the scope of current land-based limits to the online gambling environment or that tests for alternative proxies for problem gambling such as voluntary self-limiting or self-exclusion. Developing lower risk limits that are specific to the domain of online gambling is important for several reasons. First, scholars have demonstrated that there are important differences in demographics, levels of non-problem and problem gambling, and different comorbidities for land-based and internet gambling populations (Gainsbury, Russell & Hing, 2014). These key differences suggest that there could also be substantial differences in gambling involvement and levels of involvement that might predict risky play for internet gamblers. Second, given the unique structural characteristics of internet gambling (e.g., ease of betting, numerous platforms of play such as computers, smartphones and tablets, and 24/7/365 access), it is possible that different lower risk thresholds exist for this population. Third, although responsible gambling programs have proliferated in recent years in the land-based gambling sphere (see Ladouceur et al., 2017 for a review), more remains to be done among internet gambling operators. Fourth, methodological differences in data collection and measurement could also result in different limits for land-based and online gamblers. Most population-based studies of lower risk gambling limits have relied on retrospective, cross-sectional reporting of harms and gambling activity. Gamblers may intentionally (i.e., because of stigma or social desirability bias) or unintentionally (i.e., due to retrospective recall errors) underreport harms and

gambling activity (Braverman et al., 2014; Shaffer et al., 2010). In contrast, the present study uses actual prospective gambling activity data that was collected in real-time, thereby reducing the influence of social desirability and retrospective recall errors.

Measuring Potential Risks Related to Gambling to Develop Lower Risk Limits

Acceptable risk related to gambling is difficult to quantify due to differences in definitions of gambling-related harm and what level of risk is considered acceptable (Currie et al., 2019), a difficulty also encountered in alcohol studies (Stockwell & Room, 2012). This study does not resolve this thorny and potentially political question, but rather offers one possible solution that emerges from *a priori* scientific justifications. Whether to identify lower risk limits is in itself a political decision; nonetheless, such an effort might be useful in societies that accept legal gambling. To ensure that we objectively examined risk related to gambling harm, we developed our lower risk limits using a validated screen for Gambling Disorder as our primary outcome measure (Gebauer et al., 2010). Given the considerable psychological distress and associated harm experienced by those with Gambling Disorder (Subramaniam et al., 2015), developing our limits around this outcome measure ensures that we are assessing risk of harm.

Our approach to developing lower risk gambling limits follows the methodological procedures drawn from the considerable body of literature on land-based lower risk gambling limits (Currie et al., 2006; 2008; 2017; 2019). The potential risk presented by gambling can be examined in several different ways (see an alternative approach in Markham et al., 2015); we applied the relative risk approach described in Currie et al. (2017) in order to better compare online samples to those used in the prior work on land-based gambling limits. We constructed our limits using receiver operating characteristic (ROC) curves to predict a positive screen for gambling disorder, and maximized sensitivity while keeping specificity greater than or equal to

0.70 (as applied in Currie et al., 2017; also see Dowling et al., 2018, p. 51 for research in Australia that constrained specificity in ROC analyses to construct lower-risk gambling limits).

The Present Study

The present study used actual gambling record data from subscribers to bwin over several years to develop and test the predictive validity of new lower risk limits for internet gamblers. We also tested the utility of the existing land-based limits for our sample of online gamblers to determine if these limits can predict screening positive on the BBGS and four proxies for gambling problems based on the use of responsible gambling tools on the website including self-limiting, self-exclusion, closing one's account for reasons other than gambling problems, or being assigned a responsible gambling (RG) flag by customer service.

Hypotheses

1. Online gamblers who gamble online in excess of land-based lower risk gambling thresholds will be more likely to have a positive screen for Gambling Disorder when compared with online gamblers who do not exceed land-based gambling thresholds when gambling online.
2. Specific lower risk *online* gambling thresholds, developed by maximizing sensitivity while keeping specificity greater than or equal to 0.70² according to receiver operating characteristic (ROC) curves, will be able to predict risk for Gambling Disorder among online gamblers.

² We selected the 0.70 cutoff for specificity to ensure that our methodological approach was consistent with the body of literature on lower risk gambling limits (Currie et al., 2017; Dowling et al., 2018). A common approach to choosing a cut-off following ROC analysis is the application of the Youden Index where the chosen value is the point on the curve where sensitivity and specificity are maximized. However, application of the Youden index can lead to a high proportion of false positives, resulting in overly conservative limits. Very low cut-offs may not be viewed as credible among highly active, online gamblers. Hence, we used a variation of the Youden Index in which sensitivity was maximized while constraining specificity to be 0.70 or higher.

3. Online gamblers who gamble online in excess of lower risk online gambling thresholds will be more likely to have evidence of (1) voluntary self-limiting, (2) voluntary self-exclusion, (3) account closure and (4) RG account flags when compared with online gamblers who do not exceed lower risk online gambling thresholds.
 - a. The variance explained (i.e., McFadden's and Cox & Snell's pseudo- R^2) and odds ratios for predicting (1) voluntary self-limiting, (2) voluntary self-exclusion, (3) account closure and (4) RG account flags will be greater³ for lower risk online gambling thresholds than for land-based lower risk gambling thresholds.⁴

Method

We pre-registered our research and analysis plan on osf.io (<https://osf.io/6y9u4/>). The current paper addresses four (i.e., Hypothesis 1, 2, 3 and 3a) of the six hypotheses specified in that pre-registration. A planned follow-up paper will address Hypotheses 4 and 5.

Participants

We used three secondary datasets that bwin.party (bwin) made available to us between 2005 and 2011. These data consisted of gambling transaction records for all online gambling activity (i.e., online casino, online poker and sports betting) from people who were customers of the bwin Interactive Entertainment, AG (bwin) company. We derived our samples from these three separate datasets: (1) New Subscriber, (2) RG, and (3) BBGS.

In addition to the unique exclusion criteria for each dataset described below, we employed a universal set of exclusion criteria across datasets. We excluded participants if they

³ When comparing odds ratios, we examined the confidence intervals for each point estimate and determined whether they overlapped with each other. If the point estimate of the odds ratio was greater and the confidence intervals did not overlap, we designated that the limit tested was a better predictor for that particular outcome.

⁴ This finding would not negate the importance of available land-based lower risk thresholds, but rather would signify the need for thresholds specific to the online gambling space.

only used promotional money from bwin that was provided as a sign-up incentive. In addition, to ensure that participants had at least a month of potential activity, we excluded participants if they did not make a bet with their own money until less than one month before the end of the study period, as defined below for each dataset and subsample. Finally, we also excluded players who only bet on one day during the study period to ensure our samples represented individuals who engage in online gambling more than during a single trial session.

(1) New Subscriber Dataset. This dataset includes all 48,114 individuals who opened an account with bwin between February 1st and February 28th, 2005 and placed a bet by the end of the study period (i.e., February 1, 2005 through the end of February 2007). Within this dataset, we examine the betting behavior of three subsamples of subscribers compared to the rest of the sample: (a) individuals who placed a self-imposed limit on the amount they could deposit monthly at bwin between November 2005 (when bwin began to allow users to set their own deposit limits) and February 2007 (i.e., voluntary self-limiting); (b) individuals who closed their accounts for gambling problem-related reasons between the end of December 2005 (when bwin began asking subscribers to select a reason when they closed their accounts) and February 2007 (i.e., voluntary self-excluding); and (c) individuals who closed their accounts for reasons other than gambling problems between the end of December 2005 and February 2007 (i.e., account closure). For self-limiters, from the 1,241 subscribers who utilized this feature between November 2005 and February 2007, we excluded participants who set self-limits that were equal to or higher than bwin-imposed deposit limits, as we have done in previous work to ensure self-limiting serves as a more valid proxy of gambling problems. For account closers, from the 992 subscribers who closed their accounts between the end of December 2005 and February 2007, we excluded the 312 subscribers who closed their accounts for gambling problem-related reasons

and therefore comprised the self-excluder sample. Therefore, our final samples for these outcomes included 1,013 self-limiters, 312 self-excluders, and 680 account closers. For the self-limiters, voluntary self-excluders, and account closers, we considered their study period to end on the date of their first self-limit, self-exclusion, or account closure event. The study period for the descriptive statistics is based on self-limiter study period for users who were both self-excluders and self-limiters. The descriptive statistics using the self-excluder study period for users who were both self-excluders and self-limiters are almost identical.

