A Taxometric Analysis of Actual Internet Sports Gambling Behavior

Julia Braverman, Richard A. LaBrie, and Howard J. Shaffer
Harvard Medical School and The Cambridge Health Alliance, Cambridge, Massachusetts

This article presents findings from the first taxometric study of actual gambling behavior to determine whether we can represent the characteristics of extreme gambling as qualitatively distinct (i.e., taxonic) or as a point along a dimension. We analyzed the bets made during a 24-month study period by the 4,595 most involved gamblers among a cohort of 48,114 people using an Internet service to gamble on sporting events. We applied two taxometric procedures (i.e., MAMBAC and MAXCOV) to three indicators of betting behavior: total money lost, total number of bets, and total money wagered. The results fail to provide support for the view that the most involved Internet sports gamblers include a distinct category of gamblers. More research is necessary to clarify the similar features of recreational and extreme gamblers and the dimensions that scientists can use to measure these behaviors. Finally, we discuss the implications of these findings for clinical, research, and public policy activities.

Keywords: latent structure, taxometric analysis, Internet gambling, addiction, pathological gambling

Among the most long-standing debates in the psychopathology literature is whether researchers and clinicians can describe mental disorders (e.g., pathological gambling) as extreme expressions of continuously distributed traits or as qualitatively distinct patterns (Beauchaine, 2007). Participants in this debate describe the continuously distributed view as dimensional and the qualitatively distinct view as categorical, or taxonic.

To illustrate: Gambling is a common form of entertainment that the vast majority of people enjoy without any adverse consequences. However, approximately 2%–5% of those who have participated in gambling activities experience mild to serious gambling-related problems at some point during their lifetime (Kessler et al., 2008; Petry, Stinson, & Grant, 2005; Shaffer & Hall, 2001; Shaffer, Hall, & Vander Bilt, 1999; Shaffer & Korn, 2002; Shaffer, LaBrie, LaPlante, Nelson, & Stanton, 2004; Welte, Barnes, Tidwell, & Hoffman, 2008; Welte, Barnes, Wieczorek, Tidwell, & Parker, 2001). Conceptually, a dimensional view of gambling would locate gambling disorders at the end of a continuum, and despite the quantitative distinction, this extreme behavior would be qualitatively similar to behaviors located at other points along the continuum. Alternatively, a categorical view of gambling would locate disorders within a qualitatively distinct and extreme interval such that the behaviors would be sufficiently different (i.e., a unique taxon) from behaviors outside the interval.

Although this area of research is not without debate, there is evidence that some disorders (e.g., unipolar clinical depression) are categorical (Solomon, Ruscio, Seeley, & Lewinsohn, 2006). Evidence argues that other disorders (e.g., personality disorders) are extensions of normal behavior and, therefore, are best described as dimensional (e.g., Livesley, Schroeder, Jackson, & Jang, 1994; Markon, Krueger, & Watson, 2005; Widiger & Mullins-Sweatt, 2005). Diagnostic definitions (e.g., as the American Psychiatric Association offers in its Diagnostic and Statistical Manual of Mental Disorders), although not inherently categorical and often based on dimensional criteria, tend to reflect a categorical approach. This approach enhances the reliability of psychometric assessment scores and clinical evaluations. Diagnostic manuals often encourage clinicians to diagnose cases by identifying and then quantifying adverse behaviors. However, this system of classification, based on endorsing atypical behaviors, does little to advance our understanding about a target disorder’s construct validity. Consequently, there is a paucity of evidence informing clinicians, researchers and policy makers about whether the fundamental precept underlying a deviant behavior reflects a unique latent architecture (Barron, 1998; Carson, 1991; Grove & Meehl, 1996; Vaillant & Schnurr, 1988; Widiger & Sankis, 2000). To date, and perhaps because pathological gambling is a relatively new diagnostic class, most clinicians and researchers have defined and treated pathological gambling as a categorical illness, preferring nosological schemes that consider this excessive behavior pattern as a distinct disorder (Beauchaine, 2007).

