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Behavioral Characteristics of Internet Gamblers Who Trigger Corporate Responsible Gambling Interventions

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As the worldwide popularity of Internet gambling increases, concerns about the potential for gambling-related harm also increase. This paper reports the results of a study examining actual Internet gambling behavior during 10 years of play. We examined the electronic gambling records of subscribers (N = 2,066) who triggered a responsible gaming alert system at a large international online gaming company. We compared these cases with control subscribers (N = 2,066) who had the same amount of exposure to the Internet gambling service provider. We used discriminant function analysis to explore what aspects of gambling behavior distinguish cases from controls. Indices of the intensity of gambling activity (e.g., total number of bets made, number of bets per betting day) best distinguished cases from controls, particularly in the case of live-action sports betting. Control group players evidenced behavior similar to the population of players using this service. These results add to our understanding of behavioral markers for disordered Internet gambling and will aid in the development of behavior-based algorithms capable of predicting the presence and/or the onset of disordered Internet gambling.

Keywords: internet gambling, responsible gambling, disordered gambling

The popularity of Internet gambling has grown dramatically during the past decade, and experts expect it to grow even more in the coming years. For instance, Americans spend an estimated $5 billion per year in the largely "gray market" of Internet gambling (H2 Gambling Capital, 2010). Consumer demand, combined with a need for more government revenue, could result in the legalization of several forms of Internet gambling, thus creating an even bigger United States market (PricewaterhouseCoopers, 2009). Business analysts suggest that the global Internet gambling market will produce gross revenue of more than $100 billion by the year 2015 (Rogers, 2005).

Debates about the legalization and expansion of Internet gambling often include concerns about the potential for personal and societal harm. Some opponents to legalization, for example, have asserted that the Internet gambling industry derives most of its revenue from problem and pathological gamblers (Grinols, 2010). Others suggest that, within jurisdictions where Internet gambling is legal, players will tend to play and lose money "24 hours a day, 7 days a week" (Bernal, 2010). Although research related to Internet gambling is limited, history suggests that new technological advances can create important short-term population effects (LaPlante, in press). Consequently, it is important to advance the science associated with Internet gambling.

A primary goal for Internet gambling research has been to identify behavioral characteristics of Internet gamblers who might have gambling-related problems (Braverman & Shaffer, 2012; LaBrie & Shaffer, 2010; Xuan & Shaffer, 2009). The Division on Addiction of the Cambridge Health Alliance has taken steps to achieve this goal by forming a research collaborative with *bwin.party* Digital Entertainment (Shaffer, Peller, LaPlante, Nelson, & LaBrie, 2010). As part of this collaboration, *bwin.party,* an Internet gambling service, has made available to the Division detailed Internet gambling records of its subscribers (i.e., individuals who register for an account). Our research in this area has made use of potential proxy indicators of gambling-related problems, such as: (1) excessive patterns of actual Internet gambling (LaBrie, LaPlante, Nelson, Schumann, & Shaffer, 2007; LaPlante, Schumann, LaBrie, & Shaffer, 2008); (2) the use of deposit self-limit features (Nelson et al., 2008); (3) the use of account self-exclusion features (Braverman & Shaffer, 2012; LaBrie & Shaffer, 2010; Xuan & Shaffer, 2009); and (4) attempts to violate corporate deposit limit features (Broda et al., 2008).

Our investigations have revealed patterns of gambling behavior common across subscribers who meet different proxy indicators of gambling-related problems. Subscribers who eventually install deposit limits on their accounts, players who exceed preset deposit limits, and players who eventually close their *bwin.party* accounts because of gambling-related problems bet more intensely than other players (Broda et al., 2008; LaBrie & Shaffer, 2010; Nelson et al., 2008). For example, LaBrie and Shaffer (2010) observed

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that a subgroup of subscribers who closed their *bwin.party* accounts because of gambling-related problems made more bets and bet more frequently than other subscribers. This is consistent with other research indicating that spending excessive time gambling, often at the expense of other responsibilities, is a behavioral marker of disordered gambling (Currie et al., 2006). In terms of monetary indices of gambling activity, subscribers who attempt to exceed corporate deposit limits lose more money during the course of their betting history than subscribers who do not attempt to exceed deposit limits (Broda et al., 2008), potentially because they make many more bets overall. Somewhat paradoxically, however, subscribers who exceed deposit limits lose a smaller proportion of their bets compared to their more temperate counterparts (Broda et al., 2008). Research has been equivocal with regard to the size of bets; for example, self-limiters appear to place larger bets (Nelson et al., 2008) compared to those who exceed corporate deposit limits (Broda et al., 2008).

