Identifying behavioral markers of disordered Internet sports gambling

Richard LaBrie & Howard J. Shaffer
Division on Addictions, Harvard Medical School, Medford, MA 02155, USA

(Received 28 August 2009; revised 2 July 2010; accepted 26 July 2010)

Objective: To identify patterns of sports gambling that discriminate sports bettors with self-reported gambling-related problems from sports bettors without such difficulties.

Methods: Secondary data analysis of the actual betting behavior observed during the first 2 years of a longitudinal study of 47,134 subscribers to an Internet sports gambling site. This sample included the gambling behavior of 679 bettors who self-reported the reason for closing their accounts during that period. We contrasted the behavior of those who closed their accounts because of gambling-related problems (n = 215%, 32%) to the behavior of other account closers (ACs) who were either not satisfied with the service (n = 113%, 17%) or no longer interested in betting (n = 351%, 52%).

Results: Exploratory multivariate discriminant function analyses identified a sub-group of approximately half the ACs with gambling-related problems who exhibited a homogeneous and distinct pattern of sports-betting behavior. Compared to other ACs, this sub-group made more and larger bets, bet more frequently, and were more likely to exhibit intense betting soon after enrollment. The group estimation formula derived from this prototype applied to an independent sample of ACs confirmed the prevalence of this distinct gambling pattern.

Conclusion: Because Internet gambling provides a unique opportunity to study actual gambling behavior, it is possible to identify betting patterns that can lead to the development of gambling-related problems. This pattern recognition can inform the development of interventions to help disordered gamblers recognize their risky behavior and avoid further problems.

Keywords: Gambling, Internet, Internet gambling, gambling problems, self-exclusion, disordered gambling, sports betting

INTRODUCTION

Internet gambling is one of the fastest growing gambling-related industries (Christiansen Capital Advisors, 2006). Research now shows that in many jurisdictions, participation in Internet gambling has grown during the past 10 years. For example, a survey conducted during 1999 and 2000 (Welte, Barnes, Wieczorek, & Tidwell, 2004) reported that 0.4% of US adults had gambled on the Internet during the last year. During 2005 through 2007, the same research group conducted a survey of US adolescents and young adults; they observed that 2% of the sample reported Internet gambling experience (Welte, Barnes, Tidwell, & Hoffman, 2009). Using the 2007 British survey data, Griffiths, Wardle, Orford, Sproston, and Erens (2009) reported that 6% of those surveyed used the Internet to gamble in the last year (i.e., they reported gambling online, betting online, and/or gambling using a betting exchange.)

The rapid expansion of Internet gambling access stimulated public health concerns among policymakers (e.g., Richtel, 2004) and advocates (e.g., No More Gambling, 2004–2005). Researchers have echoed similar concerns (e.g., Smeaton & Griffiths, 2004) and raised additional worry that some Internet gambling features, such as ease of access, privacy of use, and gaps in the regulation of online betting services, pose special risks for the development of gambling-related problems (Griffiths, 2003).
Risk detection and markers for Internet gambling problems

Medical science makes use of biomarkers to signal normal or abnormal processes, or to identify the presence of a condition or disease. Biomarkers can measure the progress of a disease or reflect a response to treatment. The logical parallel to molecular markers is behavioral markers. Clinicians observe behavioral markers associated with disease states to aid diagnosis and treatment; later, behavioral markers can measure response to interventions. The syndrome model of addiction (Shaffer et al., 2004), for example, includes risk factors, temporally distal or proximal biomarkers, and behavioral markers for addiction. Some behaviors, such as betting patterns, can be proximal to the development of gambling-related problems. Potential primary sources of information related to risk factors and disease markers include the literature focusing on (1) gambling problems emanating from land-based gambling activities and (2) Internet gambling. Land-based gambling provides self-reported information about betting activity from gamblers traveling to public venues. Internet gambling provides actual records of betting activity from gamblers with immediate, private access to gambling. The similarities and the differences for the risk factors and disease markers between these information sources hold significant potential to enhance our understanding of gambling addiction and treatment.

