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Types of gambling and levels of harm: A UK study to assess severity of presentation in a treatment-seeking population

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Background and aim: Previous international research emphasized that some forms of gambling are more "addictive" than others. More recently, research has shown that we should shift our attention from the type of gambling activity to the level of involvement in a number of different gambling activities. The aim of our study was to verify whether a higher Problem Gambling Severity Index (PGSI) score was associated with particular gambling activities and evaluate the impact of involvement on gambling behavior. *Methods:* A total of 736 treatment-seeking individuals with gambling disorder were assessed at the National Problem Gambling Clinic in London. First, the independent two-sample *t*-test and the Mann–Whitney test were used to verify if the PGSI score changed significantly according to the gambling activity at a bivariate level. Second, we conducted a cluster analysis and finally, we fitted a linear regression model in order to verify if some variables are useful to predict gambling addiction severity. *Results:* The PGSI score was significantly higher for lower stakes gaming machine gamblers (1% significance level) and for fixed-odds betting terminal (FOBT) gamblers (5% significance level) at a bivariate level. Moreover, such finding was confirmed by cluster and linear regression analyses. *Conclusions:* The results of this study indicated that gambling addiction severity was related to gambling involvement and, for a given level of gambling involvement, gambling addiction severity may vary according to gambling type, with a particularly significant increase for FOBT and gaming machine gambling.

Keywords: gambling disorder, pathological gambling, involvement, harm, type of gambling

INTRODUCTION

In the last decades, several countries around the world began to legalize different types of gambling activities. Whereas some researchers have argued that the prevalence of pathological gambling (PG), renamed "gambling disorder" in the DSM-5 (American Psychiatric Association, 2013), increased along with an increase of gambling availability, Shaffer and Martin (2011) have argued that, as gambling availability increased, gambling problems would initially increase and then stabilize due to the fact that people would adapt relatively quickly after a new exposure to gambling. In spite of this, the impact of gambling disorder cannot be underestimated, as data from the British Gambling Prevalence Survey estimated that, in UK, the prevalence of gambling disorder was about 0.9% in 2010; the problem gambling prevalence was higher among those who had played poker at a pub/club (12.8%), followed by those who had played on online slot machine-style games (9.1%), and fixed-odds betting terminals (FOBTs; 8.8%), and lower among those who gambled on National Lottery or other lotteries (1.3% each) (Wardle et al., 2010). In addition to that, newer forms of gambling were regarded as highly engaging due to their ease of access, availability, and fast-paced gaming style. In particular, many researchers have shown the rate of PG was higher among Internet gamblers with respect to offline gamblers (Griffiths & Barnes, 2008; Matthews, Farnsworth, & Griffiths, 2009; McBride & Derevensky, 2012; Olason et al., 2011; Petry & Weinstock, 2007), and gambling on electronic gaming machines (EGMs) involved the highest risk for gambling problems (Breen & Zimmerman, 2002; Cantinotti & Ladouceur, 2008; Chóliz, 2010; Lund, 2006; Petry, 2003) and represented the riskiest form of gambling. On the other hand, some authors have suggested that range, versatility, and gambling involvement (i.e., the number of different gambling activities an individual is engaged into) predicted gambling disorder more than considering the individual game type (LaPlante, Afifi, & Shaffer, 2013; Laplante, Nelson, & Gray, 2014; LaPlante, Nelson, LaBrie, & Shaffer, 2011; Lloyd et al., 2010; Phillips,

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Ogeil, Chow, & Blaszczynski, 2013; Welte, Barnes, Tidwell, & Hoffman, 2009), and some authors highlighted the irrelevancy of gambling type in predicting gambling severity (Griffiths & Auer, 2013). In the UK, a particular type of EGM, called FOBT, provides the user with a variety of games, ranging from casino games, such as Roulette, Poker, and Black Jack, to electronic slot games and virtual racing. No other gaming machines in the UK allow such a high-speed and high-stake play; as an example, it is possible to bet up to £100 per spin every 20 s on FOBT virtual casino games. The aim of our study was to verify whether a higher Problem Gambling Severity Index (PGSI) score was associated with particular gambling activities, and we expected to find a positive relationship with FOBT gambling in particular. In the second part of the study, we evaluated the impact of the involvement on gambling behavior.

METHODS

Participants

Data were collected from clients who were voluntarily seeking treatment at the National Problem Gambling Clinic (NPGC) between January 2011 and December 2012. Over the course of this study, 736 clients were assessed at the clinic. From this initial sample, a number of clients were excluded from the study ($n = 51$) due to missing data about the type of gambling and to a PGSI score <8. The final sample, therefore, consisted of 685 clients.