The Current Study

To advance the identification of behavioral markers for problem Internet gamblers, in the current study, we examined the behavioral characteristics of subscribers who triggered corporate responsible gambling interventions (i.e., "responsible gambling cases") and compared these subscribers' behavior against controls. As described in more detail below, subscribers typically triggered corporate responsible gambling interventions by having contact with *bwin.party* customer service representatives regarding a variety of responsible gambling mechanisms (e.g., account closure, deposit limits). To our knowledge, this work represents the first attempt to identify Internet gamblers experiencing gambling-related problems in this manner.

Several hypotheses guided this research. Overall, we expected responsible gambling cases to be more engaged in Internet gambling than the controls. We defined engagement in two broad ways: (1) the intensity of betting activity (e.g., the number of bets made per betting day, the frequency of active betting days, the number of bets made throughout the entire betting history) and (2) patterns of monetary investment in gambling (e.g., the sum of wagers, the average size of wagers). Based on previous research described above, we expected responsible gambling cases to exhibit more intense betting activity compared to controls. We also expected the responsible gambling cases, due to their relatively intense betting activity, to wager more money and lose more money across the entire window of observation than controls. However, we also expected responsible gaming cases to lose a smaller proportion of their bets compared to controls. We did not form a hypothesis regarding the average size of bets.

Method

Participants

Participants were 4,132 subscribers to the Internet betting service provider, *bwin.party* Digital Entertainment (formerly *bwin* Interactive Entertainment, AG). At the time of *bwin.party* registration, the average age was 28.95 years ($SD = 9.68$). Of the 4,132 subscribers, 395 were women and 3,737 were men. The players represented in this study were from 46 countries, most commonly Germany (38%). Eight percent of the sample was from France, 7% were from Poland, 6% were from Spain, and 5% were from Austria. Greece and Portugal each accounted for 4% of the sample, and people from the 39 other countries accounted for the remaining 28% of the sample. At enrollment, participants elected to interact with the wagering system in one of 21 languages, the most common of which was German (44%). The cases included 2,066[1] individuals who triggered responsible gambling interventions. The controls included 2,066 individuals, each of which we matched to cases because they made an initial *bwin.party* deposit on the same day as a case, but did not trigger a responsible gambling intervention between November 2008 and November 2009.[2] Controls were not matched on any other variables.

Procedures

The Customer Service and Corporate Social Responsibility departments at *bwin.party* have jointly developed and refined procedures for identifying events that might indicate a need for responsible gambling intervention. The identification of these events emerged from their first-hand experience with subscribers rather than empirical validation. *bwin.party* first began systematically recording responsible gambling (RG) events using the current system during November, 2008. Within this system, *bwin.party* responses to RG events included a number of different possible interventions. To determine the type of response, the responsible gambling team considered the event features and the individual player's gambling history and records, and then matched that information to predetermined response actions. Individual subscribers can have more than one RG event. For the current paper, we classified responsible gambling cases according to the first RG event they experienced. The majority (85%) of cases experienced only one RG event. Table 1 describes the responsible gambling events and the most common intervention for each responsible gambling event. As Table 1 indicates, the most common responsible gambling event was when subscribers contacted *bwin.party* customer service to have their accounts closed due to problem gambling or reopened after having closed an account due to problem gambling (45% of cases).

bwin.party provided demographic and transaction data (covering the period August 5, 2000 to November 10, 2010) for the 4,132 case and control subscribers during November 2010. We conducted secondary analyses of these data. The Cambridge Health Alliance Institutional Review Board approved our application to conduct the secondary data analyses. The available demographic characteristics of the research sample included date of birth, gender, country of residence, and preferred language.[3]

We examined participants' use of three *bwin.party* product types: (1) fixed-odds sports betting, or bets made on the outcomes of sporting events or games in which the amount paid for a winning bet is set by the betting service; (2) live-action sports betting, or bets made on propositions about outcomes within a sporting event (e.g., whether the next tennis game in a match will

[1] We obtained daily betting transactions for a total of 2,068 responsible gambling cases, but two of these had no controls with matched exposure. We excluded these two responsible gambling cases from the analyses.

[2] For 21 of the controls, daily aggregates of gambling behavior were not available.

[3] For 167 of the matched controls, the only demographic information made available to us was gender. Included in this group are the 21 individuals for whom we have no daily aggregates of gambling behavior.

