A Method for Classifying Pathological Gamblers According to “Enhancement,” “Coping,” and “Low Emotion Regulation” Subtypes

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Abstract

Pathological gamblers vary in their personality traits, psychopathological characteristics, and motivations for gambling. Methods for classifying them according to disseminated subtyping schemes, however, are not readily available, which may hinder further research on subtypes or efforts to incorporate subtyping schemes into clinical practice. With regard to affective motivations for gambling, we describe and evaluate a method for classifying pathological gamblers according to “enhancement,” “coping,” and “low emotion regulation” subtypes. Generalized squared distance was used to determine the best profile fit for 158 pathological gamblers on the basis of their Inventory of Gambling Situations (IGS) scores and in relation to refined IGS subtype profiles obtained through cluster analysis, these refined subtypes also having been validated via Gambling Motives Questionnaire scores. No gamblers were misclassified, suggesting that this method may perform well on cross-validation. For interested researchers and practitioners, an easy-to-use tool is available that automates this profile-matching approach to classification. Additional research is needed on how this method fares in independent samples of regular gamblers and of individuals with gambling disorder.

Keywords: gambling disorder, gambling motives, subtyping, classification, assessment

Résumé

Les joueurs pathologiques varient quant à leurs traits de personnalité, leurs caractéristiques psychopathologiques et leurs motivations à jouer. Il n’existe cependant pas de méthodes facilement utilisables pour les classés selon des schémas de sous-types disséminés, ce qui risque de ralentir la recherche sur les sous-types ou les efforts déployés pour intégrer des schémas de sous-types à la pratique clinique. En ce qui concerne les motivations affectives au jeu, la présente étude décrit et analyse une méthode de classement des joueurs pathologiques reposant les sous-types suivants : la « stimulation »,
l’« adaptation » et la « faible régulation des émotions ». La distance généralisée au carré a été utilisée pour déterminer la « meilleure correspondance de profil » pour 158 joueurs pathologiques en fonction de leur score au questionnaire de la liste des occasions de jeu (LOJ) et relativement à des profils plus précis de sous-types de la LOJ obtenus au moyen d’une analyse typologique et validés à partir des résultats du questionnaire sur les motivations à jouer. Aucun joueur n’a été classé de manière erronée à l’aide de la méthode analysée, ce qui laisse entendre qu’elle peut être efficace dans le cadre d’une validation croisée. Un outil « facile d’emploi » permettant d’automatiser une telle approche de classification par association avec des profils se trouve ainsi accessible aux chercheurs et aux praticiens intéressés. Des recherches supplémentaires sont nécessaires pour déterminer l’efficacité de cette méthode avec des échantillons indépendants de joueurs ordinaires et de joueurs présentant un problème de jeu.

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**Introduction**

Individuals with gambling disorder vary in their personality traits, psychopathological characteristics, and motivations for gambling. In fact, a comprehensive review of the literature revealed 18 articles that described subtypes of gambling disordered individuals according to these variables (Milosevic & Ledgerwood, 2010). Some of these subtypes included “recurringly depressed” and “chronically understimulated” gamblers (McCormick, 1987); “escape seekers” and “action seekers” (Lesieur & Blume, 1991); “simple,” “demoralized,” and “hedonic” gamblers (Vachon & Bagby, 2009); and “behaviorally conditioned,” “emotionally vulnerable,” and “antisocial impulsivist” gamblers (Blaszczynski & Nower, 2002; Ledgerwood & Petry, 2010). Subtyping pathological gamblers in such ways may lead to a better understanding of the potentially distinct etiologies of problem gambling for each subtype, which could have implications for tailoring treatment strategies to best meet the needs of each group and improve their respective treatment outcomes. However, despite dissemination of potentially useful subtyping schemes, we are unaware of any empirically supported methods for classifying pathological gamblers according to these proposed schemes, which may hinder further research on subtypes themselves or efforts to incorporate subtyping schemes into clinical practice.