Research about Internet gambling

Our recent search of the literature (Shaffer, Peller, LaPlante, Nelson, & LaBrie, in press), using the PubMed and PsychINFO search engines with the search terms “Internet [AND] gambling,” identified 111 articles released through March 7, 2008, excluding our own Internet gambling publications. Ten of these articles met criteria for original quantitative empirical studies of Internet gambling. These original studies used convenience samples: three sampled Internet gamblers (Wood & Williams, 2007; Wood, Williams, & Lawton, 2007; Woolley, 2003), two free care medical and dental patients (Ladd & Petry, 2002; Petry et al., 2006), two college students (Petry & Weinstock, 2007; Wood, Griffiths, & Parke, 2007), one college athlete (Kerber, 2005), one casino patrons (Woodruff & Gregory, 2005), and one employees of a university health center (Petry & Mallya, 2004). We updated this search to include publications available through the end of January 2009; we also identified an additional qualifying report (not authored by us) that is the only study of Internet gamblers from a nationally representative sample (i.e., the 2007 British Gambling Prevalence Survey, Griffiths et al., 2009). The fact that the gambling behavior represented in this study is based on self-report limits and compromises our ability to draw sound conclusions from this research.

Our literature search yielded a single study in the peer-reviewed literature that used actual gambling behavior recorded within an Internet environment. Fiedler and Rock (2009) examined data from the records of poker hands to help determine whether poker is a game of skill or chance – a topic not relevant to our interest in disordered gambling.

Studies of actual gambling behavior

Internet gambling yields records of unprecedented detail: computer systems accurately record and store virtually every keystroke. Recognizing the opportunity for research, the Division on Addictions and bwin Interactive Entertainment, AG formed a research collaboration (detailed in Shaffer et al., in press) to promote responsible gambling. The computer resources integral to the Internet permit a new research paradigm that can revolutionize data collection, in general, and gambling patterns, in particular, by focusing on actual behavior rather than only self-report. Within this collaborative, bwin provides access to various Internet gambling information, including both the placing of bets on the outcome of sporting events and participation in various games (e.g., casino-type games, other games and lotteries, and poker). During the data collection period reported here, bwin was primarily a sports betting venue. More than three-quarters of the self-excluders in this study wagered a majority of their monies on sports. Compared to other betting opportunities offered by bwin, sports betting is more easily characterized and measured. At the moment, bwin offers 85 casino-type games ranging from simulated slot machines to baccarat. Similarly, there are 61 other games including backgammon and virtual horse racing. The large number of game types yields a wide range of characteristics, such as house-odds and time required to complete a game. Poker is more standard and in this data collection, there were too few self-excluders with gambling-related problems (i.e., n = 10) for analysis. This study and others mentioned below used information gathered from Internet sports gamblers.

A major goal of the bwin-division collaborative research project is to identify procedures to protect Internet gamblers who are at risk for developing problems. For example, in one study (Broda et al., 2008), we examined the effect of bwin’s defined deposit limits of €5000 within a 30-day period, and €1000 within 24 hours. That study showed that deposits seldom approached the house limits and, when exceeded, subsequent gambling behavior did not change from previous behavior. The collaborative project has already produced betting system modifications designed to promote responsible gambling. For example, our study of bwin’s system change that allows players to install their own limits on deposits (Nelson et al., 2008) revealed that sports gamblers who elected to lower their allowed deposits played a wider variety of games and placed more bets than prior to imposing their own limits. After imposing limits, self-limiters reduced their gambling frequency, but increased the amount they wagered per bet. A study of behavior...
BEHAVIORAL MARKERS OF DISORDERED INTERNET SPORTS GAMBLING