Table 1
Responsible Gambling Events and Interventions

Event label	Description	Frequency within cases	Proportion within cases	Most common *bwin.party* response(s)
Account closure/reopening	The subscriber contacts *bwin.party*; customer service (CS) to have his account closed due to problem gambling or reopened after a closure due to problem gambling	932	45.1%	Account is reopened (61.4%) Account remains closed (29.4%)
Problem reported	The subscriber reports a problem, which may or may not be justified	334	16.2%	Account blocked/closed (57.8%) *bwin.party* gives RG advice to subscriber (39.5%)
Change of limit: manual change	The user requested a change in the personal deposit limit and was advised by CS to make the limit change in the interface	307	14.9%	Daily/weekly deposit limit changed (98.7%)
Partial block	The subscriber requests *bwin.party*; CS to block one or more (but not all) products due to problem gambling	274	13.3%	Account is partially blocked as wished (88.7%)
Higher limit request	The subscriber requests a personal deposit limit which is above the standard permitted deposit limit	104	5.0%	Higher limit denied (87.6%)
Fair play complainer	The subscriber complains heavily about fair play	41	2.0%	*bwin.party* gives RG advice to subscriber (75.6%)
3rd party contact	A 3rd party (e.g., a relative) contacts CS to get the account blocked due to RG reasons.	23	1.1%	*bwin.party* gives RG advice to subscriber (78.3%)
Minor case	The subscriber or someone else identifies the subscriber is identified as a minor	20	1.0%	Account is blocked/closed (90.0%)
Cancel out-payment	The subscriber issues an out-payment from the *bwin.party* account but then calls CS to cancel the out-payment	19	0.9%	*bwin.party* complied with the subscriber's wish to cancel his out-payment (84.2%)
In-payment block request	The subscriber requests to block one method of in-payment to the *bwin.party* account (e.g., payment from *bwin.party* to the subscriber's credit card)	10	0.5%	In-payment method not blocked; *bwin.party* gives RG advice to subscriber (90.0%)
Unclassified	Even type not reported by *bwin.party* or, subscriber experienced two first events on the same day	2	0.0%	
	Total	**2,066**	**100%**	

be won at love by the server); and (3) virtual casino betting (e.g., virtual blackjack, roulette, or slots).

Participants' daily aggregates of betting activity records comprise the gambling behavior measures in this report. For each calendar day and for each product type, the activity records indicate the number of bets made, the amount wagered, and amount lost. We also had records of subscribers' first monetary deposits to *bwin.party*. We excluded from the current study transactions made before subscribers deposited their own money into their accounts (i.e., transactions made using promotional funds from *bwin.party*).

Data Analysis

For each product type, we calculated Number of Bets, Total Wagered, and Net Loss by summing the daily aggregations. We measured the duration of gambling activity as the number of days from the first eligible bet to the last (i.e., Duration). We calculated the number of days within that period that included a bet (i.e., Active Betting Days). We defined gambling frequency as the percent of active days within the duration of gambling involvement (i.e., Frequency). We obtained the average bets per betting day by dividing the total number of bets made by the total number of betting days (i.e., Bets per Betting Day). We calculated the average size of bets by dividing the total monies wagered by the total number of bets (i.e., Euros per Bet). Converting net losses to a percent of total wagers (i.e., Percent Lost) provides an index of losses that is independent of the total amount wagered. In sum, we analyzed nine indices of betting behavior for each of three product types (i.e., 27 total indices of betting behavior). Five of these concern subscribers' intensity of betting activity: Number of Bets; Active Betting Days; Duration; Frequency; and Bets per Betting Day. Four of these concern subscribers' monetary investment in gambling: Total Wagered, Euros per Bet, Net Loss, and Percent Lost. Previously, we have used these procedures successfully for aggregating across daily transaction histories (e.g., LaBrie, Kaplan, LaPlante, Nelson, & Shaffer, 2008; LaBrie et al., 2007; Nelson et al., 2008). Because most of these measures evidenced a moderately positive skew, we adjusted the data by adding a constant to eliminate negative values and applied a square root transformation.

We summarized the participants' demographics and gambling behavior using descriptive statistics. We tested for between-groups demographic differences using *t* tests and Chi Square. We used discriminant function analysis (DFA) as the primary data analytic technique to determine how well the predictor variables (i.e., the 27 indices of betting behavior described above) discriminate between cases and controls. Note that only participants who engaged in all three gambling products had data for all 27 indices of betting behavior. A total of 1,300 participants (32% of the 4,111 individuals with daily transaction data) engaged in all three products during the window of observation: 975 cases (47% of all cases) and 325 controls (16% of all controls). Because DFA uses list-wise deletion, the 2,811 individuals who did not engage in all three products could not be used in this analysis. Rather than limiting our analyses to this subgroup of 1,300 participants, we first performed a DFA with the full set of participants, imputing values of zero for products with which subscribers did not engage (i.e., "full sample").[4] We performed a second DFA using only the 1,300 subscribers who engaged in all three product types (i.e., "selected sample"). Because we did not generate hypotheses about the relative strength of associations of behavioral variables with group status (i.e., cases vs. controls), we entered all predictors into the DFA together rather than in a stepwise fashion.