The goal of this study is to examine the betting characteristics of heavily involved Internet sports gamblers for the presence of a distinct category or taxon of betting characteristics. Evidence of a taxon would imply that some heavy gamblers are qualitatively different from more involved recreational Internet gamblers.
Only three studies have focused on gambling typology and the latent structure of gambling behavior. These studies appeared during the past 2 years, indicating a growing recent interest in the conceptual architecture that represents disordered gambling. The studies include the following: (a) research focusing on older adults and gambling (Hong, Sacco, & Cunningham-Williams, 2009); (b) an investigation of community-recruited gamblers (Cunningham-Williams & Hong, 2007); and (c) a longitudinal study about the gambling activities of college students (Goudriaan, Slutske, Krull, & Sher, 2009). All of these studies used latent class analysis procedures that identified two to eight various gambler types depending on criteria from the Diagnostic and Statistical Manual of Mental Disorders (4th ed., Text Revision [DSM–IV]; American Psychiatric Association, 2000; Cunningham-Williams & Hong, 2007; Hong et al., 2009), type of games played (Goudriaan et al., 2009), source of money, or International Classification of Diseases–10 (ICD-10; World Health Organization, 1993) criteria (Cunningham-Williams & Hong, 2007). These studies used statistical techniques with important limitations for distinguishing between the presence and absence of a single categorical boundary (interested readers should see Ruscio & Ruscio, 2004a, for a brief review and a list of limitations). Therefore, no study has directly addressed the question of whether excessive gambling represents a unique category or taxon or, the alternative, a point along a continuum consistent with a dimensional view of excessive gambling.

**Taxometrics and Nosology**

Meehl and his colleagues developed the taxometric method to identify the presence or absence of taxonic (i.e., categorical) latent structure among psychiatric disorders (Meehl, 1999; Meehl & Yonce, 1996). Taxometric method includes specific statistical tools designed to determine whether deviant behavior belongs to a unique taxon or simply represents points along one or more dimensions. A categorical view suggests that distinct psychological features characterize deviant behavior and that these distinctive features are not shared with “normal” cases. The dimensional view suggests that normal behavior shares psychological features with deviant behavior but that the deviant group has more and perhaps more intense features. Taxometric statistics measure the interaction among several indicator variables. For example, consider the following: Researchers are interested in determining whether gender-related traits represent a unique category or a dimension. The correlation between voice pitch and hair length is negligible within a sample that includes only male or only female participants. However, within a mixed-gender sample, we can expect to find a substantial correlation—those who tend to have longer hair also are likely to have higher voices. This strategy, testing whether different associations among variables exist for different groups of observations defined by the values of index variables, underlies taxometric statistics. A review of taxometric statistics is beyond the scope of this article. However, readers interested in learning more about taxometrics should review the following resources as an entry to this literature (Meehl, 1995; Ruscio, Haslam, & Ruscio, 2006; Schmidt, Kotov, & Joiner, 2004; Waller & Meehl, 1998).

Taxometrics is “an increasingly popular approach for determining whether a dimensional or a categorical model of classification is more valid” (Widiger & Samuel, 2005, p. 48). More than 150 studies applied taxometric procedures to evaluate the latent structure of various psychopathological and behavioral constructs (Haslam, in press; Haslam & Kim, 2002). However, no studies have applied taxometric procedures to the study of excessive gambling behavior.

Until recently, scientists did not have the opportunity to study actual gambling behavior. Consequently, the current nosological system, as evidenced and operationalized by DSM–IV and ICD-10 criteria, rests mostly on self-report. A portfolio of new research focusing on actual gambling behavior is now available (e.g., Braverman & Shaffer, 2010; LaPlante, Schumann, LaBrie, & Shaffer, 2008; Xuan & Shaffer, 2009). A series of studies conducted with behavioral variables (e.g., total amount wagered, bet size, total amount lost, frequency, etc.) defined and described the behavior of subgroups of most involved gamblers (LaBrie, Kaplan, LaPlante, Nelson, & Shaffer, 2008; LaBrie, LaPlante, Nelson, Schumann, & Shaffer, 2007). The present study extends the research experience with actual betting behavior to answer the question of whether problematic gambling is best considered a quantitative (dimensional) or qualitative (categorical) classification.