(2) *RG Dataset*. This dataset includes 2,066 individuals who triggered corporate RG intervention flags between November 2008 and November 2009, as well as 2,066 randomly selected matched controls who did not trigger an RG flag but who made their first deposit at bwin on the same day as an RG-flagged individual. Subscribers triggered RG flags through interactions with bwin about RG features (e.g., setting limits) or direct communication that bwin determined to be related to gambling problems or excessive gambling. We obtained betting records for these individuals from May 1, 2000 (or the beginning of their betting activity, if later than May 2000) through November 10, 2010. We excluded any RG-flagged individuals or matched controls who did not have betting transaction data available resulting in a final sample of 1,845 RG-flagged individuals and 1,762 matched controls. For the RG-flagged individuals, we considered their study period to end on the date of their first RG flag event.

(3) *BBGS Dataset*. This dataset includes 2,255 individuals who responded to an invitation sent by bwin in October 2010 to an initial sample of 100,000 subscribers to complete a brief web survey hosted by [institution blinded for peer-review]. The survey included the Brief Biosocial Gambling Screen (BBGS: Gebauer, LaBrie, & Shaffer, 2010), a question asking individuals to provide their annual household income, and other items that we do not consider in these

analyses. We obtained betting records for these individuals from May 2000 (or the beginning of their betting activity, if later than May 2000) through their survey completion date. We used an ordinal measure of annual household pre-tax income in Euros based on a BBGS survey question in some of our models. We excluded from the 2,255 survey completers all respondents who did not have betting transaction data available, as well as respondents who took the survey more than one time or took a version of the survey in which there were language translation errors, for a final sample of 1,772.

We used different combinations of these three datasets to test each hypothesis. We used the BBGS Dataset to test Hypotheses 1 and 2. We used the New Subscriber and RG Datasets to test Hypotheses 3 and 3a. We used listwise deletion to exclude missing data from analyses.

Procedures

We used a prospective longitudinal study design with daily aggregates of players' online gambling data. The [institution blinded for peer-review] IRB determined these studies were exempt from IRB review. Data was transferred via secure FTP from bwin to the [institution blinded for peer-review]. All samples provide adequate statistical power to test our hypotheses.

Measures

Dependent variables

Outcomes include (1) positive screen for Gambling Disorder, (2) voluntary self-limiting, (3) voluntary self-exclusion, (4) account closure and (5) RG flag. All of the outcome measures are binary ("0" = negative for outcome; "1" = positive for outcome).

Our measure of Gambling Disorder is the Brief Biosocial Gambling Screen (BBGS; Gebauer et al., 2010), a three-item screening tool derived from the DSM-IV criteria for Gambling Disorder. Due to data limitations, we cannot replicate Currie et al.'s (2017) measures

of harm from gambling. However, the BBGS has demonstrated validity and reliability as a measure of experiencing gambling problems consistent with Gambling Disorder (Brett et al., 2014; Caler et al., 2016) and does tap a dimension of harm in its third item (i.e., During the past 12 months did you have such financial trouble as a result of your gambling that you had to get help with living expenses from family, friends or welfare?). Answering affirmatively to any of the three items resulted in a positive screen for the BBGS.

Independent Variables

We used several measures to test the applicability of land-based lower risk gambling limits for online gamblers and to develop lower risk online gambling limits in an online population using actual online gambling player records. For land-based gambling limits, we used three predictor variables to approximate Currie et al.'s (2017) land-based safer gambling limits with our online gambling data: (1) frequency of gambling per month; (2) amount wagered per month; and (3) percentage of yearly household income wagered online. For developing and testing new lower risk online gambling thresholds, we used measures⁵ including: (1) frequency of gambling per month; (2) amount wagered per month; (3) percentage of yearly household income wagered online; and (4) net outcome of gambling per month. We also recreated two measures from a study of online gamblers by Braverman and Shaffer (2010): (5) daily betting variability; and (6) betting escalation during a player's first six months of activity.⁶ We

⁵ We selected six gambling involvement measures that tap both time involvement in gambling (i.e., frequency of gambling) and financial involvement in gambling (i.e., the remaining five measures). We recognize that there are other important measures of gambling involvement that have been shown to predict increased risk of problem gambling (Brosowski, Olason, Turowski, & Hayer, 2020; Gainsbury, Abarbanel & Blaszczyński, 2017; LaPlante et al., 2014), such as number of game types (i.e., breadth involvement) or playing certain games (e.g., EGMs).

⁶ We measured betting escalation during the first six months of the duration active because research has shown that adaptation (i.e., initial escalation in betting and amount wagered followed by leveling off and decrease) has occurred among most gamblers within six months, suggesting that trajectories that continue to escalate throughout this time period are more indicative of problematic play (LaPlante et al., 2008). Studies suggest that Gambling Disorder tends

calculated each of these variables within a player's duration active. We define each of these variables below.

Duration active. We calculated duration active separately for each of the three datasets, as well as for different subgroups within the datasets to ensure we accurately measured time periods for each subscriber. For subscribers in the New Subscribers dataset who did not fall into one of the subgroups (i.e., self-limiting, self-exclusion, or account closure), duration is the number of days between their first (after initial deposit) and last bet, inclusive, within the study period. For self-limiters, self-excluders, and account closers in this dataset, duration is the number of days between their first (after initial deposit) bet and their first self-limit / self-exclusion / account closure event, inclusive. For subscribers in the RG Flag dataset who did not receive an RG flag (i.e., matched controls), duration is the number of days between their first (after initial deposit) and last bet, inclusive, within the study period. For RG-flagged individuals in this dataset, duration is the number of days between their first (after initial deposit) bet and their first RG flag event, inclusive. For subscribers in the BBGS dataset, duration is the number of days between their first (after initial deposit) bet and their date of survey completion, inclusive.

Frequency of gambling per month. This frequency measure is comparable to Currie's (2017) frequency of gambling per month measure. We defined frequency of gambling as the average number of days per month on which a player actively wagered money in online gambling during the duration in which the player was active. We calculated this measure by summing the number of days that a player placed at least one bet during their duration active, dividing by total the number of days in that player's duration active, and multiplying this value by 30.4, which is the average number of days in a month for a one-year period.

to onset in approximately the first few months to one year after initiating gambling among high-risk populations (Breen & Zimmerman, 2002; Reith & Dobbie, 2013), making the initial six-month period particularly important.

Amount wagered per month and per year. The amount wagered per month measure is comparable to Currie et al.'s (2017) money spent on gambling per month measure. We defined amount wagered per month as a monthly average of money wagered at bwin during the duration each player was active on the bwin website. We calculated this measure by summing the total wagered for each player for all days on which a bet was placed, dividing by the number of days in that player's duration active, and multiplying this value by 30.4. We also multiplied this value by 365 to create a measure of the amount wagered per year, which we used to compute the percentage of yearly household income spent on online gambling. To be consistent with the currency in our datasets, we converted the land-based limits into Euros for amount wagered per month using the historical currency conversion rates from www.xe.com, a leading provider of historical currency conversion rates.⁷

Percentage of yearly household income spent on online gambling wagers. This measure is consistent with Currie et al.'s (2017) percentage of gross family income spent on gambling per year measure. We calculated percentage of yearly household income spent on online gambling wagers by dividing the amount wagered per year measure described above by the mid-point of the income category⁸ that each individual reported in their survey response. This proportion was then multiplied by 100 to yield a percentage. For example, if a respondent reported that their income was in the €25,000 to €35,000 category and they wagered €1000 per year on bwin, their

⁷ To ensure that conversion rates are consistent with each dataset's time period, we used the historical currency conversion rate from February 1st, 2005 for the New Subscribers Dataset, from November 1st, 2008 for the RG Dataset, and from October 1st, 2010 for the BBGS Dataset.