In clinical practice, establishing why a client gambles (i.e., functional analysis) may facilitate a focused intervention that could enhance the therapeutic outcome (Stewart & Zack, 2008). The purpose of this article is to describe and evaluate a method for classifying individuals with gambling disorder according to their affective motivations for gambling, more specifically, for classifying those with gambling disorders according to the “enhancement,” “coping,” and “low emotion regulation” subtypes first described by Stewart, Zack, Collins, Klein, and Fragopoulos (2008). In their original study, Stewart et al. (2008) had pathological gamblers complete the
Inventory of Gambling Situations (IGS; Littman-Sharp, Turner, & Toneatto, 2009)—a measure of the relative frequency of heavy gambling in various high-risk situations. Principal components analysis (PCA) was performed on the IGS subscale scores and revealed two higher order factors that were inferred from the observed pattern of factor loadings of the IGS subscale scores. These higher order factors included Unpleasant Emotions (i.e., a Negative Gambling Situations factor) and Pleasant Emotions (i.e., a Positive Gambling Situations factor). The factor scores were subjected to cluster analysis, which revealed three clusters: (a) enhancement gamblers, who were characterized by low negative and high positive high-risk gambling situation factor scores; (b) coping gamblers, who were characterized by very high negative and high positive high-risk gambling situation factor scores; and (c) low emotion regulation gamblers, who were characterized by low negative and low positive high-risk gambling situation factor scores. Factors were labelled according to the primary motives suggested by the main situations in which the participants reported heavy gambling. From these observed patterns of situation-specific gambling, it was inferred that enhancement gamblers gambled purely for positive reinforcement reasons; coping gamblers gambled for both positive and negative reinforcement, but mainly for negative reinforcement reasons; and low emotion regulation gamblers gambled for reasons other than to directly alter their mood (Stewart et al., 2008). Given that these subtypes were obtained by using a single, relatively brief, self-report measure of situation-specific gambling, it was argued that this subtyping scheme had the advantage of being readily applicable in the clinical setting. However, without an easy-to-use method for classifying pathological gamblers that approximates the subtyping scheme obtained through cluster analysis, practitioners may not be able to classify new clients according to the scheme, which could hamper its possible clinical utility and which further underscores the need for an empirically based method of classification.

The method for classification described here was borrowed from the pain literature (see McKillop & Nielson, 2011; Turk & Rudy, 1988) and has been used successfully to match chronic pain patients, from their responses to a multi-item pain inventory known as the Multidimensional Pain Inventory (MPI; Kerns, Turk, & Rudy, 1985), to “dysfunctional,” “interpersonally distressed,” or “adaptive coper” subtype profiles. More precisely, generalized squared distance (D²), also referred to as Mahalanobis distance, was used in the present study to determine the best profile fit for pathological gamblers on the basis of their IGS factor scores and in relation to IGS enhancement, coping, and low emotion regulation subtype profiles obtained through cluster analysis. From some of the favourable results observed in the pain literature showing misclassification rates as low as 1.6% and 3% with kappa reliability coefficients as high as .96 and .975 (McKillop & Nielson, 2011; Turk & Rudy, 1988), we hypothesized that D² would approximate the assignment of gamblers to subtypes via cluster analysis with good precision.

Another equally important purpose of the present study was to first determine the extent to which the original subtypes derived by Stewart et al. (2008) could be refined by using an alternative, and perhaps more appropriate, clustering algorithm. It has been demonstrated that collinearity among variables can be problematic when
conducting K-means cluster analysis with Euclidean distance specified as the distance metric because it assumes independence of the clustering variables and may produce distorted results (Sambandam, 2003). In the original study by Stewart et al. (2008), K-means cluster analysis was conducted by using the moderately correlated IGS Negative Gambling Situations and Positive Gambling Situations factor scores with Euclidean distance used as the distance measure. The present article describes the results obtained from a cluster analysis by using these original IGS factor scores with Mahalanobis distance specified as the distance metric, as it has been deemed an effective solution to the problem of collinearity (Sambandam, 2003). Moreover, given that Mahalanobis distance takes the correlated nature of variables into account, both as a clustering algorithm and as a method of determining individuals’ best profile fit, it made sense to refine the original IGS subtype profiles for enhancement, coping, and low emotion regulation gamblers. In keeping with this study purpose, and consistent with the original study conducted by Stewart et al. (2008), it was also necessary to determine the extent to which a refined cluster solution could be validated via scores on a measure of explicitly defined, directly assessed gambling motives, separate from the IGS and its focus on antecedents/high-risk situations and inferred motives.

Method

Participants

The sample comprised the same 158 gamblers (mean age = 36.0 years, SD = 10.7 years; 77% men) who were recruited from the community by Stewart et al. (2008) through advertisements, and the data analyzed here are the same data obtained from that sample. Gamblers had to meet probable pathological gambler status by obtaining a score of 5 or greater on the South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987; mean score at screening = 11.8, SD = 4.0). They also had to disclose consuming alcohol at least 50% of the time when they gambled, as they were originally recruited for a study that examined the parallels between drinking and gambling motives (see Stewart & Zack, 2008). The minimum age to be eligible to participate was 19 years, and gamblers also had to be alcohol-, drug-, and medication-free during their testing session. Exclusionary criteria included a history of chronic and serious mental illness (e.g., bipolar disorder, schizophrenia).

Materials

Participants completed a variety of self-report measures. The measures of relevance to the present study included the IGS (Littman-Sharp et al., 2009), the Gambling Motives Questionnaire (GMQ; Stewart & Zack, 2008), and the SOGS (Lesieur & Blume, 1987). Sample items for these measures can be seen in Table 1, along with the number of items for each of the subscales and internal consistencies (alphas) for the subscales in the present sample.