**The Present Study**

Our research collaboration with an Internet gambling service provider, bwin Interactive Entertainment AG (hereinafter referred to as bwin), provides access to valuable information. Our longitudinal database was uniquely well suited to answering the research question. The database consists of actual bets made during a 2-year period by a cohort of 48,114 gamblers who enrolled at bwin Interactive Entertainment AG during February 2005. The use of actual betting records avoids the potential inaccuracies introduced by self-report. The large size of the cohort and the 2-year accumulation of data are sufficiently massive to permit confident investigation of a low-prevalence disorder. We have published a portfolio of studies that examined this longitudinal cohort’s aggregated gambling behavior. This work summarizes the parameters of betting such as size, frequency, and so forth (Braverman & Shaffer, 2010; Broda et al., 2008; LaBrie et al., 2008; LaBrie, LaPlante, et al., 2007; LaPlante, Kleschinsky, LaBrie, Nelson, & Shaffer, 2009; LaPlante et al., 2008; Nelson et al., 2008; Xuan & Shaffer, 2009). This longitudinal cohort enrolled at a time when bwin’s principal focus was on sports gambling. Only a small fraction (i.e., less than 3%) of the cohort did not engage in betting on sports. Our research is the first to investigate the latent structure of actual Internet gambling behavior. We used the characteristics of sports gambling to address whether the nosological structure of intermittent gambling behavior is categorical or dimensional. We applied taxometric techniques successfully used by others to determine whether a taxon of Internet sports gamblers could be identified in our analysis. If our analyses were to identify group of heavily involved gamblers who display similar behaviors that are unique and distinct from the larger group of recreational gamblers, we will have identified the characteristics of a gambling taxon. Evidence that either supports or does not support a taxon for disordered Internet sports gambling will help clinicians and policy makers more effectively identify, prevent, regulate, and treat individuals with gambling-related problems.
Method

Participants

The participants for this study derive from a cohort of 48,114 people who opened an account during February 2005 with the Internet gambling service provider, 8win Interactive Entertainment AG. Their information includes records of betting behavior from enrollment through February 2007. This longitudinal cohort supplied information for several other studies of actual gambling behavior (Broda et al., 2008; LaBrie et al., 2008; LaBrie, LaPlante, et al., 2007; LaPlante et al., 2009; LaPlante et al., 2008; Nelson et al., 2008; Xuan & Shaffer, 2009). The average age of individuals in this cohort was 31 years (SD = 10.0) and most (91.6%) were male. The players in this cohort were from 85 countries. The 40,406 cohort members who engaged in sports betting for more than 3 days comprised the analytic sample that we used to identify and select the betting behavior indicators for the taxometric analyses.

Taxometric analysis is particularly powerful when the potential proportion of taxon members comprise at least 10% of the analytic sample (Schmidt et al., 2004). The prevalence estimates of current disordered gambling among the general population are consistently low, 0.6% to 2% (Kessler et al., 2005; Shaffer, Hall, & Vander Bilt, 1997). Previous analysis of the longitudinal cohort of sports gamblers (LaBrie, LaPlante, et al., 2007) revealed a large number of occasional bettors who are unlikely to be members of a disordered gambling taxon. Consequently, a research sample with the suggested proportion of disordered gamblers would become available only after selecting participants with certain characteristics from the total longitudinal cohort. As an illustration, gambling problems are often associated with excessive betting involvement. Therefore, we increased the likelihood of including the suggested proportion of pathological gamblers in the cohort by including only excessive gamblers in the analytic sample. We defined an excessive gambler as one whose behavior was in the upper 5% on any one or more of the selected indicator variables. A description of these measures follows.