Results

Participant Characteristics

Cases and controls did not differ in terms of age at registration ($t(3963) = -0.94$). However, being male was associated with being an RG case: 1,901 (92.0%) of cases were men and 1,836 (88.9%) of controls were men, $\chi^2(1) = 11.83$, $p < .01$. More of the cases than controls resided in Germany, $\chi^2(1) = 20.50$, $p < .001$.

Table 2 presents the means, standard deviations, and medians for each group prior to square root transformation and imputed values.

Discriminant Function Analysis: Full Sample

For the first DFA, using imputed values of zero for subscribers who did not engage in particular products, the Wilks's lambda was 0.63, $\chi^2(27) = 1880.98$, $p < .001$. As Table 3 shows, all 27 variables contributed to this discriminant function model.[5] The canonical correlation was 0.61. Table 3 also presents the univariate F values for differences between cases and controls and the pooled correlations with the discriminant function. For all variables except Frequency of fixed-odds sports betting, values were statistically greater among cases than controls (all F's > 46.00, $p < .001$). Nine variables were correlated with the discriminant function at 0.50 or higher: Active Betting Days; Duration; Bets per Betting Day; Total Bets; Euros per Bet; Total Stakes; Net Loss, for live-action sports betting; and Active Betting Days and Total Stakes, for fixed-odds sports betting. One variable, Frequency of fixed-odds sports betting, was negatively correlated with the discriminant function. The discriminant function correctly classified 78.7% of subscribers, including 83.7% of controls (i.e., Specificity) and 73.7% of cases (i.e., Sensitivity).[6,7]

Discriminant Function Analysis: Selected Sample

In the second DFA, using only subscribers who engaged in all products at least once during the study period, the Wilks's lambda was 0.79, $\chi^2(27) = 301.97$, $p < .001$. As with the full sample, all 27 variables contributed to this discriminant function model, which is presented in Table 4. The canonical correlation was 0.46. Table 4 also presents the univariate F values for differences between cases and controls and the pooled correlations with the discriminant function. Values for all variables except Frequency and Percent Lost for fixed-odds sports betting, live-action sports betting, and casino betting were greater among cases than controls (all Fs > 13.00; all ps < 0.001). Values for Frequency of live-action betting and Frequency and Percent Lost for casino betting were significantly higher among controls than cases. Three variables were correlated with the discriminant function at 0.50 or higher: Active Betting Days; Duration; and Total Bets, for live-action sports betting. Six variables were negatively correlated with the discriminant function: Frequency and Percent Lost, each for fixed-odds, live-action, and casino betting. This discriminant function correctly classified 73.2% of subscribers, including 73.8% of controls (i.e., Specificity) and 73.0% of cases (i.e., Sensitivity).

Frequency

We observed that, in both models and contrary to expectations, betting frequency was negatively associated with the discriminant function and was not significantly higher among cases than controls. This was true for the frequency of fixed-odds sports betting for the full sample and the frequency of all three products in the selected sample. Because of the way we calculate frequency, individuals who played a particular game only once during their

[4] The 21 controls for whom we have no daily aggregates of gambling behavior were not included in this analysis.

[5] As with any discriminant function analysis, these coefficients reflect the contribution of one variable within the context of the other variables that are included in the model. Consequently, low standardized coefficients can indicate the presence of suppressor effects, redundancy with other variables in the model, or a combination of these characteristics.

[6] DFA is sensitive to the presence of outliers. Consequently, we identified outliers separately for each group. We observed the presence of 322 RG cases and 276 controls who were statistical outliers on at least one variable. Nearly all outliers had values on the high end of the distribution. As a result, the DFA correctly classified 84.2% of RG outliers as RG cases and misclassified 59.4% of control outliers as RG cases. In a second DFA, we removed all 598 outliers from the dataset. Results of this outlier-free DFA were highly consistent with results of the DFA that included the outliers (i.e., the original DFA). The Wilks' lambda was 0.54, $\chi^2(27) = 2158.68$, $p < 0.001$, and all 27 variables continued to contribute to the model. The case values were greater than controls (all Fs > 22.00, all ps < 0.001) with the exception of Frequency of fixed-odds sports betting. As with the original analysis, only Frequency of fixed-odds sports betting was negatively correlated with the discriminant function. Classification accuracy improved slightly; the outlier-free discriminant function correctly classified 82.9% of subscribers. Nevertheless, each variable's relative contribution to the discriminant function was similar to the original model. Across all 27 variables, the correlation between rank-ordered contribution to this model and rank-ordered contribution to the original model was $r = 0.78$.