Inventory of Gambling Situations. The IGS (Littman-Sharp et al., 2009) is a self-report questionnaire made up of 63 items that measure the relative frequency of
heavy gambling in various high-risk situations. It is used to profile possible relapse situations for problem gamblers in both research and treatment settings (Littman-Sharp et al., 2009). The IGS was modelled after the reliable and valid Inventory of Drinking Situations (IDS; Annis, Graham, & Davis, 1987; Carrigan, Samoluk, & Stewart, 1998; Stewart, Samoluk, Conrod, Pihl, & Dongier, 2000). That is, items from the IDS Unpleasant Emotions, Pleasant Emotions, Social Pressure, Urges and Temptations, Testing Personal Control, and Conflict with Others scales were worded to fit the context of gambling. Furthermore, new items were added that were specific to the context of gambling: items from the Winning and Chasing Losses, Confidence in Skills, Need For Excitement, and Worried Over Debts scales. The initial pool of items was reviewed by experts, and items were selected on the basis of psychometric analyses, including factor analysis (Littman-Sharp et al., 2009). When completing the IGS, gamblers indicate their frequency of heavy gambling over the past year (with responses ranging from 1 = almost never/never gambled heavily in that situation to 4 = almost always gambled heavily in that situation) in 10 separate categories of situations. The IGS has demonstrated strong psychometric properties (Littman-Sharp et al., 2009). It was used as the primary

<table>
<thead>
<tr>
<th>Measure/scale</th>
<th>No. items</th>
<th>( \alpha )</th>
<th>Sample item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inventory of Gambling Situations (IGS)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unpleasant Emotions</td>
<td>10</td>
<td>.91</td>
<td>When I couldn’t stand things anymore and needed to get away.</td>
</tr>
<tr>
<td>Worried Over Debts</td>
<td>5</td>
<td>.88</td>
<td>When I was worried about my debts.</td>
</tr>
<tr>
<td>Conflict With Others</td>
<td>7</td>
<td>.90</td>
<td>When I had an argument with a friend.</td>
</tr>
<tr>
<td>Testing Personal Control</td>
<td>7</td>
<td>.88</td>
<td>When I started to believe that gambling was no longer a problem for me.</td>
</tr>
<tr>
<td>Winning and Chasing Losses</td>
<td>6</td>
<td>.83</td>
<td>When I needed to win back the money I lost gambling.</td>
</tr>
<tr>
<td>Urges and Temptations</td>
<td>9</td>
<td>.87</td>
<td>When I suddenly had an urge to gamble.</td>
</tr>
<tr>
<td>Pleasant Emotions</td>
<td>5</td>
<td>.85</td>
<td>When I was happy.</td>
</tr>
<tr>
<td>Social Pressure</td>
<td>7</td>
<td>.82</td>
<td>When someone challenged me to a bet.</td>
</tr>
<tr>
<td>Need for Excitement</td>
<td>6</td>
<td>.85</td>
<td>When I wanted some action.</td>
</tr>
<tr>
<td>Confidence in Skills</td>
<td>5</td>
<td>.80</td>
<td>When I felt confident about my gambling skills.</td>
</tr>
<tr>
<td>Gambling Motives Questionnaire (GMQ)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coping Motives</td>
<td>5</td>
<td>.77</td>
<td>Because it helps when you are feeling nervous or depressed.</td>
</tr>
<tr>
<td>Enhancement Motives</td>
<td>5</td>
<td>.78</td>
<td>Because it’s exciting.</td>
</tr>
<tr>
<td>South Oaks Gambling Screen (SOGS)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOGS Total</td>
<td>11</td>
<td>.78</td>
<td>Have you ever felt guilty about the way you gamble or what happens when you gamble?</td>
</tr>
</tbody>
</table>

*Note.* IGS (Littman-Sharp et al., 2009); GMQ (Stewart & Zack, 2008); and SOGS (Lesieur & Blume, 1987).
measure of gambling motives in the present study, where motives were inferred by virtue of the primary situations in which gamblers reported gambling heavily.

**Gambling Motives Questionnaire.** Participants completed Stewart and Zack’s (2008) GMQ, a measure modelled after the reliable and valid Drinking Motives Questionnaire (DMQ; Cooper, Russell, Skinner, & Windle, 1992). The GMQ captures the relative frequency of gambling for 15 specific reasons. GMQ items were adapted directly from the DMQ, except for one item. More specifically, this one item was rephrased from “to get high” on the DMQ to “to get a high feeling” on the GMQ, so that it was more appropriate to the context of gambling. Consistent with the DMQ, there are three subscales: Social, Coping, and Enhancement gambling motives. Participants rated the relative frequency of their gambling on the same 4-point scale used for the DMQ (i.e., 1 = almost never/never; 2 = sometimes; 3 = often; 4 = almost always). Stewart and Zack (2008) demonstrated that the GMQ has strong psychometric properties.