Procedure

The NPGC is the first and only National Health Service clinic in the UK that provides treatment for pathological gamblers. Clients are offered mainly cognitive-behavioral group therapy; however, individual treatment sessions are available if needed. Clients who seek services from our treatment center for the first time were requested to complete a routine assessment, consisting of a clinical interview and a self-report form, which included the client's gambling-related information and problem gambling assessment. Socio-demographic variables were obtained from the referral form in which each client is required to fill in prior to the assessment. During the assessment, clients were informed that data collected from the referral and assessment forms would be analyzed by researchers in order to increase the understanding about problem gambling. Oral consent was obtained from clients before filling in the assessment form.

Measures

Clinical interview. During the interview, clients were asked about their gambling problem (age of onset, debts, type of gambling, current and past histories of problem gambling, and past treatment), psychiatric, medical, and forensic histories, family psychiatric history, family structure, and family-related impact of gambling, as well as personal history. Moreover, a psychologist or psychiatrist administered a specific questionnaire to better evaluate the particular form of gambling in which the clients were involved. For every type of gambling, we asked if the client had ever gambled on it, if she had gambled on it in the past year, and/or in the 30 days prior to the assessment; the client was then asked about the number of days in the past 30 days in which she had gambled, and the total time spent per typical day. The specific forms of gambling that we examined were lottery and scratch cards, Internet gambling using a computer, mobile phone, or interactive TV, casino table games, casino gaming machines, betting at bookmakers or at sports events, FOBT, gaming machines outside casinos, bingo, and other forms of gambling, such as unregulated private betting.

Assessment form. Self-administered questionnaire

- Problem Gambling Severity Index. The PGSI is a 9-item questionnaire measuring gambling severity, which was validated in a number of studies (Holtgraves, 2009). It consists of four questions assessing problematic gambling behavior and five questions assessing adverse consequences of gambling. Each item is scored from 0 to 3 (never = 0, sometimes = 1, most of the time = 2, and almost always = 3), resulting in a total score range of 0–27. The gambling risk categories are as follows: a score of 0 indicates a non-problem gambler, scores of 1–2 indicate a "low risk" gambler, scores of 3–7 indicate a "moderate risk" gambler, and scores of 8 and more indicate a problem gambler (Ferris & Wynne, 2001).

Statistical analysis

We used the SPSS 20.0 computer software program to conduct statistical analyses. The first step was to calculate the different gambling type frequencies and verify whether it was possible to reduce the complexity of the dataset by merging variables with redundant information. The gambling type dataset was reduced in the following categories: lottery/scratch cards/bingo, Internet gambling using a computer/mobile/interactive TV, betting at bookmakers/sports events, gaming machine gambling, casino table games, FOBT, and other forms of gambling. Furthermore, it was convenient to consider two sets of variables for all analyses, namely, gambling behavior in the past year and gambling behavior in the past month. This distinction was deemed important as many patients asked for help after a period of "gambling abstinence" that could last for more than a month. The second step was to conduct hypothesis testing. First, the independent two-sample t-test and the Mann–Whitney test were used to verify if the PGSI score changed significantly according to the gambling activity at a bivariate level. The Mann–Whitney test has been used to account for potential non-normality of the continuous variables. Second, we conducted a cluster analysis: such analysis allows to partition the sample of patients in different subgroups according to their gambling behavior. The clustering algorithm considered, developed by Chiu, Fang, Chen, Wang, and Jeris (2001), is designed for analyzing both continuous and categorical variables and is based on a two-step approach. In the first phase, the algorithm produces the subgroups of observations according to a given distance measure, in this case, the log-likelihood. In the second phase, a hierarchical agglomerative clustering procedure is run on the subgroups formed in the first phase to compose homogeneous clusters. The final number of clusters may be automatically determined using a goodness of fit criterion, namely, the Bayes Information Criterion (BIC) or Akaike's Information Criterion (AIC). We segmented our sample of pathological gamblers according to the seven gambling behavior variables listed above using the two-step clustering algorithm. The statistical significance of the differences between clusters for the seven variables used in the clustering procedure and for the other gambling-related and socio-demographic variables considered was investigated using the chi-square (χ^2) test for categorical variables and the analysis of variance (ANOVA) together with the Kruskal–Wallis test for continuous variables. The Kruskal–Wallis test has been used to account for potential non-normality of the continuous variables. Finally, we fitted a linear regression model in order to verify if cluster membership is a significant predictor of gambling addiction severity (i.e., the PGSI score). The cluster membership variable was split into four dummy variables indicating specific Clusters 1–4 membership. To avoid perfect collinearity (condition which would not allow the model estimate), Cluster 1 membership variable was excluded from the model, becoming the baseline category for the interpretation of the regression coefficients of the other three cluster membership variables. The same procedure has been applied to the variables "ethnicity" (baseline category: "white"), "marital status" (baseline category: "single"), and "employment status" (baseline category: "employed"). The PGSI score (i.e., the dependent variable of the model) was then regressed against Clusters 2–4 dummy variables, gender, age, and the dummy variables regarding ethnicity, marital status, and employment status (without the baseline categories aforementioned). Clusters 2–4 membership variables were our independent variables of interest, while the other socio-demographic factors included in the model were variables useful to "clean" the relation between the cluster membership and the PGSI score (control variables that account for some of the variation in the PGSI score). After the model estimate, we checked the assumptions underlying the linear regression model and we looked for potential outliers. Finally, we fitted another regression model with the same variables without the outliers identified to check the robustness of the results obtained with the initial model estimate.