⁸ In the survey administered to the BBGS sample, respondents answered the following question on annual household income: "Looking at the options below, please select the option that best represents your total household income during the past 12 months, before taxes. Include yourself and all family members who lived with you. Your best estimate is fine." The response categories were < €0, €0, €1 to €19,999, €20,000 to €39,999, €40,000 to €59,999, €60,000 to €79,999, €80,000 to €99,999, €100,000 to €119,999, €120,000 to €139,999, €140,000 to €159,999, €160,000 to €179,999, €180,000 to €199,999, and €200,000+.

percentage calculation would be $([\text{€}1000/\text{€}30,000]*100=3.33\%)$. Respondents who reported their annual household income as €200,000 or greater had their percentage calculated based on €200,000. For respondents who reported their annual household income as less than or equal to €0 or had a yearly wagered amount that exceeded their annual income, we set their⁹ percentage of yearly household income spent on online gambling wagers to 100%.

Net outcome of gambling per month. We defined net outcome of gambling per month as the monthly average of the difference between total amount wagered and total winnings during the duration that each player was active. We calculated this measure by first summing each player's total amount wagered across their duration active, then subtracting total winnings to create an overall net outcome, and then dividing by the number of days in that player's duration active to get an average net outcome per day. To create a per month measure, we then multiplied this value by 30.4, which is the average number of days in a month for a one-year period. Positive values on this measure indicate a net loss from gambling and negative values indicate a net gain.

Betting Variability. Betting variability was defined as the standard deviation across days of each individual's amount wagered per active betting day during their duration active.

Betting Escalation (i.e., trajectory). To compute betting escalation, we coded each individual's active betting days sequentially (e.g., day 1, day 2, day 3, etc.). We then estimated an ordinary least squares regression model with amount wagered per active betting day during the first six months of the duration active as the dependent variable and the day number as the explanatory variable. The estimated slope coefficient from the regression model for each player thus represented their wagering trajectory during the first six months of their duration active, with

⁹ For this variable, 17 users reported 0 Euros for annual household income and had their percentage for annual household income spent on gambling fixed at 100%. There were also 85 users with percentage of annual household income spent on gambling of greater than 100%, who were also recoded to 100% for percentage of annual household income spent on gambling. These 102 users represented 5.76% of the total sample.

positive slopes indicating increasing wagering patterns and negative slopes indicating decreasing wagering patterns.

Land-based Lower Risk Gambling Limits

Using three of the variables described above — *frequency of gambling per month*, *amount wagered per month*, and *percentage of yearly household income spent on online gambling wagers* — we calculated dichotomous variables to measure the existing land-based gambling thresholds (Currie et al., 2017). We operationally defined these thresholds as (1) frequency of gambling of more than eight days per month on the bwin platform, (2) wagering more than 53 Euros per month on gambling wagers on the bwin platform,¹⁰ and (3) spending more than 1.7% of yearly household income on online gambling wagers on the bwin platform. These three dichotomous variables are equal to “1” if an individual surpassed that land-based limit and “0” if they did not surpass that land-based limit.

Analytic Strategy

Hypothesis 1

Using the BBGS dataset, we ran three separate logistic regressions to estimate the odds of having a positive screen for Gambling Disorder if an online gambler exceeded each of the land-based gambling thresholds, defined above.

Hypothesis 2

Using the BBGS dataset, we identified new lower risk online gambling limits through receiver operating characteristic (ROC) analysis. First, we estimated separate logistic regression

¹⁰ We converted the upper bound of Currie et al.’s (2017) land-based limit (i.e., 75 CAD) from Canadian dollars into Euros for the BBGS sample using the conversion factor of 0.7114758021, which is the historical currency conversion rate from October 1st, 2010 from www.xe.com. The result is 53.3606851 Euros, which we rounded to 53 Euros. As described in footnote 6 above, we used this same process to convert the land-based 75 CAD limit for the other two samples based on their respective study periods, resulting in a limit for amount wagered per month of 49 Euros for the RG dataset and 47 Euros for the New Subscriber dataset.

models with the positive BBGS screen outcome for (1) frequency of gambling, (2) amount wagered per month, (3) percentage of yearly household income wagered on gambling, (4) net outcome of gambling, (5) betting variability (i.e., standard deviation of amount wagered per active betting day during the duration active) and (6) betting escalation (i.e., slope of amount wagered per active betting day during the first six months of the duration active). Next, we used the risk scores from the logistic regression equations to test the performance of various cut-offs with ROC analysis. We selected the cut-offs that optimized our ability to discriminate BBGS-positive status by optimizing the area under the curve (AUC) and maximizing sensitivity with the constraint that specificity be 0.70 or higher.

Hypotheses 3 and 3a

To test for the predictive ability of the newly created limits from the ROC analysis, we created new dichotomous variables for each of the six predictors that are equal to “1” if an individual surpassed a limit and “0” if they did not surpass a limit. Using the New Subscribers dataset and the RG dataset, we examined the robustness of our lower risk online gambling limits by running logistic regressions to estimate the odds of having (1) self-limited, (2) self-excluded, (3) closed an account for reasons other than self-exclusion, or (4) been assigned an RG flag by bwin customer service agents. We also regressed these outcomes on the land-based lower risk limits. Using odds ratios (ORs) and McFadden’s and Cox & Snell’s pseudo- R^2 , we compared the effect sizes and goodness-of-fit for each univariate logistic regression model, examining differences between models with the land-based lower risk limits and models with our new online lower risk limits.

Results

Planned Descriptive and Confirmatory Analyses

Table 1 shows the descriptive statistics for the BBGS dataset, RG dataset, and New Subscriber dataset. Three features of this table are important to note. First, across all three datasets, all gambling involvement variables are highly skewed, with substantially higher means than medians and extremely large ranges. For example, the maximum value for amount wagered¹¹ per month for the BBGS sample was 142,031.156 Euros, meaning that this user wagered an average of more than 140,000 Euros on online gambling on bwin per month during their study period. Second, about one-third of users were BBGS-positive (27.1%), and less than 3% of users self-limited (2.3%), self-excluded (0.7%), or closed their account (1.5%) during their respective study periods. Third, the majority of users across all three samples experienced an average net loss per month during their time gambling on bwin, with slight differences across samples (BBGS Median [Mdn] = 14.011; RG [Mdn] = 30.729; New Subscriber [Mdn] = 10.491).

*** Table 1 about here ***

Hypothesis 1: Online gamblers who gamble online in excess of land-based lower risk gambling thresholds will be more likely to have a positive screen for Gambling Disorder when compared with online gamblers who do not exceed land-based gambling thresholds when gambling online.

The results from the univariate binary logistic regression models revealed that all three of the land-based lower risk gambling limits significantly predicted screening positive on the BBGS. The magnitude of the odds ratios were 1.419 (CI = 1.150–1.750, $p < 0.05$) for exceeding

¹¹ In response to a reviewer comment, we calculated the correlation between amount wagered and betting variability ($r = 0.649$) in the BBGS sample. This moderate to strong correlation coefficient suggests that these two measures of gambling involvement are related, yet are still conceptually distinct.

the land-based limit for frequency of 8 times per month, 2.413 (CI = 1.916–3.038, $p < 0.05$) for exceeding the land-based limit for amount wagered per month of 53 Euros, and 2.501 (CI = 1.874–3.338, $p < 0.05$) for spending more than 1.7% of one's annual household income on online gambling.¹² Hypothesis 1 was supported.

Hypothesis 2: Specific lower risk online gambling thresholds, developed by maximizing sensitivity while keeping specificity greater than or equal to 0.70 according to receiver operating characteristic (ROC) curves, will be able to predict risk for Gambling Disorder among online gamblers.

Creating Lower Risk Online Gambling Thresholds.

Table 2 shows the results from the Receiver Operating Characteristic (ROC) analysis of the six gambling involvement measures used to create lower risk online gambling thresholds and the BBGS outcome. Figure 1A-F shows the ROC curves for these six analyses with 1-Specificity (x-axis) plotted against Sensitivity (y-axis). The newly-developed lower risk online gambling thresholds were as follows: (1) 11 days or less for frequency of gambling per month, (2) 167.973 Euros (236.091 CAD) or less for amount wagered each month, (3) 6.713% or less for percentage of annual income spent on online gambling wagers, (4) 26.109 Euros or less (36.697 CAD) in amount of wagers lost per month, (5) variability (i.e., standard deviation) in daily amount wagered of 35.137 Euros or less (49.386 CAD) and (6) trajectory (i.e., slope of daily amount wagered) in daily amount wagered of 0.065 or less.¹³ The AUC (i.e., 0.497) for

¹² Though it was not part of our planned analyses, we also examined the overall classification accuracy of our logistic regression models predicting BBGS-positive status. The overall classification accuracy for the land-based frequency of gambling per month, amount wagered per month and percentage of annual household income spent on gambling measures were 72.86%, 72.86% and 72.16%, respectively. In all three models, none of the participants were classified as BBGS-positive.