**South Oaks Gambling Screen.** The SOGS (Lesieur & Blume, 1987) is a 20-item self-report measure that taps respondents’ lifetime gambling habits. The 20 items used to obtain the SOGS total score were derived from problem gambling counsellors, Gamblers Anonymous 20 questions, and the *Diagnostic and Statistical Manual of Mental Disorders* (3rd ed., American Psychiatric Association, 1980). Those with a likely gambling disorder (i.e., “probable pathological gamblers”) are usually identified by using a total score of 5 or more as the SOGS cut-off score; the psychometric properties of the SOGS are acceptable (see Lesieur & Blume, 1987).

**Procedure**

This secondary analysis used the data set obtained by Stewart et al. (2008). In the original study, testing was completed individually. Participants were asked to abstain from alcohol consumption for a period of at least 12 hours prior to their appointment, and breath alcohol tests were used upon arrival at the laboratory in order to confirm abstinence. A computerized reaction time task was completed first (see Zack, Stewart, Klein, Loba, & Fragopoulos, 2005, for results). After a short break, participants completed the aforementioned self-report questionnaires.

**Results**

**Reducing the IGS Data**

In the original study by Stewart et al. (2008), prior to cluster analyzing the data from the IGS, factor analysis was performed on the IGS subscale scores in order to reduce the 10 subscales to a more parsimonious number of core types of gambling situations. The factor structure, factor labels, and factor scores for the participants in the original study were retained for the present study. To summarize, Stewart et al. (2008) conducted PCA on the 10 subscale scores of the IGS. The researchers could proceed with PCA on the given data set, as the Kaiser-Meyer-Olkin measure of
sampling adequacy was > .50 (i.e., .92). Oblique rotation was selected to permit inter-correlation among factors, and both inspection of the scree plot and use of Kaiser’s eigenvalue > 1 rule indicated a two-factor solution. The two-factor solution obtained demonstrated excellent simple structure, with only one observed complex loading: The Urges and Temptations scale loaded on both factors. Furthermore, there were no hyperplane items, and there were a large number of salient loadings on each factor. It should be noted that the two factors obtained were found to be moderately inter-correlated ($r = .64$). Together, these two factors were found to account for 81.2% of the variance in IGS item scores. Because the first factor showed strong salient loadings on the Unpleasant Emotions, Conflict with Others, and Worried Over Debts subscales, it was labelled Negative Situations for gambling. Prior to rotation, the first factor was found to account for 70.1% of the variance in IGS subscale scores. Because the second factor showed strong salient loadings from the Pleasant Emotions, Need for Excitement, and Social Pressure subscales, it was labelled Positive Situations for gambling. Prior to rotation, the second factor was found to account for an additional 11.1% of the variance in IGS subscale scores.

**Refining the Stewart et al. (2008) Subtypes of Pathological Gamblers With the Alternative Clustering Algorithm**

In the original study (Stewart et al., 2008), initial clusters were first obtained via Ward’s squared Euclidean distance method by using the factor scores for each participant. The scree plot method indicated a three-cluster solution for the number of clusters in the data set. Next, Stewart et al. (2008) conducted a K-means cluster analysis by using the IGS factor scores for each participant, and this analysis was constrained to produce a three-cluster solution. Euclidean distance was specified as the distance metric. In the present study, cluster analysis was re-run on the original IGS factor scores with Mahalanobis distance specified as the distance metric. The K-means cluster analysis conducted in the present study was similarly constrained to produce a three-cluster solution. Again, a cluster was identified that was characterized by high scores on both the Negative Gambling Situations factor (mean factor score = 1.128) and the Positive Gambling Situations factor (mean factor score = 0.577), with a notably higher elevation on the Negative Gambling Situations factor; thus, the cluster was inferred to involve gamblers who gamble primarily to cope with negative situations and was thus labelled the coping gamblers cluster ($n = 50; 32\%$ of the entire sample). As in the original study, another cluster was identified that was characterized by negative scores on the Negative Gambling Situations factor (mean factor score = -0.395) and positive scores on the Positive Gambling Situations factor (mean factor score = 0.321); thus, this cluster was again labelled as enhancement gamblers ($n = 70; 44\%$ of the entire sample) because of the relatively higher elevation on the Positive Gambling Situations factor. The third cluster was characterized by low scores on both the Negative Gambling Situations (mean factor score = -0.756) and the Positive Gambling Situations (mean factor score = -1.349) factors. This cluster was similar to the third cluster observed in the original study; thus, the cluster was again inferred to be motivated to gamble by reasons other than desires to regulate emotions.
and was labelled low emotion regulation gamblers \((n = 38; \, 24\% \, \text{of \, the \, entire \, sample})\) because of their low scores on both factors of the IGS.

For comparative purposes, the three clusters of gamblers obtained in the original study and those obtained in the present study are profiled in Figure 1. As can be seen in the figure, the three profiles of gamblers obtained via the K-means cluster analysis by using Euclidean distance (original study) were similar to the K-means cluster analysis obtained by using Mahalanobis distance (present study). Moreover, there was moderate agreement between the two clustering algorithms \((kappa = .59, \, p < .001; \, \text{Landis} \, \& \, \text{Koch, 1977})\). More specifically, 118 cases \((75\% \, \text{of \, the \, entire \, sample})\) were assigned to similarly labelled clusters by both clustering algorithms.