The Internet equivalent of land-based casino self-excluders is account closers (ACs) who identify the reason for excluding themselves as having problems due to gambling (problem gambling account closers (PGACs)). We expect PGACs, like their land-based casino counterparts, recognize that their gambling behavior is becoming unhealthy and are taking steps toward remediation: in this case, closing their account. However, unhealthy behavior is not synonymous with excessive risks and intolerable losses. For example, Internet sports bettors who chose to limit the amount of money they could bet (Nelson et al., 2008) included self-limiters who did not exhibit excessive betting behavior prior to the decision to limit play. Similarly, we expect that some PGACs will not exhibit recognizable extreme betting patterns and might include winners. Neglecting other responsibilities to gamble and excessive time spent deciding on a bet are examples of non-monetary problematic behaviors. It is also possible that positive betting outcomes at *bwin* were inconsistent with large losses at other gambling venues. However, excessive and intolerable losses are the most common causes of problems for bettors and their significant others, and these patterns are observable in betting records. We hypothesize that there will be PGACs who share common, exaggerated gambling behaviors that are distinct from the behavior of people who gamble without problems. The Internet’s data collection capabilities allow scientists to analyze the accurate records of actual gambling behavior unconstrained by the problems associated with self-recall (e.g., Baumeister, Vohs, & Funder, 2007; Nisbett & Wilson, 1977) and self-reporting (e.g., Shaffer et al., in press; Williams & Wood, 2004). This study represents the first ever investigation of actual gambling dynamics that mark a path to the emergence of Internet gambling-related problems. Our goal was to determine whether it is possible to identify individuals who self-identify as having gambling-related problems based on their Internet gambling behavior. We hypothesized that sports gamblers who decided to exclude themselves from further gambling for gambling-related reasons would: (1) include sports gamblers who exhibit shared problematic gambling behaviors; (2) represent an homogeneous gambling pattern that would be distinct from the gambling behavior of their counterparts who also identified gambling-related problems as a reason for excluding themselves; and (3) be distinct from people who excluded themselves from further gambling for other reasons. The research objective for this study was to generate a predictive formula that could mark patterns of Internet sports gambling behaviors that lead to gambling-related problems. We further hypothesized that application of this strategy to an independent validation sample would confirm that these behavioral markers were not unduly influenced by sample-bound idiosyncrasies.

METHODS

There are many clustering strategies and procedures that might achieve the research objectives of this study. In all cases, we would need to analyze the resulting groups (i.e., clusters of people with similar characteristics) further to define the characteristics that discriminate these groups. For example, we can identify defining characteristics that distinguish groups by submitting them to a multivariate discriminant function analysis (MDFA). In this exploration for distinct PGACs, we created the three group study sample by using the three different reasons for account closing. We used MDFA to identify the homogeneous groups within PGACs by first analyzing the differences between PGACs and other ACs and then comparing the PGACs who could be discriminated from other ACs to PGACs who were not distinct. The objective of this analysis is to define a “pure group.” A “pure group” analysis hypothesizes that there exist homogeneous groups of individuals whose gambling-related behavior distinguishes them from other gamblers in a reliable and predictable way. This strategy yields a set of markers for the development of gambling-related problems by successively identifying and removing from consideration the groups of individuals whose sports gambling behavior is NOT distinctive and therefore not able to be discriminated from other...
sports gamblers. When repeated discriminative analyses no longer identify for removal of any indistinct groups of individuals, the remaining individuals represent a ‘‘pure group,’’ ready for characterization and testing. In this case, testing means determining that the behavior of the group is distinct and that the members are part of a defined group of interest; here, self-identified problem gamblers. Gamblers who chose not to identify themselves as having problems may also exhibit this distinct behavior. The variables, or clusters of variables, which completely discriminate the ‘‘pure group’’ from similar others represent predictive markers for the development of gambling-related problems.

Participants
During the first 2 years of the collaborative longitudinal study, bwin had a procedure in place that offered ACs the opportunity to choose one of the three reasons for closing their account. This procedure provided us with the opportunity to acquire purposive samples of ACs who did and did not endorse gambling-related problems as their motive for closing their accounts. This study relies on two samples: (1) a model development sample and (2) a model validation sample. Figure 1 presents the procedure that resulted in the model development sample of 689 ACs identified during the 2-year follow-up of the longitudinal cohort of 48,114 sports bettors. As Figure 1 shows, we employed four selection criteria to identify study participants: (1) formally closing an account before the end of the 2-year study period; (2) at the closing, choosing to offer the reason for closing by selecting one of the three proffered choices (i.e., they were not satisfied with bwin services or they had no further interest in gambling, or gambling-related problems); (3) being a sports bettor, operationally defined as making bets on sporting events for more than 3 days and placing the majority of total stakes on sporting events; and (4) experiencing a net loss in sports bets.