Measures

Previous analyses of individual Internet sports bets yielded eight aggregates describing participant-level gambling involvement (LaBrie, Nelson, et al., 2007). These measures were the following: (a) total amount wagered, (b) total number of bets, (c) average bet size (i.e., total amount wagered divided by total number of bets), (d) duration of betting (i.e., the difference in days between a participant’s first and last betting day), (e) frequency of betting (i.e., the number of betting days divided by the duration); (f) number of bets per day (i.e., the total number of bets divided by the number of betting days); (g) total amount lost (i.e., losses minus winnings); and (h) percent lost (i.e., total amount lost divided by total amount wagered). Having too many indicator replicates the interpretation of results, presents substantial calculation loads (Strack, 2006), and decreases the power of the analysis if the indicators happen to be redundant (Ruscio et al., 2006). The taxometric method requires a minimum of three indicators that should be positively and nontrivially correlated with each other. However, many instances of psychopathology are multidimensional concepts; that is, mental disorders often contain characteristics that belong to multiple diagnostic “domains” that are negatively related or independent (e.g., positive and negative symptoms of schizophrenia; Cuesta, Ugarte, Goicoca, Eraso, & Peralta, 2007). For this reason, some taxometric researchers have used items from a single domain to select a set of appropriately related indicators for use within the taxometric analysis (Olutunji, Williams, Haslam, Abramowitz, & Tolin, 2008). In this study, to select the appropriate indicators, we identified the underlying independent domains (i.e., factors) among the existing variables. We performed a principal-components analysis followed by an orthogonal rotation using the complete longitudinal cohort of 40,406 Internet sports bettors. Next, we selected items from within a single factor to ensure that we have positively correlated indicators for the taxometric analysis.

Taxometric Procedures

To identify the latent structure of actual sports gambling behavior, we used two distinct taxometric procedures: MAXCOV and MAMBAC. We used Ruscio’s taxometric R program (http://www.tcnj.edu/~ruscio/taxometrics.html) to produce taxometric plots and perform all calculations (Ruscio et al., 2006).

We applied the MAXCOV (maximum covariance) procedure to the three selected variables. Each variable, in turn, acts as an index variable. The index variable is ordered, and the observations are divided into groups, termed windows, according to their index variable value. For each of these groups, the procedure computes the covariance between the other two variables. For the MAXCOV, we used the maximum possible number of intervals with the recommended minimum of 25 cases per interval. The larger the number of intervals, the more likely the procedure will reveal a taxonic latent structure (Ruscio et al., 2006; Ruscio et al., 2010). By dividing our sample (N = 4,595) into equal intervals, we obtained 184 intervals: 183 intervals of 25 cases each and one interval with 20 cases.

We calculated and plotted the covariance between the two other indicators for each interval as defined by the input variable. We performed three iterations using a different input variable for each iteration. To ensure reliability of the results and to minimize the sampling error (Ruscio et al., 2006), we conducted the MAXCOV using 50 internal replications. Internal replications are particularly useful when a fixed number of cases define the intervals because cases with the same score might be distributed into several different adjacent intervals. To ensure that this arbitrary assignment did not affect the reliability of our results, we replicated the random assignment of like observations 50 times (Ruscio et al., 2006). To improve the clarity and interpretability of the results, we applied a smoothing technique using the locally weighted least squares (Cleveland, 1979) method to all curves.

MAMBAC (mean above minus below a cut) is an external consistency test of the MAXCOV procedure. A MAMBAC anal-

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1 Recent studies demonstrated the possibility to discover taxa with much lower base rates given favorable data conditions (Ruscio & Marcus, 2007; Ruscio & Ruscio, 2004b; Ruscio, Walters, Marcus, & Kaczetow, 2010).  
2 Originally, Meehl did not specify the equal-N condition as a part of the MAXCOV procedure.
ysis requires only two variables. One variable acts as the index variable to MAXCOV and divides the range of its values into intervals with the same number of observations. The other variable is the output variable and provides the taxonic measurement. In MAXCOV, the measure was the covariance between and among variables. In MAMBAC, the mean is the taxonic measure, and differences in size are added to the search for taxons. The observations in each interval constitute a group, and adjacent intervals can be combined to form a larger group. MAMBAC starts with the first interval and defines observations in that group as below the cut and all other observations as above the cut. The difference between the averages of the output variable above and below cut is calculated and plotted against the value of the index variable. The procedure is repeated by including subsequent intervals in the group below the cut. We applied MAMBAC using the same 184 intervals used for the MAXCOV analyses and for the six combinations of two of the three measures alternating the index and output variables in each pair.

Taxonic Plots

Each taxometric procedure yields several plots. MAXCOV results in three plots, one for each of the three study variables as the index variable. MAMBAC produces six plots to accommodate all pairs of the three variables and alternating the index variable used in each pair. We constructed a single aggregated plot for each procedure to summarize the outcomes of the taxonic analysis.