**Validation of the Refined Cluster Analysis with the GMQ**

Stewart et al. (2008) performed a factor analysis on the GMQ prior to validating the original IGS cluster solution. Again, these factor analytic results were used for validating the refined IGS cluster solution. To summarize, a PCA with oblique rotation was conducted on the GMQ. This analysis produced the three expected GMQ factors of Enhancement, Social, and Coping motives, using Kaiser’s eigenvalue \(> 1\) rule to determine the number of factors to retain. Scores on the factors for each participant were saved for hypothesis testing, so that each gambling motive score was weighted for the relative contributions of each of the GMQ items. As in the original study, a 3 (refined IGS cluster group) \(\times\) 2 (GMQ subscale) analysis of variance was conducted with the Enhancement and Coping GMQ factor scores entered again as the dependent variables. Consistent with the results of the Stewart et al. (2008) original study, the analysis indicated a main effect of IGS cluster group, \(F(2, \, 151) = 27.03, \, p < .001\). As with the original study, this result was qualified by the predicted significant Refined IGS Cluster Group \(\times\) GMQ Subscale interaction \(F(2, \, 151) = 15.78, \, p < .001\), which again reflected relatively higher GMQ Enhancement factor scores \((M = .502; \, SD = .562)\) versus GMQ Coping factor scores \((M = -.113; \, SD = .774)\) in the IGS enhancement gambler cluster, as compared with relatively higher GMQ Coping factor scores \((M = .990; \, SD = .765)\) versus GMQ Enhancement factor scores \((M = .578; \, SD = .634)\) in the IGS coping gambler cluster. As in the original Stewart et al. (2008) study, there was a significant simple effect of refined IGS cluster group membership for the GMQ Enhancement motives factor scores, \(F(2, \, 151) = 13.05, \, p < .001\). Games-Howell post hoc tests showed that, as was hypothesized in the original study, the IGS enhancement gambler cluster again obtained significantly higher \((p < .01)\) GMQ Enhancement factor scores than did the IGS low emotion regulation gambler cluster \((M = -.085; \, SD = .810)\). Similarly, the IGS coping gambler cluster again obtained significantly higher GMQ Enhancement factor scores \((p < .001)\) than did the IGS low emotion regulation gambler cluster; however, these clusters did not obtain significantly higher GMQ Enhancement factor scores \((p > .05)\) than did the IGS enhancement gambler cluster. Consistent with the original Stewart et al. (2008) study, there was another significant simple effect of refined IGS cluster group membership for the GMQ Coping...
Figure 1. Comparison of gambler profiles obtained by using K-means cluster analysis on Inventory of Gambling Situations factor scores with simple Euclidean distance specified as the distance metric (original study) versus Mahalanobis distance specified as the distance metric (present study).
motives factor scores, $F(2, 151) = 27.53$, $p < .001$. As was hypothesized in the original study, the IGS coping gambler cluster obtained significantly higher GMQ Coping factor scores ($p < .001$) than did the IGS low emotion regulation gambler cluster ($M = -.024; SD = .997$) and significantly higher GMQ Coping factor scores ($p < .001$) than did the IGS enhancement gambler cluster. As was the case in the original study, GMQ Coping factor scores did not differ significantly between the IGS enhancement gambler and low emotion regulation gambler clusters in the present study ($p > .05$).

For comparative purposes, the GMQ Coping and Enhancement motives factor scores for the clusters of gamblers obtained with the IGS in the original study and the clusters of gamblers obtained in the present study with the IGS are plotted in Figure 2. (Note that the $ns$ for each cluster in Figures 1 and 2 are not identical because full data on the GMQ were unavailable for four participants.) As can be seen in Figure 2, consistent with the results of the original study, the clusters of gamblers identified with the IGS in the present study were similarly cross-validated by a discriminating elevation in GMQ Coping motives in coping gamblers and by noteworthy elevations in GMQ Enhancement motives in both enhancement and coping gamblers.

### Determining Profile Goodness of Fit for Individual Cases of Pathological Gambling

The method used by Turk and Rudy (1988), and later by McKillop and Nielson (2011), for comparing a respondent’s scores on the MPI (Kerns et al., 1985) with three MPI psychosocial profiles—dysfunctional, interpersonally distressed, and adaptive coper—was used in the present study to compare a gambler’s scores on the IGS with the refined IGS enhancement, coping, and low emotion regulation gambler profiles. More specifically, generalized squared distances ($D^2$) were calculated for each gambler by comparing his or her scores on the IGS factors with the three refined gambler profiles. These calculations yielded three $D^2$ values for each gambler, the lowest value representing the best profile fit for the gambler. $D^2$ is defined as follows:

$$D^2 = (x_i - x_j)'S^{-1}(x_i - x_j)$$

McKillop (2010) provided a description of the steps required for calculating $D^2$, as well as an example of how to compare a respondent’s profile of scores on the MPI to the adaptive coper profile. In a similar manner, the following example describes the comparison of a gambler’s profile of IGS factor scores to the coping gambler profile to demonstrate these calculations in the context of the present study. More specifically, in the preceding formula, the terms $x_i$ and $x_j$ represent any two points in multivariate space, and the term $S^{-1}$ represents the inverse covariance matrix of the IGS factor scores. The term $x_i$ represents a vector or profile of factor scores for any particular gambler. As an example, assume that a gambler’s Negative Gambling Situations factor score and Positive Gambling Situations factor score on the IGS are 2.196 and 1.566, respectively. Again, assume that this gambler’s profile is being compared to the coping gambler profile, which has mean
Figure 2. Comparison of Gambling Motives Questionnaire factor scores for subtypes of gamblers obtained by using K-means cluster analysis on Inventory of Gambling Situations factor scores with simple Euclidean distance specified as the distance metric (original study) versus Mahalanobis distance specified as the distance metric (present study).
values of 1.128 and 0.577 on the Negative Gambling Situations and Positive Gambling Situations factors, respectively. Thus, in matrix algebra form, \((x_i - x_j)'\) is expressed as follows:

\[
\begin{bmatrix}
2.196 - 1.128 \\
1.566 - 0.577
\end{bmatrix}
\]

\[
= \begin{bmatrix}
1.068 \\
0.989
\end{bmatrix}
\]

The next step is to pre-multiply this vector by the inverse covariance matrix, which is expressed as follows:

\[
\begin{bmatrix}
1.068 & 0.989
\end{bmatrix}
\begin{bmatrix}
1.694 & -1.084 \\
-1.084 & 1.694
\end{bmatrix}
\]

\[
= \begin{bmatrix}
1.068 \times 1.694 & 1.068 \times (-1.084) \\
0.989 \times (-1.084) & 0.989 \times 1.694
\end{bmatrix}
\]

\[
= \begin{bmatrix}
1.809 & -1.158 \\
-1.072 & 1.675
\end{bmatrix}
\]

\[
= \begin{bmatrix}
0.737 & 0.517
\end{bmatrix}
\]

Then, post-multiply to obtain the distance value between the gambler’s profile and the coping gambler profile:

\[
\begin{bmatrix}
0.737 & 0.517
\end{bmatrix}
\begin{bmatrix}
1.068 \\
0.989
\end{bmatrix}
\]

\[
= \begin{bmatrix}
0.737 \times 1.068 \\
0.517 \times 0.989
\end{bmatrix}
\]

\[
= \begin{bmatrix}
0.787 \\
0.511
\end{bmatrix}
\]

\[
= \begin{bmatrix}
1.298
\end{bmatrix}
\]

Generalized squared distance approximates a chi-square \((\chi^2)\) distribution with degrees of freedom being equal to the number of profile or vector variables (McKillop, 2010). Thus, goodness of fit for this particular example can be expressed as follows:

\[
\chi^2(2) = 1.298, p = .52
\]

For the present study, a spreadsheet was created to automate the calculations for generalized squared distances \(D^2\) for each gambler on the basis of his or her IGS factor scores. Thus, the spreadsheet also determined the best profile fit for each
gambler, as the lowest of the three obtained $D^2$ values indicated his or her best profile fit. This spreadsheet and the user guidelines are available from the authors upon request. In the same manner as McKillop and Nielson (2011), we compared the best $D^2$ for each gambler with the refined K-means cluster assignment for each gambler. Classification agreement was perfect, as none of the gamblers were misclassified (kappa = 1.0, $p < .001$), indicating that generalized $D^2$ approximated the refined cluster solution with precision.

**Discussion**

The coping, enhancement, and low emotion regulation subtypes of pathological gamblers derived by Stewart et al. (2008) were refined when the data used to derive them were subjected to an extended cluster analysis by using an alternative clustering algorithm—an algorithm that used Mahalanobis distance specified as the distance metric instead of Euclidean distance. Consistent with the results from the original study, enhancement gamblers appeared to gamble purely for positive reinforcement; coping gamblers appeared to gamble for both positive and negative reinforcement, but primarily for negative reinforcement; and low emotion regulation gamblers appeared to gamble for reasons other than the direct modulation of mood. There seemed to be a moderate level of agreement between the clustering algorithm used in the original study and the algorithm used in the present study, suggesting that the results of the original study were not overly distorted by the use of Euclidean distance. The results obtained in the present study, however, could be considered somewhat refined because the cluster analysis that relied on Mahalanobis distance took into account the correlated nature of the clustering variables: gambling in negative situations and gambling in positive situations.