As noted earlier, we did not expect that all PGACs closed their accounts because of intolerable losses. Some PGACs (n = 21%, 10%) were net winners. We eliminated the net winners because they could not contribute to the focus of this study. Consequently, the sample for analyses of betting behavior that might mark gambling-related problems is composed of 113 unsatisfied ACs, 351 no longer interested ACs, and 215 ACs with self-identified gambling-related problems.

The validation sample comprised of an independent but matched group of sports bwin bettors who were not members of our already established longitudinal cohort. We evaluated a cohort of sports bettors who enrolled in bwin during March 2005, using the same criteria as our longitudinal cohort. This process identified 65 ACs who closed their accounts for gambling-related problems during the same period of observation as the original longitudinal sample. This validation sample is smaller due to the monthly variation in total enrollments experienced during the early days of bwin’s development.

Measures
The dependent measures of gambling behavior summarize the participants’ daily aggregates of betting activity from the bettors’ first to last day of sports betting for the 2 years of observation beginning February 1, 2005. bwin offers two types of bets within their sports betting propositions; fixed-odds bets on the outcomes of sporting events or games and live-action bets on propositions about outcomes within a sporting event. This study aggregated the bets made on both fixed-odds and live-action type bets. The daily betting activity records include winnings credited to the bettors’ accounts on that day and can include outcomes from wagers made on previous days.

We employed four composite measures of gambling behavior that summed the daily information: (1) the total Number of Bets; (2) Total Money Wagered; (3) Total Winnings; and (4) Active Days, the total number of days with a recorded transaction. We computed the Duration of sports gambling involvement as the number of days from the date of the first bet to date of the last bet. The Frequency of involvement is the percent of Active Days within the Duration period. We calculated the average bets per day (Bets per Day) by dividing the total Number of Bets made by the Active Days and the average size of bets (Average Bet) by dividing the Total Money Wagered by the total Number of Bets. The net result of gambling (i.e., Net Loss) is the difference between Total Money Wagered and Total Winnings. The dominant outcome is a loss and, by subtracting Total Winnings from Total Money Wagered, positive values of Net Loss indicate the total cost of gambling. Converting Net Loss to a percent of Total Money Wagered (i.e., Percent Lost) provides an index of losses that is independent of the total amount wagered. The large number of cohort members who wager infrequently and moderately skew these measures of betting behavior (LaBrie, LaPlante, Nelson, Schumann, & Shaffer, 2007). We removed the skew by converting measures to natural logs.

Statistical analyses
We applied a series of MDFAs to investigate the presence of a sub-group of PGACs whose betting behavior would accurately discriminate them from other PGACs. A stepwise discriminant function analysis entered measures from the battery of 10 gambling measures. We entered each measure in the order of its contribution to discrimination as measured by Wilks Lambda (SPSS Inc., 2008). This procedure entered dependent measures until the contribution to discrimination of the best remaining measure was not statistically significant. At that point, the classification procedure grouped subjects according to their discriminant scores from the estimation equation assuming equal a priori probabilities of group membership.
of participants, categorized by their self-reported account closing reason. This analysis identified two statistically significant discriminators, Duration and Total Winnings. The group of bettors who closed their accounts because they were not satisfied with the service they received could not be discriminated from the other groups. Because of the poor contrast to the other groups presented by this non-homogeneous group, we eliminated them from subsequent analyses.

The second MDFA compared ACs who reported that they were no longer interested in bwin services with the PGACs. Eliminating the non-distinct ACs who reported their dissatisfaction with the service had little effect and the two-group analysis selected the same significant discriminators as before, Duration and Total Winnings. This model correctly estimated the membership of two-thirds ($n = 236\%, 67.2\%$) of the no longer interested ACs. Half ($n = 108\%, 50.2\%$) of the

**RESULTS**

**Modeling distinctive sports gambling behavior**

We conducted the first exploratory MDFA to identify the variables that discriminated the three groups of participants, categorized by their self-reported account closing reason. This analysis identified two statistically significant discriminators, Duration and Total Winnings. The group of bettors who closed their accounts because they were not satisfied with the service they received could not be discriminated from the other groups. Because of the poor contrast to the other groups presented by this non-homogeneous group, we eliminated them from subsequent analyses.