To accommodate the effect of data characteristics on the shapes of taxonic plots, we used the bootstrap procedure developed by Ruscio and his colleagues (Ruscio & Kaczetow, 2009; Ruscio, Ruscio, & Meron, 2007). The bootstrap method generates plots for idealized taxonic and dimensional outcomes derived from the actual analytic data. These idealized data sets share important features with the actual data set such as indicator correlations, data skew, and kurtosis.

Curve Fitting

The comparison curve fit index (CCFI) measures the similarities between the plots of taxonic test results and both the idealized taxonic and idealized dimensional distributions. The several taxonic results produced by different combinations of variables are aggregated into a single plot for each procedure. CCFI values range from 0.0, indicating agreement with the ideal dimensional curve, to 1.0, indicating agreement with the ideal taxonic curve. Ruscio et al. (2007) suggested that CCFI values in the range of 0.4 to 0.6 be interpreted with caution.

Results

Index Variable Selection

Factor analysis of a Spearman correlation matrix comprising the total set of eight gambling behavior measures (i.e., total amount wagered, total number of bets, bet size, duration, frequency, number of bets per day, total amount lost, and percentage lost) followed by an orthogonal rotation to a simple structure revealed four factors. The fourth factor included only a single measure, percentage lost. This measure was confounded by the large difference in the designed house advantage between fixed odds bets (about 10%) and live action bets (about 3%) and by the need to be immediately involved during the course of a game to place live action bets. Because of its uniqueness and conceptual remoteness from other measures of gambling activity, we excluded percentage lost from the input variables and repeated the factor analysis and rotation with the remaining seven measures of gambling behavior. Entering these seven variables, this analysis revealed three factors measuring the dimensions that we describe as Activity (number of bets, total amount wagered, total amount lost, and bets per day), Amount Risked (bet size), and Time Spent (frequency and duration). This solution explained 82% of the variance. The only factor that contained more than three variables was Activity, which was the largest of the three factors, explaining 43% of the variance. We selected the four variables that loaded .5 or more on this factor to select the research sample.

Research Sample

The research sample of 4,595 sports gamblers comprised 11% of the total longitudinal cohort. These bettors were among the 5% of the total sample with the largest values on one or more of the analytic variables (i.e., total amount wagered, total amount lost, total number of bets, and bets per day) This sample was not different from the total sample by age \( M = 32, SD = 10.2 \) or gender (91% males) and represented 51 different countries. As Table 1 shows, this group displayed behaviors that are an extreme departure from the entire longitudinal sample.

Using the final analytic cohort, the analysis of Spearman correlation coefficients revealed nontrivial positive correlations among three indicators: total amount wagered, total amount lost, and number of bets. These statistically significant \( p < .01; N = 4,595 \) correlation coefficients ranged from .34 (between total amount lost and total amount wagered) to .56 (between total amount lost and total amount wagered). The fourth indicator—bets per day—was negatively correlated with total amount lost and total amount wagered. Taxometric analysis requires positive correlation between the indicators; therefore, we excluded bets per day from the following taxometric procedures.

As Table 2 shows, the distributions of all indicators were positively skewed and evidenced substantial kurtosis.

Taxometric Analysis

MAXCOV. The MAXCOV procedure yielded three plots; these are presented in Appendix A, each using one of the three variables as an index variable. A visual inspection of the individual plots did not indicate the outcomes to be characteristic of an underlying taxonic structure. As Figure 1 illustrates, the aggregated plot was more similar to the dimensional comparison data. However, the CCFI (Ruscio et al., 2007) was ambiguous (.49),

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3 We extend special thanks to John Ruscio and William Grove for providing valuable suggestions regarding indicator selection and general interpretation of the results.
4 We used Spearman correlation to adjust for abnormal distribution of the data and to match the previously published analysis (Shaffer & Hall, 2001). However, Pearson correlation analysis produced similar results.
failing to provide evidence to support either a taxonic or a dimensional view of Internet sports gambling.

MAMBAC. The MAMBAC procedure produced six plots as shown in Appendix B. As with the MAXCOV procedures, a visual inspection of the MAMBAC plots failed to yield evidence of a characteristic underlying taxonic structure. In addition, as with the MAXCOV analysis, the CCFI (Ruscio et al., 2007) was ambiguous (.56) and consistent with the comparison aggregate curve presented in Figure 2, which does not clearly indicate the research data to be similar to either prototype. Taken together, these results fail to provide evidence supporting either a taxonic or a dimensional view of Internet sports gambling.