In the original study, the obtained cluster solution was based on gamblers’ self-reported primary antecedents for gambling, as measured by the IGS (Littman-Sharp et al., 2009), and was validated with a measure of self-reported gambling motives, as measured by the GMQ (Stewart & Zack, 2008). Consistent with these original results, the cluster solution obtained in the present study also was “cross-validated” by selective elevations in GMQ Coping motives in coping gamblers and by elevations in GMQ Enhancement motives in both enhancement and coping gamblers (Stewart et al., 2008, p. 263). Given these findings, readers may ask: why not subtype gamblers according to their GMQ scores? Certainly this is a possibility that could be empirically tested. It should be pointed out, however, that one advantage of subtyping gamblers according to the method described here is that it does not require them to have insight into their gambling motives. Rather, it requires only that they have memory or knowledge of the situation(s) in which they have gambled most heavily.

Borrowing from the literature that described a method for matching chronic pain patients to dysfunctional, interpersonally distressed, or adaptive coper profiles on the basis of their responses to a multi-item pain inventory (McKillop & Nielson, 2011; Turk & Rudy, 1988), we used generalized squared distance ($D^2$) in the present study
to determine each individual gambler’s best profile fit in relation to the refined coping, enhancement, and low emotion regulation gambler profiles. On this point, and consistent with the favourable results observed in the pain literature, $D^2$ approximated the refined cluster solution with precision. User guidelines and the spreadsheet that was created to determine each gambler’s best profile fit are available from the authors upon request. This tool provides a means for making objective and empirically based decisions for classifying gamblers according to the refined subtypes; thus, it could be used by researchers or practitioners with an understanding of psychometric theory and skills in clinical assessment to determine other pathological gamblers’ best profile fit for various purposes. On this point, it is worth mentioning that, because $D^2$ approximates a chi-square ($\chi^2$) distribution, with degrees of freedom being equal to the number of profile variables (McKillop, 2010), a bonus of using $D^2$ is that it allows the user to comment on the significance of the values obtained (an option that is not available with the use of Euclidean distance). Given that the refined subtyping scheme is based on scores from a fairly brief self-report measure that is available for professional use at no cost (i.e., the IGS), classification of pathological gamblers according to these subtypes could be incorporated into clinical practice with relative ease. From the evidence from randomized controlled trials supporting the efficacy of motivation-matched treatments for substance misuse developed in recognition of subtyping schemes that incorporated underlying motivations and personality factors (e.g., Conrod et al., 2000), it has been hypothesized that motivation-matched treatments for pathological gamblers might help improve treatment outcomes (Stewart et al., 2008). Clinicians who specialize in the provision of gambling treatment could use this tool to match their clients to the aforementioned profiles and then tailor their treatments accordingly. As another example of its potential use, researchers could use the tool to identify the subtypes of gamblers in order to study their possible etiologies, as this provides one method of operationally defining them.

The potential limitations of the original study that were addressed by Stewart et al. (2008) still apply to the findings concerning the refined subtyping scheme (e.g., reliance on self-report measures, cross-sectional study design, use of a sample of participants who drank alcohol at least 50% of the time when they gambled) and are not discussed in detail again here. With regard to limitations of the method used to match gamblers to the refined profiles, this method requires cross-validation on samples of gamblers that are independent of the development sample; thus, research aimed at cross-validation would be a logical step forward, ideally on even larger samples of gamblers.

On these notes, the promising findings from the present study suggest that the proposed method for classifying subtypes should hold up well on cross-validation. However, the development sample was not necessarily representative of all problem gamblers given the inclusion criteria (e.g., drinking regularly while gambling; Stewart et al., 2008). For example, coping gamblers might be over-represented in this sample of problem gamblers who regularly drink while gambling because prior work has shown that coping gamblers drink more frequently and problematically than other
gambler subtypes (Stewart et al., 2008). Thus, future research should focus on the extent to which the method used to classify gamblers according to the present subtyping scheme can be used with other samples, including non-problem gamblers and those who do not regularly drink while gambling.

Intuitively appealing subtyping schemes for those with gambling disorders have not been incorporated routinely into clinical practice, perhaps because “easy-to-use” assessment methods for classifying gamblers have not been provided (Stewart et al., 2008, p. 258). It is our hope that the method of classification described in this article, along with the tool offered that automates classification according to gamblers’ affective motivations for gambling, may make the option of subtyping those with gambling problems more of a possibility for practitioners who would like to use this research to inform their clinical work. We also hope that dissemination of this classification method facilitates future research on these subtypes, as well as research on other subtyping schemes in general. Future investigations may reveal better models for subtyping pathological gamblers, better statistical procedures for subtyping them, and better methods for classifying them; however, we believe that the present work represents a positive step forward in dealing with the complex heterogeneity of those with gambling disorders in both research and practice.

References


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Appendix A


The supplementary material for this article is a spreadsheet that assists in the determination of whether a probable pathological gambler who meets the same study inclusion criteria described in the Method section of this article may be best considered an enhancement gambler, a coping gambler, or a low emotion regulation gambler (first described by Stewart et al., 2008) according to the gambler’s raw responses to the Inventory of Gambling Situations (IGS; Littman-Sharp et al., 2009) and according to the refined profiles of IGS Negative Gambling Situations and Positive Gambling Situations factor scores for the enhancement, coping, and low emotion regulation subtypes described in the Results section of this article.