The second MDFA compared ACs who reported that they were no longer interested in bwin services with the PGACs. Eliminating the non-distinct ACs who reported their dissatisfaction with the service had little effect and the two-group analysis selected the same significant discriminators as before, Duration and Total Winnings. This model correctly estimated the membership of two-thirds ($n = 236\%, 67.2\%$) of the no longer interested ACs. Half ($n = 108\%, 50.2\%$) of the
PGACs had distinct behaviors that discriminated them from the no longer interested ACs and the remaining half of the PGACs.

The next MDFA compared the distinctive PGACs (n = 108) to the other PGACs (n = 107). In this model, four measures contributed significantly to estimation: Frequency, Bets per Day, Duration, and Total Wagers. The classification correctly identified 92% of the participants as distinctive or not. The accuracy of classification was similar across groups: 93% (100 of 108) for distinctive PGACs and 91% (97 of 107) for other PGACs. As noted earlier, to identify a marker of potential risk for developing gambling-related problems, we sought a completely accurate formulation of the distinctive behavior. To that end, we eliminated the misclassified ACs and conducted another MDFA. This reformulation again identified Frequency, Bets per Day, Duration, and Total Wagers as significant discriminators. This MDFA yielded slightly modified discriminant function weights, and accurately classified the 100% of the PGACs as distinctive or not. The final discriminant function reduced the number of no longer interested ACs that exhibited the distinctive PG-related behavior from 115 to 96.

Describing the distinctive sports gambling behavior

Table I presents descriptive statistics for the final MFDA measures that distinguish the distinct and non-distinct PGACs. To orient these statistics to the original metric, the gambling behavior of the two PGAC groups differed significantly on all MFDA measures. The effect sizes derived from the univariate test statistics indicate a large group effect for all behaviors. To orient the behavioral characteristics to the original metric, Table I also includes the median values of the untransformed measures. The distinct PGACs exhibit a significant positive relation between Frequency and (1) Bets per Day and (2) Active Days; non-distinct PGACS had a smaller, negative coefficient for the non-distinct group ranging from –4.60 to –0.06 and for the distinct group from 0.06 to 4.53. This formulation defines negative discriminant scores as associated with non-distinct PGACs and positive scores associated with PGACs who have a distinctive betting behavior.

Table I. Discriminating gambling behavior of participants who closed their accounts for gambling-related problems (ACs) grouped by distinct (N = 97) and non-distinct (N = 100) patterns of behavior.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Distinct ACs</th>
<th>Non-distinct ACs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Frequency</td>
<td>3.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Bets per Day</td>
<td>2.1</td>
<td>0.8</td>
</tr>
<tr>
<td>Average Bet*</td>
<td>2.0</td>
<td>1.4</td>
</tr>
<tr>
<td>Active Days</td>
<td>4.1</td>
<td>1.1</td>
</tr>
</tbody>
</table>

Notes: SD, Standard deviation.

*In Euros.

**Groups significantly different (p<0.01) on all measures.

Table II. Pearson correlations between log-transformed discriminating measures for participants who closed their accounts for gambling-related problems grouped by distinct (N = 97, above the diagonal in bold) and non-distinct (N = 100, below the diagonal) patterns of behavior.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Frequency</th>
<th>Bets per Day</th>
<th>Average Bet</th>
<th>Active Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>–0.21*</td>
<td>–0.12</td>
<td>–0.32**</td>
<td>–0.09</td>
</tr>
<tr>
<td>Bets per Day</td>
<td>–0.33**</td>
<td>+0.04</td>
<td>+0.40**</td>
<td>+0.18</td>
</tr>
<tr>
<td>Average Bet</td>
<td>+0.80**</td>
<td>–0.04</td>
<td>–0.15</td>
<td>–</td>
</tr>
</tbody>
</table>

Note: *p<0.01; **p<0.001.

for several measures. The correlations between Frequency and (1) Bets per Day and (2) Active Days are statistically significant for non-distinct PGACs but not for the distinctive PGACs. Conversely, distinctive PGACs exhibit a significant positive relation between Active Days and Bets per Day; non-distinct PGACS exhibit no correlation between these measures.