[7] Homogeneity of variance-covariance matrices is also an assumption of DFA. Consequently, as suggested by Tabachnick and Fidell (2001), we performed classification on the basis of separate covariance matrices, with cross-validation. These results were largely consistent with results of the original DFA. For the first validation sample, the discriminant function correctly classified 78.1% of subscribers. Across all 27 variables, the correlation between rank-ordered contribution to this model and rank-ordered contribution to the original model was $r = 0.95$. For the second validation sample, the discriminant function correctly classified 79.4% of subscribers. Across all 27 variables, the correlation between rank-ordered contribution to this model and rank-ordered contribution to the original model was $r = 0.97$.

Table 2
Descriptive Summary of Subscribers' Gambling Behavior as a Function of Group

	Controls				Responsible Gambling Cases			
	N	Mean	*SD*	Median	*N*	Mean	*SD*	Median
Total Stakes, fixed-odds sports betting	1780	1219.46	7704.95	132	2001	8697.59	27290.04	1353
Total Bets, fixed-odds sports betting	1780	201.30	892.40	29	2001	1060.67	4634.02	155
Active Betting Days, fixed-odds sports betting	1780	41.44	86.04	12	2001	127.72	202.66	54
Duration, fixed-odds sports betting	1780	496.95	611.77	241	2001	884.85	692.94	774
Frequency, fixed-odds sports betting	1780	0.30	0.35	.12	2001	0.21	0.25	.11
Bets per Betting Day, fixed-odds sports betting	1780	3.17	4.02	2	2001	5.33	14.25	3
Euros per Bet, fixed-odds sports betting	1780	13.01	32.47	4	2001	24.02	58.58	8
Net Loss, fixed-odds sports betting	1780	161.44	970.42	30	2001	1321.00	4376.18	193
Percent Lost, fixed-odds sports betting	1780	0.32	0.69	.30	2001	0.23	0.49	.21
Total Stakes, live-action sports betting	1290	5263.08	54125.16	86	1863	62774.37	194415.32	4624
Total Bets, live-action sports betting	1290	277.15	1866.54	19	1863	2198.08	5345.43	414
Active Betting Days, live-action sports betting	1290	27.78	78.35	6	1863	151.59	217.23	65
Duration, live-action sports betting	1290	377.82	531.26	101	1863	867.72	671.86	774
Frequency, live-action sports betting	1290	0.38	0.41	.15	1863	0.25	0.28	.14
Bets per Betting Day, live-action sports betting	1290	4.61	5.74	3	1863	9.45	10.21	6
Euros per Bet, live-action sports betting	1290	11.82	23.58	4	1863	27.20	43.85	12
Net Loss, live-action sports betting	1290	290.94	2283.46	13	1863	3538.73	9944.54	339
Percent Lost, live-action sports betting	1290	0.23	0.56	.16	1863	0.14	0.33	.09
Total Stakes, casino betting	494	16438.74	117169.93	266	1098	108948.88	567892.92	3336
Total Bets, casino betting	494	1703.51	6326.37	116	1098	15366.54	81995.24	747
Active Betting Days, casino betting	494	11.60	30.02	3	1098	46.42	103.94	9
Duration, casino betting	494	299.64	487.25	15	1098	514.21	599.54	298
Frequency, casino betting	494	0.48	0.45	.27	1098	0.29	0.36	.10
Bets per Betting Day, casino betting	494	103.86	220.57	37	1098	185.34	312.06	73
Euros per Bet, casino betting	494	11.13	38.48	2	1098	14.80	61.88	4
Net Loss, casino betting	494	239.36	3004.87	25	1098	2587.61	10994.01	162
Percent Lost, casino betting	494	0.21	0.31	.11	1098	0.11	0.32	.06

Note. These are original values before square-root transformation and imputing with zero.

betting history would necessarily have the highest possible frequency value (i.e., 100%) for that game. To the extent that this pattern is more common among controls than cases, this effect could inflate mean frequency values for the control group, thus producing unexpected results. We examined this possibility first by determining the proportion of cases and controls who only played games once during their betting history. Indeed, 10.7% of controls (n = 190) and only 4.1% (n = 82) of cases played fixed-odds for only one day, $\chi^2(1) = 61.02$, $p < .0001$. We observed similar trends for live-action betting, $\chi^2(1) = 166.35$, $p < .0001$ and casino betting, $\chi^2(1) = 68.74$, $p < .0001$. If we remove all 272 individuals with exactly one active fixed-odds betting day from the analysis (82 cases, 190 controls) and perform the DFA on the full sample (imputing zeros for missing values), we find that cases have higher fixed-odds betting frequency than controls, $F(1, 3839) = 4.85$, $p < .05$ and the frequency of fixed-odds betting is positively, albeit only slightly, correlated with the discriminant function (loading = 0.05).