More specifically, the spreadsheet calculates generalized squared distances ($D^2$) for a gambler by computing and comparing the gambler’s scores on the IGS factors with the IGS factor scores for the three refined enhancement, coping, and low emotion regulation gambler profiles. Thus, the spreadsheet produces three $D^2$ values for the gambler. The lowest of these three $D^2$ values represents the best profile fit for the gambler. Interested users may refer to the Results section of this article for an example of how to perform these calculations manually.

Because the spreadsheet calculates $D^2$ by using IGS factor scores, it calculates IGS Negative Gambling Situations and Positive Gambling Situations factor scores for each gambler that are based on input of his or her raw responses to the individual IGS items and that are based on the results of the principal components analysis (PCA) described in the Results section of this article (also see Stewart et al., 2008). As an intermediary step, because this PCA was performed on IGS subscale scores (e.g., Conflict with Others, Urges and Temptations, Need for Excitement), the spreadsheet also calculates the gambler’s IGS subscale scores on the basis of his or her raw responses to the individual IGS items (interested users may refer to Littman-Sharp et al., 2009, for instructions on how to manually calculate and interpret these scores).

The spreadsheet was created by using Microsoft Office Excel 2003 and should function with later versions of this program. The spreadsheet may be distributed and shared without permission, but it cannot be resold or distributed for profit.

Instructions

1. Download and open the Microsoft Excel Worksheet file named “Gambler Profile Match.” Right-click on icon next to Appendix A title.
2. Type the gambler’s responses to the individual IGS items into the cells directly below those labelled “igs1” through “igs63.” For example, if the gambler circled the number 2, indicating that he or she “rarely” gambled heavily in response to the first item on the IGS (i.e., “When I almost won and felt that I would win very soon”; Littman-Sharp et al., 2009), then type the number 2 into cell A4 of the spreadsheet. If the gambler circled the number 3 in response to the second item, then type the number 3 into cell B4, and so on.

3. After the gambler’s responses to all of the IGS items have been typed into the spreadsheet, press the Enter button.

It should be noted that the spreadsheet is meant to handle data from a gambler who provides a response to all of the IGS items. It should also be noted that the spreadsheet does not flag data entry errors on the part of the user (e.g., entering a value of 40 instead of 4 as a response to an individual IGS item). Furthermore, copying and pasting a gambler’s data from another spreadsheet or data set has been found to result in calculation errors; thus, manual entry of a gambler’s responses to the IGS items is recommended.

Interpreting Output

After the gambler’s raw responses to all of the IGS items have been entered into the spreadsheet and double-checked, the spreadsheet automatically calculates the gambler’s IGS subscale scores and displays them in cells E20 through E29. As mentioned previously, interested users may refer to the work of Littman-Sharp et al. (2006) for direction on how to interpret IGS subscale scores.

The spreadsheet also automatically calculates the gambler’s IGS Negative Gambling Situations and Positive Gambling Situations factor scores according to the PCA described in the present article and in Stewart et al. (2008). The gambler’s IGS Negative Gambling Situations and Positive Gambling Situations factor scores are displayed in cells B35 and C35, respectively.

Finally, the spreadsheet automatically calculates $D^2$ for the gambler by comparing his or her scores on the IGS factors with the three refined gambler subtype IGS profiles (Steps 1 through 3 within the spreadsheet are provided for users who are interested in how the spreadsheet performs these calculations). The spreadsheet produces three $D^2$ values for the gambler in cells I33, I34, and I35 under the “Chi-square” heading. It should be noted that $D^2$ approximates a chi-square ($\chi^2$) distribution, with degrees of freedom being equal to the number of profile variables (McKillop, 2010; i.e., two profile variables in this context). Cells I33, I34, and I35 are $D^2$ values in relation to the enhancement gambler profile, low emotion regulation gambler profile, and coping gambler profile, respectively. The lowest of the three $D^2$ values in these cells represents the best profile fit for the gambler. Thus, if the lowest value is in cell I33, then the gambler may be best considered an enhancement gambler. Alternatively, if the lowest value is in cell I34, then the gambler may be best considered a low emotion regulation gambler, or, if the lowest value is in cell I35, then the gambler may be best considered a coping gambler.
The values produced in cells J33, J34, and J35 are corresponding p values for the chi-square values displayed in cells I33, I34, and I35, respectively, which could be used to comment on the significance of profile fit if desired.

As an example, the default values saved within the spreadsheet upon first downloading it represent those of a hypothetical low emotion regulation gambler, as the lowest $D^2$ value can be seen in cell I34. Thus, goodness of fit for this hypothetical gambler can be expressed as follows:

$$\chi^2(2) = 0.575, \ p = .75$$