The standardized discriminant function coefficients (SC) indicate each variable’s relative contribution to discrimination and the association with the distinct behavior pattern. Frequency of play made the largest contribution to discrimination (SC = 1.077). The distinctive PGACs made more Bets per Day (SC = 0.598) and larger Average Bets (SC = 0.556) than the non-distinct PGACs. The total number of Active Days had a smaller, negative coefficient (SC = –0.322). The discriminant function identifies distinct gamblers by the combination of Frequency play days in relative briefer periods of play compared to their non-distinct counterparts. The discriminant scores for the non-distinct group ranged from –4.60 to –0.06 and for the distinct group from 0.06 to 4.53. This formulation defines negative discriminant scores as associated with non-distinct PGACs and positive scores associated with PGACs who have a distinctive betting behavior.
We applied the discriminant function to the validation group, i.e., PGACs in the cohort of bwin sports bettors who enrolled during the month after the original longitudinal sample enrolled. The discriminant scores for 32 PGACs (49.2%) were negative (−4.18 to −0.11) and indicated that they exhibited non-distinct patterns of gambling behavior. The other 33 PGACs (50.8%) had positive discriminant scores (0.07–4.32) consonant with the distinctive betting pattern. As with the original longitudinal sample, the discriminant function scores of the two groups of PGACs in the validation sample did not overlap (i.e., there were no scores in the region between the largest score in non-distinct group score, −0.11, and the smallest score in the distinct group, +0.07).

**DISCUSSION**

This study illustrates the process of identifying behavioral markers for health risks, in general, and pathological gambling, in particular. By taking advantage of an opportunity to acquire a targeted (i.e., purposive) sample of Internet sports gamblers who closed their gambling accounts and identified having gambling-related problems as the reason for doing so, we identified a pattern of behavior unique to about half of the ACs. A discriminant function based on four empirically derived behaviors was 100% accurate in estimating membership in the two groups. The behavioral markers in this model were: (1) placing more bets; (2) placing larger bets; (3) betting more frequently; and (4) betting intensely soon after enrollment. We applied the behavioral markers to an independent validation sample and confirmed that we could replicate the identification of the distinct behavior pattern associated with the onset of gambling-related problems. The prevalence of ACs with the behavioral marker in the independent sample matched the prevalence in the original sample, thus confirming that the original formulation was not unduly influenced by sample-bound idiosyncrasies.

The distinct PGACs risked and lost more money than non-distinct PGACs. The distinct PGACs lost more money in a shorter period (i.e., a median of 252 days from the first to the last bet compared to 353 days for other PGACs) by betting more frequently (i.e., a median of 64 days compared to 30 days.) Figure 2 shows Frequency (the percent of days active within the total duration of play) distributed by Active Days (total betting days from the first to the last betting day.)

Figure 2 illustrates a behavior that is characteristic of the more intense players. Distinct PGACs rarely let a day go by without betting. Frequent betting is clearly
marked for the distinctive group with relatively few total days of betting. Figure 3 shows another measure, Bets per Day, distributed by Active Days. The distinct PGACs make more Bets per Day than the non-distinct PGACs. In this case, the distinct group with relatively more total days of betting also tends to place more bets, an acceleration not exhibited by the other PGACs. These figures suggest that the distinct patterns of gambling behavior associated with PGACs might be recognizable after relatively few betting days for some players because of their very frequent play. The pattern of play also has measures that are distinct among PGACs with relatively many days of active play.