¹³ The AUC, sensitivity and specificity values for amount wagered per month and percentage of annual household income spent on gambling were similar to those found in Currie et al. (2017) which were based on the Quinte Longitudinal Study sample. The specificity for frequency of gambling per month was similar to those in Currie et al.

trajectory was not statistically different from the null value (0.500), so we do not find empirical support for a trajectory limit in this study.

*** Table 2 and Figure 1 about here ***

Describing Lower Risk Online Gambling Thresholds.

Table 3 shows the planned descriptive statistics for the existing land-based limits and the newly-developed online limits for the BBGS dataset, RG dataset, and New Subscriber dataset. Less than half of the users in the BBGS dataset exceeded the land-based limit for frequency per month (45.4%), while more than half of the users in the BBGS dataset exceeded the land-based limits for amount wagered per month (59.0%) and percentage of annual income spent on gambling (62.4%). A substantially lower percentage of users from the BBGS dataset exceeded the six online limits, with about one-third of users exceeding each of the six limits.

For the RG sample, 33.6% of users exceeded the land-based limit for gambling frequency per month and 70.8% of users exceeded the land-based limit for amount wagered per month. For the online limits, the percentage of users who exceeded each of the six limits ranged from 25.0% for the frequency limit of 11 days per month to 59.8% for the variability limit of 35.137 Euros. For the New Subscriber sample, 27.5% of users exceeded the land-based limit for gambling frequency per month and 57.7% of users exceeded the land-based limit for amount wagered per month. For the online limits, the percentage of users who exceeded each of the six limits ranged from 19.5% for the frequency limit of 11 days per month to 32.4% for the amount wagered per month limit of 167.973 Euros.

*** Table 3 about here ***

(2017), yet our results for the AUC and sensitivity were considerably smaller for this variable. We discuss these comparisons in greater detail in the Discussion section.

Evaluating Lower Risk Online Gambling Thresholds. Each of these six newly-developed lower risk limits for internet gambling were tested in univariate binary logistic regression models with the BBGS-positive outcome. As shown in Table 4, and expected from the ROC analyses, exceeding five of the six lower risk limits (excluding trajectory in daily amount wagered of 0.065 or less; OR = 1.136, CI = 0.907–1.422, $p = 0.266$) significantly predicted BBGS-positive status ($p < 0.05$). Hypothesis 2 was supported.

*** Table 4 about here ***

Hypothesis 3: Online gamblers who gamble online in excess of lower risk online gambling thresholds will be more likely to have evidence of (1) voluntary self-limiting, (2) voluntary self-exclusion, (3) account closure and (4) RG account flags when compared with online gamblers who do not exceed lower risk online gambling thresholds.

Table 5 includes the results from the binary logistic regression analyses of the three land-based and six online lower risk limits for gambling outcomes including self-limiting, self-excluding, closing one's account for reasons other than gambling problems and being assigned an RG flag by customer service.

There were three online limits that significantly predicted self-limiting. Users who exceeded the online limit for frequency of gambling of 11 times per month were *less likely to* self-limit than those who did not exceed the limit for frequency of gambling per month (OR = 0.747, CI = 0.629–0.887, $p < 0.05$). Users who exceeded the online limit for net outcome of 26.109 Euros per month were *less likely to* self-limit than those who did not exceed the online limit for net outcome of gambling per month (OR = 0.833, CI = 0.726–0.956, $p < 0.05$). Also, exceeding the online limit for variability predicted 1.25 times greater odds of self-limiting (CI = 1.098–1.424, $p < 0.05$).

Four online limits significantly predicted voluntary self-exclusion. Exceeding the online limit for amount wagered of 167.973 Euros per month, exceeding the online limit for a net loss from gambling per month of 26.109 Euros, variability in daily wagers of greater than 35.137, and trajectory of wagers greater than 0.065 all significantly ($p < 0.05$) predicted voluntary self-exclusion. Variability in daily wagers was the strongest predictor (OR = 3.036, CI = 2.424–3.803, $p < 0.05$).

Four online limits significantly predicted closing one's account for reasons other than gambling problems. Users who surpassed the online limit for frequency of 11 days per month (OR = 0.650, CI = 0.522–0.810, $p < 0.05$) were *less likely* to close their account for reasons not related to gambling problems. In contrast, exceeding the online limit for amount wagered of 167.973 Euros per month, variability in daily wagers of greater than 35.137, and trajectory of wagers greater than 0.065 significantly ($p < 0.05$) predicted a greater likelihood of closing one's account for reasons other than gambling problems.

Finally, four out of the five online limits (excluding exceeding the limit for frequency of 11 times per month) positively predicted receiving an RG flag. The largest odds ratio was 9.098 (CI = 7.781–10.638, $p < 0.05$) for exceeding the online limit for variability in amount wagered per day of 35.137.

*** Table 5 about here ***

Hypothesis 3a: The variance explained (i.e., McFadden's and Cox & Snell's pseudo- R^2) and odds ratios for predicting (1) voluntary self-limiting, (2) voluntary self-exclusion, (3) account closure and (4) RG account flags will be greater for lower risk online gambling thresholds than for land-based lower risk gambling thresholds.

Before we describe our observations comparing land-based and online limits, we review the land-based limits' ability to predict our four proxy outcomes. First, the results for the voluntary self-limiting outcome show that users who exceeded the land-based limit for frequency of gambling of 8 times per month or amount wagered of 47 Euros per month were not more likely to self-limit than users who did not exceed either limit. Second, for the voluntary self-exclusion outcome, users who exceeded the land-based limit for amount wagered of 47 Euros per month were more likely to voluntarily self-exclude from online gambling (OR = 1.562, CI = 1.230–1.982, $p < 0.05$). Third, the results for the account closure for reasons other than gambling problems showed that users who exceeded the land-based limit for amount wagered per month of 47 Euros per month were not significantly more likely to close their account for reasons not related to gambling problems. Users who exceeded the land-based limit for frequency of 8 days per month were less likely to close their account for reasons other than gambling problems (OR = 0.711, CI = 0.591–0.855, $p < 0.05$). Fourth, turning to the RG flag outcome, the results indicate that both land-based limits predicted this outcome in the expected direction. The magnitude of the odds ratios ranged from 1.218 (CI = 1.060–1.399, $p < 0.05$) for exceeding the land-based limit of gambling 8 times per month to 4.397 (CI = 3.753–5.152, $p < 0.05$) for exceeding the land-based limit for amount wagered of 49 Euros per month.

To compare the newly-developed limits with the existing land-based limits as described in our pre-registered analyses, we examined the mean sensitivity value and mean specificity value for each of the five online limits across the five outcomes (i.e., the four proxies and the BBGS-positive outcome) and compared these values with the highest sensitivity value (i.e., 0.72) and highest specificity value (i.e., 0.85) for the land-based limits based on longitudinal data in Currie et al. (2017). For the percentage of annual household income spent on gambling limit, we

reported the sensitivity and specificity values instead of their means across outcomes, because only the BBGS sample (and hence, the BBGS-positive outcome) included data on income. The mean sensitivity value was 0.219 (range from 0.137 to 0.403) for exceeding the online limit for frequency of 11 days per month, 0.504 (range from 0.320 to 0.726) for exceeding the online limit for amount wagered of 167.973 Euros per month, 0.562 for exceeding the online limit for percentage of annual income of 6.713 percent, 0.464 (range from 0.283 to 0.698) for exceeding the online limit for net outcome of gambling of 26.109 Euros per month, 0.563 (range from 0.357 to 0.832) for exceeding the online limit for daily betting variability of 35.137 Euros, and 0.397 (range from 0.326 to 0.488) for exceeding the online limit for slope of daily amount wagered in the first six months of 0.065. The mean specificity value was 0.773 (range from 0.706 to 0.805) for exceeding the online limit for frequency of 11 days per month, 0.678 (range from 0.658 to 0.700) for exceeding the online limit for amount wagered of 167.973 Euros per month, 0.700 for exceeding the online limit for percentage of annual income of 6.713 percent, 0.679 (range from 0.659 to 0.700) for exceeding the online limit for net outcome of gambling of 26.109 Euros per month, and 0.685 (range from 0.648 to 0.700) for exceeding the online limit for daily betting variability of 35.137 Euros, and 0.678 (range from 0.666 to 0.700) for exceeding the online limit for slope of daily amount wagered in the first six months of 0.065. Therefore, the average sensitivity and specificity values were all lower than the maximum values obtained for the land-based limits in previous studies.