Discussion

This study is the first taxometric analysis of actual Internet sports gambling behavior. The results of two taxometric procedures failed to provide support for the presence of a taxonic structure underlying Internet sports gambling. The essence of taxometric analysis lies in the consistency among and within different procedures. Neither taxometric procedure in this study demonstrated clear evidence of taxonicity.

Researchers sometimes interpret the lack of consistent evidence of taxonicity as evidence for a dimensional latent structure (Cuesta et al., 2007; Frazier, Youngstrom, & Naugle, 2007; Ginestet, Mitchell, & Wellman, 2008; Silove et al., 2007). Given that this is a new area of inquiry, we prefer a more conservative interpretation. More research is necessary to clarify whether other measures of gambling activity and/or other aggregation methods (e.g., maximums and periods of peak activity) and/or other types of gambling might reveal several taxa or an underlying taxonic structure.

Identifying taxa is a complex process that can yield mixed results. For example, the taxometric research focusing on nicotine and alcohol dependence provides conflicting results regarding the latent structure of these disorders. Ginestet et al. (2008) demonstrated dimensional structure of nicotine dependence; however, other researchers reported that smoking variables might reflect both an underlying categorical structure and an underlying dimensional one (Goedeker & Tiffany, 2008). Similarly, Slade et al. identified a dimensional structure underlying alcohol dependence (Slade, Grove, & Teesson, 2009), but other researchers report that a taxonic structure better represents this disorder (Walters, Hennig, Negola, & Fricke, 2009). Disordered gambling can be added to nicotine and alcohol dependence as disorders needing further research to clarify their underlying nature.

The goal of this study was to examine whether there is a distinct category or taxon associated with extreme Internet gamblers as defined by their betting characteristics. Evidence of such a taxon would imply that recreational Internet gamblers are qualitatively different from those who gamble excessively. Understanding the distinct categories and characteristics between recreational and disordered gamblers would help to guide researchers and clinicians alike to the important influential associations between excessive gambling and player attributes. For example, a taxon is likely to reflect distinct patterns of comorbidity, neural substrates, and neuropsychological and genetic correlates associated with recreational gamblers compared with disordered gamblers. Identifying the characteristics of a taxon for disordered gambling would have important implications for clinicians, policy makers, regulators, the health care industry, and the gaming industry. For example, currently few gamblers receive insurance reimbursement for the treatment of pathological gambling despite its inclusion in the DSM–IV. Identifying a uniquely, and qualitatively different group of gamblers compared with recreational gamblers suggests that disordered gambling has an underlying architecture similar to other taxonic psychopathologies. For example, schizotypy (Golden & Meehl, 1979; Korfine & Lenzenweger, 1995; but see Rawlings, Williams, Haslam, & Claridge, 2008, for dimensional results) and autism-related cognitive dysfunction (Munson et al., 2008) have a strong evidence base supporting a categorical perspective. As with these other disorders, if a discrete taxonic structure reflects the features of disordered gamblers, this finding holds important implications for accurate diagnosis, effective treatment, early identification of risk, and improved understanding of etiology (Beaucaine, 2007). Armed with such a finding, researchers and clinicians should be able to stratify disordered gamblers and their unique characteristics to better inform treatment, gambling-related public policy, neurogenetic research, and treatment outcome measures.

Alternatively, a dimensional view of Internet sports gambling would suggest that there is no qualitative distinction between the characteristics of recreational and disordered gamblers. This conclusion would have important implications for public policy, the

Table 1

Means (and Standard Deviations) for Research Sample and Total Cohort of Internet Sports Bettors

<table>
<thead>
<tr>
<th>Variable</th>
<th>Analytic sample (n = 4,595)</th>
<th>Remainder of cohort (n = 35,811)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total amount wagered</td>
<td>€26.511 [$34,355] (€58,735 [€76,117])</td>
<td>€964 [$1,249] (€1,644 [$2,129])</td>
</tr>
<tr>
<td>Total amount lost</td>
<td>€2.307 [$2,987] (€5.313 [$6,879])</td>
<td>€116 [$1,50] (€319 [$413])</td>
</tr>
<tr>
<td>Total number of bets</td>
<td>2,601 (4,683)</td>
<td>198 (274)</td>
</tr>
<tr>
<td>Bets per day</td>
<td>17 (19)</td>
<td>4 (3)</td>
</tr>
</tbody>
</table>

Note. € = Euro. Approximate monetary equivalents are provided in U.S. dollars.