The discussion above indicates how cumulative sports betting records identify a homogeneous group of people who got into trouble because of their behavior. However, the discussion above suggests that some problem gamblers evidenced behavioral markers early in their gambling pattern. Their number of bets and the size of those bets are markedly larger than gamblers without these markers. For example, betting every other day is unusual given the tendency for many sporting events to take place weekly. For some distinct PGACs their intense gambling was telescoped into a relatively short period of time. The discriminant function that provides scores indicate how likely the observed measures match those of the distinctive PGACs. An application of these findings could be used to calculate discriminant scores of players at specific and successive accumulations of behavior. Once calculated, these markers permit proprietors to alert individuals whose successive scores move in the direction of gamblers with problems of their behavior beginning to resemble that of a group of bettors who had to quit gambling because of problems related to gambling.

The data in this study represent the cumulative record of betting from the beginning to the end of play at bwin. Live-action sports bets provide betting choices with variable odds (i.e., the proposition that a tennis game will be won at love has higher odds than a win at add). Previous research with bwin ACs (Xuan & Shaffer, 2009) used live-action sports bets to examine "chasing" during the days immediately preceding account closing. PGACs lost more money due to placing larger bets, but contrary to conventional expectation, they selected more conservative betting propositions with shorter odds. It is possible that we might observe the distinct multivariate profile of cumulative betting behavior exhibited by some PGACs among continuing sports bettors. Among the somatic illnesses, there are many reasons why a marker might fail to identify an illness. Similarly, players might have large resources, and excessive losses do not result in problems. Further, the disordered behavior might be episodic and not revealed in the total cumulative behavior; the behavior might have been only recently adopted; participants exhibiting the pattern might not close their account but simply not use this portal for gambling activities; the pattern of gambling evidenced by distinct PGACs might be adopted by players with large personal resources for...
ongoing research collaboration procedures to provide additional information that will support of our quest for behavioral markers.

The pattern of behavioral markers identified in this study is distinct within the context of typical sports betting behavior. For most participants, sports betting is a rather slow-moving activity: many sporting events take place weekly. More rapid cycling games, such as casino games might require different measures and different formulations to identify behavioral markers of disordered gambling across game types.

Despite these limitations, one strength of this study is that it provides the opportunity to use an information base of actual individual betting transactions. However, these records are limited to those bets placed with our collaborating research partner, bwin Interactive Entertainment, AG. Some ACs might have placed bets at other venues and any disordered behavior associated with these venues might not be evident from the bwin information.

CONCLUDING THOUGHTS

This study supports the proposition that monitoring actual betting behavior is an appropriate initiative with the potential to promote responsible gambling and avoid disordered gambling. This study shows that we can recognize a sports betting pattern evidenced by players who later declare that they are having gambling-related problems. The elements of this pattern are markers associated with account closing. Continuing research will need to identify markers early in the process, perhaps at the cost of some precision, so that these markers will trigger interventions early in the sequence of events that can interrupt behavior and reduce associated penalties. It might be that the pattern described here is an identifiable phase within the development of responsible gambling. There is evidence that this cohort shows a general tendency to exhibit a period of initial enthusiastic betting followed by an adaptation to behavior that is more moderate (LaPlante, Schumann, LaBrie, & Shaffer, 2008). Scientists and clinicians need to determine how to integrate the information about distinct patterns of betting behavior into a system of markers and interventions. However, until a system is in place, the ability to detect, and perhaps even anticipate, disordered behavior demonstrated by this research has immediate application to promoting healthier behaviors.

ACKNOWLEDGMENTS

bwin, Interactive Entertainment, AG provided primary support for this study. The Division on Addictions receives funding from the National Center for Responsible Gaming, the National Institute on Drug Abuse (NIDA), the National Institute of Mental Health (NIMH), National Institute of Alcohol Abuse and Alcoholism (NIAAA), the Massachusetts Council on...
Compulsive Gambling, the State of Nevada Department of Public Health, the Massachusetts Family Institute, and others. The authors extend special thanks to Christine Thurmond for her support of this project, and Drs Debi LaPlante and Sarah Nelson for their helpful suggestions and comments. Dr. LaBrie had full access to all of the data in the study and he takes responsibility for its integrity and the accuracy of the data analyses.

Declaration of interest: Neither author has personal interests in bwin.com and its associated companies that would suggest a conflict of interest.

REFERENCES