Next, we compared the magnitude of the odds ratios and the two pseudo- R^2 measures (i.e., Cox & Snell and McFadden's) for the land-based limits and online limits for the voluntary self-limiting, voluntary self-exclusion, account closure and RG account flag outcomes to determine which types of limits were better predictors of these outcomes. If the specific odds

ratio was greater and the confidence intervals did not overlap, we designated that the limit tested was a better predictor for that particular outcome. The only pair of odds ratios that did not have intersecting confidence intervals was for the exceeded limit for amount wagered per month measure and account closure outcome. The new limit for amount wagered per month of 167.973 Euros (236.091 CAD) was a stronger predictor of account closure (i.e., $OR = 1.346, p < 0.05$ vs. $OR = 0.982, p = 0.811$) than the land-based limit for amount wagered per month of 47 Euros (75 CAD).

Most of the pseudo R^2 values were very small (i.e., < 0.01), but two comparisons are important to note. First, the McFadden's R^2 was considerably higher (i.e., 0.02 vs. 0.004) for exceeding the online limit for amount wagered per month and the voluntary self-exclusion outcome, when compared with the land-based limit. Second, both the Cox & Snell R^2 and McFadden's R^2 were substantially higher (0.141 and 0.110 vs. 0.098 and 0.075) for exceeding the online limit for amount wagered per month and the RG flag outcome, when compared with the land-based limit. Thus, Hypothesis 3a received very limited support for the new limit for amount wagered per month of 167.973 Euros (236.091 CAD) for account closure, voluntary self-exclusion and RG flag outcomes.

Unplanned Exploratory Analyses

In addition to the confirmatory analyses we describe above, we also ran a set of unplanned exploratory analyses involving risk curves that assess the dose-response relationship between gambling involvement and BBGS status. We created risk curves showing the proportion of users who screened BBGS-positive at different levels of frequency of gambling, amount wagered per month, percentage of annual household income spent on online gambling wagers, net outcome of gambling per month, variability in daily amount wagered and slope of amount

wagered during the first six months of activity. We completed these unplanned exploratory analyses to show the relationship between each of these six gambling involvement measures and BBGS-status. These risk curve analyses are consistent with the general methodological approach of Currie et al. (2017; 2019), who also used risk curves to test lower risk gambling limits. Our risk curves are different in that we used quintile ranges on the x-axis instead of the ranges based on survey response options that Currie et al. (2017) used.

Figure 2A-F shows these risk curves including quintile ranges for each gambling involvement measure on the x-axis and the proportion of users screening BBGS positive on the y-axis. The figure includes vertical lines for the online limits (blue solid lines) and, where applicable, land-based limits (red dashed lines). The overall shape of each risk curve (i.e., j or reverse-L shaped) is similar to risk curves produced from Canadian and Australian population datasets (see Currie et al. 2019; Dowling et al. 2018 for examples). Furthermore, on most curves the online lower risk limits coincide with the point on the curve where the slope changes and risk of harm visually increases.

*** Figure 2 about here ***

We also conducted additional unplanned exploratory analyses using a measure of breadth involvement¹⁴ (i.e., the number of different game types that a subscriber wagered money on during their study period). These unplanned exploratory analyses (see Online Supplement: *** link to Online Supplement goes here ***) revealed that exceeding an existing land-based limit for breadth from Brosowski et al. (2015) of 2 game types significantly predicted BBGS-positive

¹⁴ We followed a similar approach to operationalizing breadth as LaPlante et al. (2014), who also measured breadth among bwin subscribers in the BBGS dataset, yet used a different study period. Subscribers could select from a total of 21 different game types that were offered on the bwin platform during the study period (e.g., sportsbook fixed odd, sportsbook live action, poker bwin, casino BossMedia, mobile casino, bingo, supertoto, etc.). See p. 399 in LaPlante et al. (2014) for more details about the specific game types offered on bwin.

status (OR = 1.770, CI = 1.430–2.191, $p < 0.05$). Using the same ROC analysis approach as the other six limits, we found that 3 game types was the optimal cutoff that maximized sensitivity while keeping specificity ≥ 0.70 (AUC = 0.596, CI = 0.566–0.625, Sensitivity = 0.291; Specificity = 0.809). For limits for breadth in the BBGS sample, 36.7% of subscribers surpassed the land-based limit of 2 game types and 21.8% of subscribers surpassed the online limit of 3 game types.

Exceeding the new online limit of 3 game types significantly predicted screening positive on the BBGS (OR = 1.735, CI = 1.364–2.208, $p < 0.05$). Moreover, risk curves of breadth involvement in five categories (i.e., 1-5+ game types) and BBGS-positive status showed that the risk of screening positive on the BBGS increased linearly between 1 and 3 games played, was similar for 3 and 4 games played, and then increased substantially for 5 or more games played. Odds ratios for both exploratory breadth limits (i.e., exceeding 2 game types and exceeding 3 game types) in predicting BBGS-positive status were considerably smaller (i.e., both less than 1.8) when compared to those for the four best-supported limits (i.e., for amount wagered, percentage of annual income spent on gambling, net outcome, and variability), which had odds ratios that were all greater than 2.8.

Discussion

This study examined whether current land-based lower risk gambling limits (Currie et al., 2017) apply to online gamblers and whether limits developed specifically for online gamblers perform better than the existing land-based limits. We found that all three land-based limits that we tested significantly predicted screening positive for Gambling Disorder. We identified five potential optimal online limits with adequate sensitivity and specificity based on our ROC

analysis. The five new online limits we developed¹⁵ were: 1) gambling 11 days or less per month; 2) wagering 167.973 Euros or less each month; 3) spending 6.713% or less of annual income on online gambling wagers; 4) losing 26.109 Euros or less on online gambling per month, and 5) demonstrating variability (i.e., standard deviation) in daily amount wagered of 35.137 Euros or less during a user's duration active. Although our mean sensitivity and specificity were lower than the maximum values in Currie et al. (2017), we suggest that our online limits have validity for predicting a positive Gambling Disorder screen and, four limits related to amount wagered, percentage of income spent, net losses, and variability also have some validity for predicting proxies for gambling problems among online gamblers.

Key Findings

We found different levels of empirical support for each online limit's prediction of a positive screen for Gambling Disorder and the four gambling harm proxies (i.e., voluntary self-limiting, voluntary self-exclusion, account closure, and receiving an RG flag from customer service). We discuss each online limit in the following section based on the support they received, starting with the best supported limits.

We observed the greatest AUC for the online limit for percentage of income spent on gambling per year. Likewise, the OR for predicting a positive screen for Gambling Disorder was among the two largest ORs we observed. Examination of the risk curve shows that the limit intersects the j-shaped curve at the point the curve accelerates, indicating good demarcation of

¹⁵ To provide context for readers more familiar with U.S. dollars, we converted the three new online limits to U.S. dollars (\$) using the historical currency conversion rate for October 1, 2010 from xe.com. Next, we converted these U.S. dollar values to their present values with an inflation adjustment factor for February, 2020, the most recent month of available inflation figures from the U.S. Bureau of Labor statistics (BLS, 2020). After conversion, the online limit for amount wagered per month was \$273.30, the online limit for net outcome of gambling per month was \$42.48 and the online limit for variability in amount wagered was \$57.17.

increased risk. Unfortunately, because household income was not available for the RG dataset or the New Subscriber dataset, we were not able to test this online limit for the four proxy outcomes. Because we could not perform these tests, although the AUC, OR, and risk curve evidence for predicting BBGS are promising, this limit represents a special case that we cannot directly rank along with the others. Nonetheless, with additional validation against independent proxy outcomes, it could be an important tool to help online gamblers gamble within safe limits.