Table 2

Indicator Distribution Skew and Kurtosis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Skew</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total amount wagered</td>
<td>8.03</td>
<td>102.03</td>
</tr>
<tr>
<td>Total amount lost</td>
<td>5.93</td>
<td>65.04</td>
</tr>
<tr>
<td>Total number of bets</td>
<td>7.57</td>
<td>91.50</td>
</tr>
</tbody>
</table>
For example, finding a clear dimensional structure of gambling behavior encourages the development of public policy that targets responsible gambling programs, which should encourage new technology that can limit excessive patterns of play instead of trying to identify players with distinctive personal risk characteristics. These responsible gambling programs also might emphasize limits to gambling opportunities. Similarly, researchers need to develop and implement continuous measures of gambling to replace the more common existing categorical diagnostic tools that are traditionally included in most psychiatric classification systems. As an illustration, the DSM–IV typically uses a categorical diagnostic approach for most psychiatric disorders, including pathological gambling; that is, an individual either has the disorder or does not. However, a dimensional view of gambling suggests that nosologists need to develop tools that can identify the quantitative differences among gamblers with mild, subdiagnostic signs and symptoms compared with gamblers who have more moderate or severe signs and symptoms. Advancing an improved understanding of these dimensional differences will permit clinicians to refine treatment planning distinctions so that they can allocate clinical resources to patients with different levels of need.

A dimensional model of Internet sports gambling also would have important implications for the treatment of gambling and co-occurring problems (Widiger & Mullins-Sweatt, 2005). Research shows that, in some cases, dimensional models provide more valid explanations of comorbidity than do categorical models (Widiger & Samuel, 2005). For many disorders, including alcohol dependence, substance dependence, and pathological gambling, comorbidity is more common than not (Cunningham-Williams, Cottler, Compton, Spitznagel, & Ben-Abdallah, 2000). A dimensional model of disordered gambling implies that co-occurring gambling, alcohol, and drug use disorders might reflect a single addiction syndrome (e.g., the syndrome model of addiction (Shaffer, LaPlante, et al., 2004) instead of co-occurring distinct and separate psychopathologies. Dimensional findings would encourage clinicians to assess pathological gambling, like most anxiety and mood disorders, using behavioral features that are shared by the general population.

In the absence of definitive results, it is important to emphasize that there is value to both a categorical and a dimensional view of gambling (Peralta & Cuesta, 2007). Clinicians can integrate the categorical and dimensional approaches; they should apply each for specific purposes (Kraemer, Noda, & O’Hara, 2004). For example, the dimensional perspective can guide clinicians and researchers to track symptom intensity and severity during treatment or when evaluating the efficacy of prevention efforts. A dimensional approach can help clinicians prepare patients for long-term treatment outcomes: gambling and risk taking are inherent in many aspects of life, so researchers should evaluate treatment outcomes and prevention efficacy against a continuous landscape of risk taking instead of a gambling–no gambling dichotomy. Alternatively, a categorical approach is useful to solve the pragmatic administrative needs associated with patient grouping, insurance billing, or public health program resource allocation.

The categorical interpretation of dimensional data may have important public health value. For example, there are commonly
applied cutoffs for cholesterol and blood pressure used to identify patients who need treatment. In our research, we are making similar efforts to identify cutoffs to distinguish gamblers who need early interventions.