Discussion

The current study represents a continued effort to identify disordered Internet gamblers and describe their gambling behavior. Ultimately, this research is building toward the generation of behavior-based algorithms for predicting the development of gambling-related problems. In this study, we grouped participants according to whether they had experienced at least one "responsible gambling event" during a 1-year window of recording responsible gambling events (i.e., November 2008–November 2009). We observed a pattern of excessively engaging with Internet gambling, largely consistent with our expectations and with previous research. We organize this discussion according to two aspects of Internet gambling engagement: (1) the intensity of betting activity; and (2) patterns of monetary investment.

The Intensity of Betting Activity

Supporting our hypotheses, both discriminant function analyses revealed that nonmonetary indices of the intensity of betting activity, particularly total bets placed, the number of active betting days, and the duration of gambling activity, reliably discriminated responsible gambling cases from controls. Cases evidenced significantly greater betting activity for all three gambling products. These results are consistent with previous research highlighting the importance of elevated gambling activity as a distinguishing feature between players who experience and do not experience gambling problems. As noted earlier (Nelson et al., 2008), excessive activity might create unique psychosocial consequences (e.g., a failure to meet family or work demands) and might demand unique approaches to treatment. In both discriminant function analyses, the nonmonetary indices of betting activity had stronger relationships with the discriminant function than the assessed monetary variables. However, both discriminant function analyses indicated that the frequency of fixed-odds sports betting was negatively

Table 3
Standardized Canonical Discriminant Function Coefficients, Correlations With Discriminant Function, and Tests of Equality of Group Means for the Full Sample

Variable	Discriminant function coefficient	Correlation with discriminant function	F (1, 4,109)
Active Betting Days, live-action sports betting	0.59	0.71	1,210.84**
Bets per Betting Day, live-action sports betting	0.54	0.60	857.58**
Euros per Bet, live-action sports betting	0.40	0.52	648.80**
Active Betting Days, casino betting	0.35	0.40	387.95**
Bets per Betting Day, casino betting	0.28	0.38	337.77**
Duration, live-action sports betting	0.23	0.69	1,156.03**
Bets per Betting Day, fixed-odds sports betting	0.22	0.30	208.85**
Active Betting Days, fixed-odds sports betting	0.19	0.51	627.92**
Net Loss, casino betting	0.19	0.42	420.68**
Percent Lost, casino betting	0.17	0.40	391.45**
Percent Lost, fixed-odds sports betting	0.13	0.23	129.87**
Euros per Bet, fixed-odds sports betting	0.12	0.28	184.79**
Euros per Bet, casino betting	0.05	0.30	208.79**
Net Loss, fixed-odds sports betting	0.03	0.21	100.93**
Frequency, live-action sports betting	–0.00	0.14	46.93**
Total Stakes, fixed-odds sports betting	–0.05	0.50	601.37**
Total Stakes, casino betting	–0.07	0.29	202.12**
Total Bets, casino betting	–0.09	0.32	240.74**
Percent Lost, live-action sports betting	–0.09	0.44	454.00**
Duration, fixed-odds sports betting	–0.12	0.49	578.77**
Frequency, fixed-odds sports betting	–0.13	–0.04	3.58
Total Bets, fixed-odds sports betting	–0.16	0.40	375.19**
Total Stakes, live-action sports betting	–0.19	0.52	647.58**
Frequency, casino betting	–0.22	0.19	84.22**
Total Bets, live-action sports betting	–0.23	0.59	838.44**
Duration, casino betting	–0.24	0.40	381.72**
Net Loss, live-action sports betting	–0.29	0.50	606.70**

** $p < .001$.

associated with the discriminant function; univariate tests revealed that controls bet more frequently than cases. Based on our supplemental analyses, we attribute this unexpected result to the fact that a greater number of control-group participants compared to RG participants engaged in very limited fixed-odds sports betting (i.e., gambling on just one day) and therefore achieved 100% frequency of active betting days.