The online limit for variability probably would be most difficult for a gambler to self-monitor, but appears to be among the two most robust of the online gambling limits that we were able to assess fully across datasets and outcomes. The AUC for this limit was nearly as high as for the percentage of income spent on gambling per year and the OR for predicting the BBGS was the largest among the online limits. The variability limit was the only one to uniformly predict all four proxy outcomes in the expected manner (i.e., exceeding the limit was associated with increased risk of harmful outcomes). Users who exceeded online limits for variability in daily amount wagered were more likely to have voluntarily self-limited, voluntarily self-excluded, closed their account, and to have received an RG flag from customer service. Indeed, the highest OR observed for any association was for exceeding the variability limit and having received an RG flag. Inspection of the risk curve might suggest that the variability limit intersects too far after risk begins increasing, which weakens support for the limit value. But, overall, this limit shows strong promise for an important boundary to safer online gambling.

Like variability, the online limit for amount wagered shows strong promise. We suggest this because of its high AUC and OR for predicting the BBGS. Also, the risk curve showing this relationship suggested that the limit was relatively closer to the point at which risk accelerates. Although online gamblers who exceeded the online limit for amount wagered per month were

more likely to have voluntarily self-excluded, have closed their account or to have received an RG flag from customer service than those who did not exceed the limit, they were not more likely to have voluntarily self-limited. However, the online limit for amount wagered per month was the only limit that distinguished itself from corresponding land-based limits by its higher Pseudo R^2 values, specifically, related to voluntary self-exclusion and receiving an RG flag. The ORs predicting account closure for amount wagered per month were also substantially higher than those for land-based limits. Thus, despite the absence of predictive value for voluntary self-limitation, support for this limit is in line with support for variability, showing strong promise.

The recommendations are more complicated for the remaining online limits. To start, the next most promising limit relates to net losses per month. Although this limit had a reasonable AUC and OR for predicting a positive Gambling Disorder screen, an examination of the ORs for predicting the four proxy outcomes is mixed. Specifically, users who exceeded the online limit for net losses per month were more likely to have voluntarily self-excluded or to have received an RG flag from customer service, but not more likely to have voluntarily self-limited or engaged in account closure¹⁶. Despite this, examination of the j-shaped risk curve suggests that the limit is a good marker for increasing risk. Taken together, we suggest that the net losses per month limit received good empirical support.

The evidence related to the online limit for frequency of gambling was even more mixed. Users who exceeded the online limit for frequency of gambling per month were more likely to have screened positive for Gambling Disorder. Exceeding the frequency of gambling per month

¹⁶ It is possible that account closure, and to some extent self-limiting, are poorer indicators of gambling harm than self-exclusion and RG flags because of the potential heterogeneity of subscribers who use these features. The account closure outcome did not include self-exclusion, so did not include subscribers who explicitly stated they were closing their accounts for gambling-related reasons. There are many reasons subscribers might close their accounts, only some of which might relate to gambling harms. Similarly, some people without any gambling problems might place limits on their accounts proactively.

limit also predicted voluntary self-limiting and account closure, but in the opposite direction than we hypothesized. There are at least three possible explanations for these observations. First, users who gamble more frequently may be less likely to self-limit because even though they have more time involvement with gambling, their financial involvement might still be low to modest, making them less concerned about moderating their gambling behavior. Indeed, studies have found that time involvement is a weaker and less significant predictor of problem gambling when compared with financial involvement (Griffiths, Parke, Wood & Rigbye, 2010). Second, users who gamble more frequently might be less likely to close their account (for reasons other than gambling problems) because they feel enjoyment and are entertained by their online gambling, making them less motivated to cease playing on their account with bwin. Third, it is possible that some people who self-limited or closed their accounts might have done so before an entire month of gambling had elapsed, making their average monthly frequency totals lower than they otherwise would be. Exceeding the frequency of the gambling per month limit was not predictive of voluntary self-exclusion or receiving an RG flag. Furthermore, the risk curve itself does not appear to have an easily discernible j-shape, as would be important to identifying optimal limits. We therefore suggest that the frequency limit currently has limited support as a key online gambling limit.

Finally, the online limit that held the weakest support was trajectory. In fact, the AUC was the lowest for this prospective limit, and exceeding the limit was not associated with BBGS screening outcome. The risk curve for trajectory holds a u-shape, rather than a j-curve, which makes it difficult to conclude that this limit can easily demarcate a safe playing trajectory. One possible explanation for this pattern might be that players with decreasing slopes are more likely to have negative outcomes because we're seeing their own attempt to curb behavior before they

intervene by self-excluding or self-limiting. Nonetheless, because of the empirical observations, we conclude that the trajectory limit currently has weak support as a key online gambling limit.

Although it was not part of our pre-registered confirmatory or exploratory analysis plan, unplanned exploratory analyses of a potential lower risk limit for breadth – conducted in response to reviewer comments – showed that exceeding an existing land-based limit of 2 game types (Brosowski et al., 2015) and a newly-developed online limit of 3 game types, both predicted screening positive on the BBGS. Risk curves revealed a generally linear relationship between breadth and BBGS-positive status, with accelerating risk for more than 4 game types. However, the AUC (0.596) and sensitivity (0.291) were both low for this exploratory lower risk gambling limit, and the odds ratios for predicting BBGS-status were lower than most online limits, so we suggest that a breadth limit has limited support for predicting risk of gambling disorder among internet gamblers at this time.

Our findings have implications for research on the application of land-based lower risk gambling guidelines to a population of online gamblers, as well as for research extending this established conceptual and theoretical framework to internet gamblers. Although our limits were higher than those developed in Currie et al. (2017), the four limits that were empirically supported in our study (i.e., for amount wagered, percentage of annual income spent on gambling, net outcome and variability) revealed similar j-shaped (with slightly reversed L-shapes) risk curves to those in Currie et al. (2017) and did not yield r-shaped risk curves as were found by Markham et al. (2015). Thus, our findings show that one's risk of screening positive for Gambling Disorder remains relatively low until exceeding limits, at which point risk substantially increases.

Because the land-based and four online limits received empirical support in our analyses, we suggest that both sets of limits have utility for understanding and predicting the potential for gambling-related harm and Gambling Disorder among users. We provided evidence that some of our newly-developed online limits might have greater empirical support because they have larger odds ratios; however, in most cases the odds ratios were not outside the confidence interval of the land-based odds ratios, so it is possible that these differences were due to measurement error or heterogeneity in samples (i.e., different sample compositions between our online gambler data from the E.U. and the land-based survey data from Canada). Importantly, while our lower risk online limits can help individuals to gamble in healthier ways, some gamblers might still experience gambling-related problems while gambling below the limits. To better understand how these new online limits apply to different populations, we suggest that additional studies replicate our analytic approach with different samples of internet gamblers specifically and samples of gamblers from the adult population more generally.

Directions for Future Research

Based on our study, at least five avenues for future research are promising. First, future studies should test the utility of the four limits with other samples of online gamblers to see how they predict symptoms of Gambling Disorder, self-limiting/self-exclusion, and other measures of gambling harm. With such additional tests, it will be possible to make policy recommendations to improve RG recommendations. For example, with confirmation of these findings, it might be possible to design policies that include specific limit-based warning messages (Wohl et al., 2013), in both static and dynamic modalities as part of RG programs (Blaszczynski et al., 2011). Second, future research should use qualitative approaches (e.g., focus groups) with internet gamblers to understand the face validity of the limits, and how gamblers perceive and interpret

them. Third, future studies should examine how these limits apply differently across game types (e.g., for online casino, poker and sports gambling), as research suggests that certain games with continuous play formats (e.g., those that feature a high speed of play and betting frequency), such as slots, scratch cards, in-game sports betting, or poker, are associated with greater risk for problem gambling behaviors (e.g., Brosowski et al., 2020). Indeed, Abbott (2007) speaks to the importance of examining gambling limits across game types, suggesting that unlike lower risk drinking limits, “there is no standard gambling unit. Gambling forms and settings differ in ways that elude simple classification” (p. 2021). Fourth, studies should investigate additional gambling involvement measures such as session time, as well as time duration of play per day, week and month, to determine if there is an optimal limit for lower risk play depending on the absolute time involvement on a particular gambling product and platform. Research suggests that excessive time involvement, in addition to excessive financial involvement, could predict an elevated probability of problem gambling (Matarese, Walker, Blaszczynski & Sharpe, 2002), so examining potential safer thresholds for time is an important direction for future research. Fifth, new research should further probe the potential for trajectory-based limits to provide guidance and identify the mechanisms that allow variability to demarcate risk for gambling harm. Developing a better understanding of what is driving the relationship between variability and harmful outcomes might yield new insights that are valuable to mitigating such harm.