Limitations and Strengths

As with all research, this study is not without its limitations. Similar to the research focusing on other potential expressions of addiction (e.g., nicotine and alcohol use), our findings were ambiguous, failing to provide evidence for a disordered gambling taxon. This uncertainty might be the result of methodological considerations, such as indicator selection, data distribution abnormalities, and/or the multidimensionality of the phenomenon under investigation. The results indicating whether disordered gambling behavior is continuous or categorical depend on the selection of indicators. Our indicator selection was informed by previous studies (LaBrie et al., 2008; LaPlante et al., 2008) and the data reduction analyses specific to this study. Therefore, it is possible that other indicators (e.g., duration, frequency) might be more sensitive indices of an underlying categorical structure. We have no external criteria such as diagnostic criteria of DSM-IV-based gambling-related problems) that could be examined for concurrent validity of the indicators. Our data have strong positive skews for all variables, and gambling behavior is liable to substantial kurtosis. However, several simulation studies demonstrated the robustness of MAMBAC and MAXCOV procedures using skewed indicators (Cleland & Haslam, 1996; Haslam & Cleland, 1996; Ruscio & Kaczetow, 2009).

Taxometric analyses of low base-rate behaviors can be problematic. Schmidt et al. (2004) recommended that members of the assumed taxon compose at least 10% of the analytic sample. General population surveys, however, reveal that the prevalence of people who currently satisfy clinical criteria to qualify as disordered (e.g., pathological) gamblers is considerably less than 10% (Kessler et al., 2005; Shaffer et al., 1997). However, these surveys did not indicate the relative prevalence of disorder among Internet sports gamblers. Absent such a prevalence estimate, we considered it necessary to limit the analytic sample to increase the proportion of potential taxon members: those Internet gamblers most likely to qualify as pathological gamblers. Further, because excessive financial costs often accompany characteristics of disordered gambling, we limited the analytic sample to the most heavily involved bettors because this group loses the most money. Nevertheless, these efforts do not guarantee that the analytic sample has an adequate mix of taxonic and nontaxonic gamblers. If the sample was composed almost exclusively of one group or the other, we could not identify a taxonic outcome.

In this study, we measured gambling involvement by aggregating behaviors over time. Among behavioral problems, measures of total involvement or consumption might not identify excessive episodic behavior (e.g., binge drinking.) Aggregations also might not recognize people who were once heavily involved but who adapt and continue to gamble moderately or people with a long history of moderate gambling who are just beginning to enter a period of excessive play. Although these conditions might allow some disordered gamblers to escape detection, excessive financial burdens generally exhaust resources and force gamblers to discontinue play. bwin does not extend credit or arrange for other than cash and cash equivalent bets.

Previous taxometric studies frequently used another taxometric procedure—MAXEIG—in addition to MAXCOV and MAMBAC. However, recent research demonstrated almost complete redundancy between MAXEIG and MAXCOV procedures (Ruscio et al., 2010; Walters & Ruscio, 2010). Consequently, we decided to report the results of only two procedures.

Despite these limitations, this study has many important strengths. One of the substantial advantages of our analysis is the use of a large sample. Increasing the sample size is the best solution for avoiding many hazards associated with taxometric analyses, including the difficulty of graph interpretation (Schmidt et al., 2004). However, even with a large sample size, it is important to recognize the importance of indicator validity and indicator correlations within putative groups for the analysis. Another important advantage of this study is that we used continuously distributed indicators. Taxometric analyses often fail because of the absence of continuous measures. For example, psychiatric research often uses Likert-type interval scales as operational measures of one or more variables (Schmidt et al., 2004). Interval scales typically divide indicator variables into few intervals; this decreases the power of the taxometric analysis and limits the likelihood of identifying a taxon. To provide a robust taxometric test of excessive gambling, we used continuous measures of gambling behavior (i.e., total number of bets, total money wagered, and total money lost). With a substantial sample size and continuous measures, our study had appropriate design parameters for its investigative objectives.

Conclusion

Despite optimizing the opportunity to identify the taxonic latent structure underlying excessive gambling, our results failed to support a categorical understanding of excessive Internet sports gambling behavior. Given the limitations of the analyses and the fact that this article represents the first attempt to address the question of latent structure of actual Internet sports gambling data, it is important to use caution while interpreting these results. It might be too early to declare that excessive gambling behavior is not qualitatively different from recreational sports gambling. Current evidence suggests that excessive gamblers share the behavioral features of gambling with their recreational gambling counterparts and that disordered gamblers reside at the extreme of the dimensions that underlie the distributions that characterize these behaviors.

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Appendix A

MAXCOV Curves Plots

Note. Ind = Indicator.
Appendix B

MAMBAC Curves Plots

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