Patterns of Monetary Investment

Supporting our hypotheses, monetary variables, including greater total stakes and net loss, also reliably discriminated RG cases from controls. Larger bet size also was associated with being an RG case. This is consistent with the observation that problem gamblers invest more money into their gambling activities than recreational gamblers (e.g., Currie et al., 2006). To illustrate, people who spend more than $501–1000 per year gambling are about 14 times more likely to experience gambling-related harm (Currie et al., 2006). In the current study, the raw median value for the RG cases' total wagers per year was € 1,840, or about $2,570 US, compared to € 29, or about $40 US, for controls. Depending upon their financial resources, cases likely experienced some negative consequences because of this financial outlay (e.g., lack of funds for necessities or other leisure activities, the need to cover up gambling losses).

It is interesting to note, however, that the percentage of losses was lower among cases than controls according to the raw data and the second discriminant function analysis. We have observed previously that (1) gamblers who exceed deposit limits lose less per bet than others (Broda et al., 2008), and (2) the top 1% of our large longitudinal sample, in terms of amount wagered, had lower percent losses than the rest of the sample (LaBrie et al., 2007). This is consistent with the observation that, at the population level, individuals who bet more often lose proportionately less than others (LaBrie et al., 2007). The reason for this circumstance is that, generally speaking, the more frequently an individual places bets, the more closely their losses will approximate the expected house cut. The current *bwin.party* house cut for casino products is 3% (bwin, 2011), which is closer to the median proportion lost among cases (6%) than controls (11%). This result also might stem from a more conservative better strategy; we have reported that players about to close their accounts for gambling-related problems place larger but more conservative bets as they move closer to closing their accounts (Xuan & Shaffer, 2009). In any case, it is particularly important to note that RG cases still lost more money during the course of their betting history than controls. We did not observe smaller percent lost among cases in the first DFA. This is likely because, in that analysis, a greater proportion of controls than cases had values of zero for percent lost because they did not engage in particular gambling products.

In addition to these behavioral differences, we observed two demographic differences between cases and controls. Specifically,

Table 4
Standardized Canonical Discriminant Function Coefficients, Correlations With Discriminant Function, and Tests of Equality of Group Means for the Selected Sample

Variable	Discriminant function coefficient	Correlation with discriminant function	F (1, 1,298)
Active Betting Days, live-action sports betting	0.72	0.63	137.97**
Active Betting Days, casino betting	0.45	0.40	56.40**
Bets per Betting Day, casino betting	0.36	0.33	36.36**
Active Betting Days, fixed-odds sports betting	0.35	0.46	74.05**
Euros per Bet, live-action sports betting	0.33	0.45	68.61**
Bets per Betting Day, live-action sports betting	0.32	0.43	63.89**
Euros per Bet, fixed-odds sports betting	0.26	0.33	38.23**
Bets per Betting Day, fixed-odds sports betting	0.23	0.21	14.67**
Duration, live-action sports betting	0.14	0.60	123.37**
Euros per Bet, casino betting	0.09	0.22	17.33**
Percent Lost, live-action sports betting	0.03	−0.01	0.02
Net Loss, fixed-odds sports betting	0.02	0.22	16.49**
Total Stakes, casino betting	0.00	0.34	40.55**
Percent Lost, fixed-odds sports betting	0.02	–0.06	1.13
Net Loss, casino betting	–0.07	0.20	13.64**
Percent Lost, casino betting	–0.07	–0.22	16.46**
Total Bets, live-action sports betting	–0.09	0.53	96.03**
Net Loss, live-action sports betting	–0.09	0.31	33.35**
Total Bets, casino betting	–0.11	0.36	43.47**
Total Stakes, fixed-odds sports betting	–0.12	0.47	76.77**
Total Bets, fixed-odds sports betting	–0.16	0.35	42.34**
Frequency, fixed-odds sports betting	–0.20	–0.01	0.06
Frequency, live-action sports betting	–0.26	–0.15	7.43*
Frequency, casino betting	–0.27	–0.27	24.98**
Duration, casino betting	–0.27	0.32	35.17**
Duration, fixed-odds sports betting	–0.28	0.38	49.99**
Total Stakes, live-action sports betting	–0.31	0.45	70.49**

* $p < .01$. ** $p < .001$.

men and residents of Germany were overrepresented among RG cases. The gender difference is perhaps not surprising given that males exhibit higher rates of disordered gambling compared to females (Shaffer, Hall, & Vander Bilt, 1997). In terms of nationality, previous research (LaBrie et al., 2007) has revealed some behavioral differences between German versus non-German subscribers; however, these differences were typically offsetting (e.g., Germans had a longer duration of gambling activity but lower total wagers than non-Germans). It is unclear whether the overrepresentation of Germans among the RG cases was due to actual differences in gambling behavior or to other differences that influenced subscribers' interactions with *bwin.party* customer service representatives.