Study Limitations

Of course, our study is not without limitations. First, the response rate for the BBGS sample was very low, so it is possible that our sample of online gamblers who completed the BBGS survey was potentially different from those who did not complete the survey (i.e., they might have been interested in the survey because they were more involved with gambling or

potentially had concerns about their sample). However, the survey invitation did not specifically indicate the survey asked about gambling problems, only that it asked about gambling experiences. Second, the BBGS has been shown to be a valid measure of the risk of Gambling Disorder, yet is also a self-reported measure, so it may have some degree of measurement error. Third, our measures of gambling-related harm and gambling involvement were not identical to those used by Currie and colleagues. These slightly different measurement approaches could have influenced the relationships that we observed. For example, the BBGS only includes three items, one of which could represent harm, whereas Currie et al (2017) used the PGSI, which has several items that could be understood to measure harm. Whereas our focus in the present study was predicting a positive screen for Gambling Disorder and four outcomes potentially associated with gambling problems, future studies should incorporate additional measures of gambling-related harm, such as those proposed in the taxonomy developed by Langham et al. (2015) and Browne et al. (2016). Fourth, Currie et al. (2017) used ordinal measures of monthly gambling involvement, whereas our study used monthly averages created from users' actual gambling behavior, so these measures are not directly comparable. Fifth, our data represent gambling activity for only one internet gambling platform (i.e., bwin), so it is possible that users in our sample had involvement in other internet and land-based gambling venues. Thus, our gambling involvement measures could underestimate the totality of users' gambling activity for those who do not solely gamble on the bwin platform.

Sixth, all three datasets are more than nine years old, so our limits should be understood within the socio-historical time period in which the data were collected and should be replicated with more recent samples. Seventh, our AUC values for the four limits that received the most empirical support were lower than those suggested for maximizing accuracy by Swets (1988),

yet they are in a similar range to the AUC values found in Currie et al.'s (2017) study that developed land-based limits with longitudinal data. Moreover, we suggest, consistent with Streiner and Cairney (2007), that AUC values might be lower in research examining mental health diagnoses (vs. research on physical health diagnoses), because the screening tests themselves (e.g., the BBGS screener) are not "gold standards" (vs. medical tests such as a tuberculosis test) and might yield varying results across different populations. Eighth, though empirically justified, our preregistered decision to use a specificity of 0.70 or greater might be challenged, and different decisions might lead to the identification of different safer gambling limits.

Practical Implications

Readers might wonder whether the four identified limits should be put to immediate use and guide interventionist policy. We suggest that, at this point, using these limits as a hard stop would be premature. We observed that the limits have low sensitivity, which suggests that they are not very precise and, in particular, might fail to identify problems. However, because of the overall lack of precision, setting limits that are more sensitive would reduce specificity to a level where many of those identified by the limit would not actually be at risk. We suggest that these limits can be utilized to guide informational messaging to online gamblers (e.g., emails or pop-ups that alert users to available RG resources) as part of internet gambling consumer protection programs (Marionneau & Järvinen-Tassopoulos, 2017). Research suggests that internet gamblers typically perceive such programs positively (Gainsbury, Parke, & Suhonen, 2013) and incorporating lower risk limits into these types of responsible programs might be especially effective for limits that are more difficult for gamblers to self-monitor (e.g., variability). Additionally, a tiered system can use more of the available information to guide intervention

even when precision is low. This kind of system would have some interventions (e.g., responsible gambling email communications or hyperlinks to help resources for problem gambling) tied to cut-offs that maximize sensitivity (i.e., identify almost everyone who might be experiencing problems, as well as many who are not at-risk), those that balance sensitivity and specificity, and those that maximize specificity (i.e., identify only those who are very likely experiencing problems, at the expense of missing some individuals who might have problems). See Shaffer, Gray, Nelson, & LaPlante (in press) for an example of such a system for online sports gambling.

Conclusions

We agree with other research (e.g., Currie et al., 2017; 2019) that suggests lower risk gambling limits might be an important tool to help individual gamblers manage their gambling involvement. We also suggest that the online gambling environment might require unique lower risk limits. Currently, we recommend that scholars, policymakers and gambling operators focus on further development of online limits for (1) amount wagered, (2) percentage of income spent on gambling, (3) net losses from gambling and (4) variability in daily amount wagered as markers of potential harm from gambling. By better understanding how these gambling involvement and performance metrics predict the possibility of harm both among land-based and online populations of gamblers, the economic, social, and personal consequences of problem gambling can be reduced worldwide.

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Manuscript Body Tables and Figures

Table 1. Descriptive statistics for all variables

	Mean/ Percentage (count)	SD	Median	Minimum	Maximum
BBGS Dataset					
BBGS status	27.144 (481)	—	—	—	—
Frequency of gambling per month average	9.175	7.211	7.179	0.092	29.736
Amount wagered per month average	930.602	5194.261	78.655	0.075	142031.156
Percentage of yearly household income wagered online	16.923	29.441	3.211	0.003	100.000
Net outcome of gambling per month average	53.686	195.107	14.011	-4329.300	2805.544
Standard deviation of amount wagered per active betting day	156.062	707.762	17.321	0.000	14618.057
Slope of first six months of wagers per active betting day	-3.220	124.929	-0.013	-5196.530	300.693
RG Dataset					
RG case status	51.151 (1845)	—	—	—	—
Frequency of gambling per month average	7.715	7.948	4.751	0.045	30.400
Amount wagered per month average	2657.536	9661.348	215.382	0.033	214380.800
Net outcome of gambling per month average	137.061	599.659	30.729	-21053.768	5826.134
Standard deviation of amount wagered per active betting day	642.143	2586.205	66.273	0.000	71241.113
Slope of first six months of wagers per active betting day	5.117	180.775	-0.007	-4085.500	6780.000
New Subscriber Dataset					
User is a self-limiter	2.264 (1013)	—	—	—	—
User is a self- excluder	0.697 (312)	—	—	—	—
User is an account closer	1.519 (680)	—	—	—	—

Frequency of gambling per month average	6.698	7.257	3.864	0.083	30.400
Amount wagered per month average	819.016	10820.168	67.007	0.056	1901664.400
Net outcome of gambling per month average	67.017	389.205	10.491	-18610.441	16679.471
Standard deviation of amount wagered per active day	142.560	1130.555	15.216	0.000	114276.014
Slope of first six months of wagers per active betting day	4.707	870.760	-0.091	-14051.500	128203.500

Note: BBGS dataset $n = 1,772$; RG dataset $n = 3,607$; New Subscriber dataset $n = 44,754$.

Table 2. Receiver Operating Characteristic (ROC) curve analysis of online lower risk gambling limits in the BBGS survey dataset

	Online gambling data from bwin and BBGS outcome (in Euros)	Online gambling data from bwin and BBGS outcome (converted from Euros to CAD)
Frequency of gambling per month		
AUC (95% CI)	0.580* (0.550–0.609)	
Optimal cut-off	10.881 days/month	
Sensitivity/specificity	0.405/0.700	
Amount wagered per month		
AUC (95% CI)	0.656* (0.626–0.685)	
Optimal cut-off	167.973	236.091
Sensitivity/specificity	0.549/0.700	
% of yearly income spent on wagers		
AUC (95% CI)	0.664* (0.628–0.699)	
Optimal cut-off	6.713%	
Sensitivity/specificity	0.562/0.700	
Net outcome of gambling per month		
AUC (95% CI)	0.655* (0.625–0.685)	

Optimal cut-off	26.109	36.697
Sensitivity/specificity	0.557/0.700	
Variability (SD of daily amount wagered)		
AUC (95% CI)	0.657* (0.627–0.686)	
Optimal cut-off	35.137	49.386
Sensitivity/specificity	0.565/0.700	
Trajectory (slope of daily amount wagered for first six months)		
AUC (95% CI)	0.497 (0.466–0.529)	
Optimal cut-off	0.065	
Sensitivity/specificity	0.326/0.700	

Note: Currency was converted based on the historical currency conversion rate of 1.4055291789, which is the Euros to Canadian dollar rate for October 1, 2010 and corresponds to the month of the BBGS survey administration. Area Under the Curve (AUC) values with an * are significantly ($p < 0.05$) larger than the hypothetical value of the AUC under the null hypothesis, which is 0.5.