Ethics

Ethical approval was not needed as collected data were a part of the clinic's standard battery of assessment forms.

RESULTS

The initial sample was composed by the pathological gamblers who were assessed at the NPGC ($n = 736$) over the course of the years 2011–2012.

Gambling participation

The gambling type data in the year prior to the assessment were available for 685 individuals, while when we analyzed the type of gambling in the last 30 days, only the 527 subjects who had gambled at least once in the last 30 days were included. At the assessment, we collected data on 13 different gambling types; however, as stated before, we reduced the complexity of the dataset by merging the variables with redundant information, both for the 1 year and 30 days gambling data. The most popular gambling activities in the year prior to the assessment were lottery/scratch tickets and bingo (78.8%), FOBT gambling (65.8%), betting at bookmakers or at sports events (65.3%), and Internet gambling (60.6%). The most popular gambling activities in the 30 days prior to the assessment were FOBT gambling (58.6%), lottery/scratch tickets and bingo (54.5%), and betting at bookmakers or at sports events (52.6%) (Table 1).

Bivariate analysis

We analyzed whether the PGSI score changed significantly in relation with individual gambling activities at a bivariate level, considering only one gambling activity at a time. The *t*-test and the Mann–Whitney test always produced the same result in terms of statistical significance; because of that, we decided to report only the results of the *t*-test in Table 2. The 1-year results were gathered on the 678 subjects who had gambled at least once in the previous year and for whom the PGSI score was available. Our analysis found significantly higher PGSI scores for gaming machine gamblers (1% significance level) and for FOBT gamblers (5% significance level). No significant difference was found for any other gambling activity. The results concerning the 30 days prior to the assessment were gathered on the 522 subjects who had gambled at least once in the month prior to the assessment and for whom the PGSI score was available. We found significantly higher PGSI scores, once again, for FOBT and gaming machine gamblers (1% significance level) and for casino table gamblers (5% significance level) (Table 2).

Table 1. Participation in all types of gambling

	Gambled in the last year ($n = 685$)	Gambled in the last 30 days ($n = 527$)
Lottery, scratch card, or bingo	78.8% (540)	54.5% (287)
FOBT	65.8% (451)	58.6% (309)
Betting at bookmakers or sports events	65.3% (447)	52.6% (277)
Internet gambling using a computer, mobile phone, interactive TV, or telephone	60.6% (415)	40.8% (215)
Gaming machine	53.9% (369)	40.0% (211)
Casino table games	41.5% (284)	19.2% (101)
Other	13.0% (89)	7.2% (38)
PGSI score	Avg. = 19.69; st. dev. = 5.07 ($n = 678$)	Avg. = 20.00; st. dev. = 4.86 ($n = 522$)

Note. FOBT = fixed-odds betting terminal; PGSI = Problem Gambling Severity Index.