Live-Action Sports Betting

In both discriminant function analyses, indices of the intensity of live-action sports betting most reliably distinguished RG cases from controls. Previously, we have observed that self-limiters (Nelson et al., 2008) and individuals who exceed corporate deposit limits (Broda et al., 2008) are more likely to engage in live-action sports betting than their counterparts. If there is a connection between the tendency to engage in live-action sports betting and disordered gambling, the direction of this effect remains unclear. It is possible that, because it produces a shorter delay between a wager and an outcome, live-action sports betting is particularly attractive to people who are highly impulsive and at greater risk for disordered gambling (Alessi & Petry, 2003). Alternatively, engaging in live-action sports betting might play a more direct role in the development of disordered gambling. Future research is needed to resolve this issue.

Limitations

With the addition of status as a responsible gambling case, our research now has investigated five proxy indicators of gambling-related problems: excessive gambling patterns (LaBrie et al., 2007; LaPlante et al., 2008), the use of deposit and account close self-limit features (Braverman & Shaffer, 2012; LaBrie & Shaffer, 2010; Nelson et al., 2008), the violation of corporate deposit limits (Broda et al., 2008), and status as an RG case. Each proxy indicator of potential problem gambling presents both advantages and disadvantages. An advantage of using self-limits as proxy indicators is that these outcomes have "real-world" significance. In other words, those who elect to lower their deposit limits or close their accounts for gambling-related reasons are likely experiencing at least some negative consequences of excessive gambling. However, these proxies do not account for gamblers who fail to instigate self-limit or self-exclusion efforts. An advantage of corporate responsible gambling features, such as those used in the current study, is that they do not require individuals formally to recognize and deal with their gambling problems. A limitation of the current approach, however, is that triggering a corporate responsible gambling feature does not necessarily indicate the presence of a meaningful gambling-related problem. In other words, subscribers who triggered these responsible gambling interventions might not have experienced behavioral problems (e.g., gambling as a way of escaping problems), negative consequences (e.g., family discord), or financial consequences (e.g., depleting savings). At the same time, subscribers who did experience such consequences might not necessarily have triggered a corporate "flag." Another limitation of the current approach is that it relies on contact between *bwin.party* customer service and the subscriber or a third party. This strategy therefore does not identify gamblers who play excessively but are not associated with unusual forms of contact with *bwin.party.*

We also did not have access to participants' income levels. Past work has indicated that the impact of gambling depends, in part, upon the gambler's financial means; consequently, it is important to consider the amount spent gambling as a function of total money available (Currie et al., 2006; Shaffer, LaBrie, LaPlante, Nelson, & Stanton, 2004). The next logical step in this line of inquiry is to gather self-report data about personal characteristics (e.g., income) and negative consequences of gambling (e.g., disordered gambling symptoms) and to combine this information with records of actual Internet gambling to develop models that can predict the development of gambling-related problems.

Implications

This first study of actual responsible gambling cases provides additional confirmation that a set of monetary and nonmonetary behaviors distinguishes individuals who might be experiencing gambling problems from other subscribers to an Internet gambling service who are not experiencing such problems. Those who appear to be experiencing problems bet on more days, make more bets (both overall and per day), and make larger bets. While they lose more money to the service overall, their losses represent a smaller proportion of their bets. These findings provide support for other work indicating that problem gamblers engage in a wider variety of Internet gambling products compared to their nonproblem counterparts (Nelson et al., 2008) and have greater variation in their wager size and fail to adapt in terms of time spent gambling (Braverman & Shaffer, 2012). However, despite these important differences, it is worth noting that taxometric research with Internet sports gamblers fails to identify a unique taxon (Braverman, LaBrie, & Shaffer, 2011). Consequently, if disordered gamblers and their healthier counterparts are not qualitatively different, it will become increasingly important to study the quantitative differences between these groups.

To conclude, these results indicate that the subscribers *bwin.party* identifies as "responsible gambling cases" gamble more intensely than their nonidentified gambling counterparts. This behavioral intensity reflects both monetary and temporal involvement. These results provide evidence supporting the use of this set of gambling behaviors as markers for potential problem gambling. In terms of *bwin.party's* broader responsible gambling policies, these results add to the body of research (e.g., Braverman & Shaffer, 2012; Broda et al., 2008; LaBrie & Shaffer, 2010; LaPlante et al., 2008; Nelson et al., 2008) supporting the development of behavioral algorithms that can predict the emergence of gambling-related problems before these fully manifest. We need additional research to test the validity of such behavioral algorithms and to develop appropriate interventions designed to stop or ameliorate excessive gambling

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