Table 3. Descriptive statistics for newly-developed lower risk limits for online gambling

BBGS sample	Percentage (count)
Exceeds land-based limit for frequency of 8 days per month	45.429 (805)
Exceeds land-based limit for amount wagered of 53 Euros (75 CAD) per month	59.029 (1046)
Exceeds land-based limit for % of annual income of 1.7 percent	62.405 (742)
Exceeds online limit for frequency of 11 days per month	32.393 (574)
Exceeds online limit for amount wagered of 167.973 Euros per month	36.738 (651)
Exceeds online limit for percentage of annual income of 6.713 percent	37.258 (443)
Exceeds online limit for net outcome of gambling of 26.109 Euros per month	36.964 (655)
Exceeds online limit for daily betting variability of 35.137	37.190 (659)
Exceeds online limit for daily wagers in first six months slope of 0.065	30.643 (543)
RG sample	
Exceeds land-based limit for frequency of 8 days per month	33.574 (1211)
Exceeds land-based limit for amount wagered of 49 Euros (75 CAD) per month	70.807 (2554)
Exceeds online limit for frequency of 11 days per month	25.007 (902)
Exceeds online limit for amount wagered of 167.973 Euros per month	53.867 (1943)
Exceeds online limit for net outcome of gambling of 26.109 Euros per month	52.315 (1887)
Exceeds online limit for daily betting variability of 35.137	59.773 (2156)

Exceeds online limit for daily wagers in first six months slope of 0.065	40.116 (1447)
New Subscriber sample	
Exceeds land-based limit for frequency of 8 days per month	27.522 (12317)
Exceeds land-based limit for amount wagered of 47 Euros (75 CAD) per month	57.653 (25802)
Exceeds online limit for frequency of 11 days per month	19.502 (8728)
Exceeds online limit for amount wagered of 167.973 Euros per month	32.404 (14502)
Exceeds online limit for net outcome of gambling of 26.109 Euros per month	32.095 (14362)
Exceeds online limit for daily betting variability of 35.137	30.898 (13828)
Exceeds online limit for daily wagers in first six months slope of 0.065	33.371 (14935)

Note: Self-reported household income was only available for the BBGS sample, so we were unable to create a land-based or online limit for the percentage of household income spent on online gambling for the RG or New Subscriber samples. The land-based limit for amount wagered per month differs slightly across samples because the original land-based limit was in Canadian dollars and was converted to Euros based on the time period for each sample.

Table 4. Binary logistic regression analysis of online lower risk gambling limits for BBGS-positive outcome

Variables	Online gambling data from bwin and BBGS outcome (in Euros)	
	OR (95% CI) C & S R ² M R ²	p-value
Gamble more than 11 days per month	1.621 (1.303–2.015) 0.010 0.009	< 0.001
Spend more than 167.973 Euros (236.091 CAD) per month on wagers	2.842 (2.291–3.525) 0.050 0.044	< 0.001
Spend more than 6.713% of yearly income on gambling	3.000 (2.309–3.897) 0.056 0.049	< 0.001
Lose more than 26.109 Euros per month while gambling	2.939 (2.369–3.647) 0.053 0.047	< 0.001
Variability in wagers of greater than 35.137	3.040	< 0.001

	(2.449–3.773) 0.057 0.050	
Trajectory of wagers greater than 0.065	1.136 (0.907–1.422) 0.001 0.001	0.266

Note: C & S R^2 is Cox & Snell's R^2 and M R^2 is McFadden's R^2 .

Table 5. Binary logistic regression analysis of online and land-based lower risk gambling limits for self-limiting, self-exclusion, account closure and RG flag outcomes

Variables	Online gambling data from bwin and voluntary self-limiting outcome (in Euros)		Online gambling data from bwin and voluntary self-exclusion outcome (in Euros)		Online gambling data from bwin and account closure outcome (in Euros)		Online gambling data from bwin and RG flag outcome (in Euros)	
	OR (95% CI) C & S R^2 M R^2	<i>p</i> -value	OR (95% CI) C & S R^2 M R^2	<i>p</i> -value	OR (95% CI) C & S R^2 M R^2	<i>p</i> -value	OR (95% CI) C & S R^2 M R^2	<i>p</i> -value
Land-based Limits								
Gamble more than 8 days per month	0.888 (0.770–1.025) 0.000 0.000	0.105	0.923 (0.716–1.190) 0.000 0.000	0.538	0.711 (0.591–0.855) 0.000 0.002	< 0.001	1.218 (1.060–1.399) 0.002 0.002	0.005
Spend more than 47 Euros (75 CAD) per month (New Subscribers) or 49 Euros (75 CAD) per month (RG file)	0.899 (0.793–1.018) 0.000 0.000	0.094	1.562 (1.230–1.982) 0.000 0.004	< 0.001	0.982 (0.842–1.144) 0.000 0.000	0.811	4.397 (3.753–5.152) 0.098 0.075	< 0.001
Online Limits								
Gamble more than 11 days per month	0.747 (0.629–0.887) 0.000 0.001	0.001	0.768 (0.566–1.043) 0.000 0.001	0.091	0.650 (0.522–0.810) 0.000 0.002	< 0.001	0.946 (0.814–1.100) 0.000 0.000	0.471
Spend more than 167.973 Euros (236.091 CAD) per month on wagers	0.981 (0.858–1.121) 0.000 0.000	0.773	2.418 (1.934–3.024) 0.001 0.016	< 0.001	1.346 (1.153–1.573) 0.000 0.002	< 0.001	5.100 (4.425–5.878) 0.141 0.110	< 0.001
Lose more than 26.109 Euros per month while gambling	0.833 (0.726–0.956) 0.000 0.001	0.010	1.821 (1.456–2.277) 0.001 0.007	< 0.001	0.991 (0.843–1.166) 0.000 0.000	0.915	4.467 (3.884–5.138) 0.122 0.094	< 0.001
Variability in wagers of greater than 35.137	1.250 (1.098–1.424) 0.000	0.001	3.036 (2.424–3.803) 0.002	< 0.001	2.135 (1.835–2.485) 0.002	< 0.001	9.098 (7.781–10.638) 0.222	< 0.001

	0.001		0.025		0.013		0.181	
Trajectory of wagers greater than 0.065	1.013 (0.888–1.156) 0.000 0.000	0.842	1.449 (1.156–1.816) 0.000 0.003	0.001	1.423 (1.220–1.659) 0.000 0.003	< 0.001	2.126 (1.855–2.436) 0.033 0.024	< 0.001

Note: C & S R^2 is Cox & Snell's R^2 and M R^2 is McFadden's R^2 . The percentage of income spent on gambling per year measure described in the BBGS sample results was not available for the analyses in the table because no income data was provided for the RG and New Subscriber samples.

Figure 1. Receiver Operating Characteristic (ROC) curves of 1-specificity (x-axis) and sensitivity (y-axis) for six measures of gambling involvement and BBGS-positive outcome

Figure 2. Risk curves showing proportion of subscribers who are BBGS-positive as a function of six measures of gambling involvement with land-based and online lower risk gambling limits

Data description: The data reported in this manuscript has been used in other published manuscripts. The present study differs from other studies that used these data because it: 1) asked novel, pre-registered research questions related to developing lower risk limits for online gambling using receiver operating characteristic curve analysis, 2) tested existing land-based lower risk gambling limits with online gamblers, 3) examined the generalizability of newly-developed online gambling limits across three datasets, and 4) investigated how these new online gambling limits predicted four outcomes that are proxies for problem gambling.

Figure 1

Figure 1: Receiver Operating Characteristic (ROC) curves of 1-specificity (x-axis) and sensitivity (y-axis) for six measures of gambling involvement and BBGS-positive outcome

Figure 2

Figure 2: Risk curves showing proportion of subscribers who are BBGS-positive as a function of six measures of gambling involvement with land-based and online lower risk gambling limits

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