Table 2. Analysis at a bivariate level between type of gambling and the Problem Gambling Severity Index (PGSI) score

Variable	PGSI average score (st. dev.) Did not gamble	Gambled	*t*-test	Cohen's *d*
Lottery, scratch card, or bingo				
Gambled last years	19.13 (5.10) [$n = 144$]	19.84 (5.06) [$n = 534$]	$t = -1.49$	0.14
Gambled last 30 days	19.99 (4.66) [$n = 244$]	20.01 (5.04) [$n = 278$]	$t = 0.05$	0.00
Internet gambling using a computer, mobile phone, interactive TV, or telephone				
Gambled last years	19.45 (5.37) [$n = 265$]	19.85 (4.88) [$n = 413$]	$t = -1.00$	0.08
Gambled last 30 days	19.93 (4.89) [$n = 308$]	20.11 (4.83) [$n = 214$]	$t = -0.42$	0.04
Betting at bookmakers or at sports events				
Gambled last years	20.15 (4.58) [$n = 234$]	19.45 (5.31) [$n = 444$]	$t = 1.72$	−0.14
Gambled last 30 days	20.14 (4.60) [$n = 248$]	19.88 (5.08) [$n = 274$]	$t = 0.61$	−0.05
Gaming machine				
Gambled last years	19.09 (4.96) [$n = 310$]	20.19 (5.12) [$n = 368$]	$t = -2.83$**	0.22
Gambled last 30 days	19.54 (4.96) [$n = 312$]	20.68 (4.63) [$n = 210$]	$t = -2.62$**	0.23
Casino table games				
Gambled last years	19.39 (5.25) [$n = 396$]	20.11 (4.80) [$n = 282$]	$t = -1.81$	0.14
Gambled last 30 days	19.75 (4.95) [$n = 423$]	21.08 (4.31) [$n = 99$]	$t = -2.47$*	0.28
FOBT				
Gambled last years	19.14 (4.86) [$n = 230$]	19.97 (5.16) [$n = 448$]	$t = -2.03$*	0.16
Gambled last 30 days	19.25 (4.87) [$n = 214$]	20.52 (4.79) [$n = 308$]	$t = -2.97$**	0.26
Other				
Gambled last years	19.80 (4.98) [$n = 590$]	18.93 (5.61) [$n = 88$]	$t = 1.50$	−0.17
Gambled last 30 days	20.07 (4.75) [$n = 484$]	19.16 (6.08) [$n = 38$]	$t = 1.11$	−0.19

Note. FOBT = fixed-odds betting terminal; PGSI = Problem Gambling Severity Index.
*$p < .05$, **$p < .01$.

Cluster analysis

About 158 (23%) of the 685 patients who had gambled during the past year did not gamble in the 30 days prior to the assessment; therefore, the results concerning the gambling behavior in the 30 days prior to the assessment have to be interpreted with caution. For this reason, the next steps of our analysis were based on the data concerning the past-year gambling behavior.

The two-step clustering algorithm applied to the data concerning the past-year gambling behavior was useful to identify the complex gambling profiles characterizing the individuals included in the sample. When verifying the statistical significance of the differences between clusters for the variable considered, the ANOVA and the Kruskal–Wallis test produced always the same result. Because of that, we decided to report only the results of the ANOVA in Table 3. Information about ethnicity, marital status, and employment status were not available for all the 669 individuals considered. The algorithm segmented the total sample into four clusters: (a) Cluster 1 (mainly interactive gamblers): characterized by the high proportion of interactive gamblers (87% vs. 61% in the total sample). Moreover, this group shown a much lower proportion of gaming machine gamblers (27% vs. 54%) and the absence of FOBT gamblers; (b) Cluster 2 (mainly FOBT gamblers): characterized by a high proportion of FOBT gamblers (86% vs. 66%). Moreover, this group was characterized by the absence of lotteries, scratch cards, and bingo gamblers, as well as a lower proportion of interactive gamblers (35% vs. 61%); (c) Cluster 3 (FOBT and lotteries, scratch cards, and bingo gamblers): characterized by the highest proportions of FOBT (87% vs. 66%) and lotteries, scratch cards, and bingo gamblers (100% vs. 79%). This group shown a lower proportion of interactive gamblers (43% vs. 61%) as well as the absence of casino table gamblers and of people practicing other gambling activities; (d) Cluster 4 (very heavy gamblers): characterized by higher proportions of gamblers for every activity considered, indicating that this group included very heavy gamblers. The χ^2 tests indicated that all the gambling activities considered differ significantly across clusters (Table 3).

The PGSI average score increased monotonically from Clusters 1 to 4. Clusters 1 and 2 had an average PGSI score lower than the average score of the total sample (19.28, 19.60 vs. 19.91), while this average score was higher for Clusters 3 and 4 (19.93, 20.63). The average number of games played (i.e., gambling involvement) illustrated that Cluster 2 was characterized by a much lower level of involvement with respect to the total sample (3.20 games played on average vs. 4.64 games played on average in the total sample), while Clusters 1 and 3 shown a similar and a slightly lower level of involvement (around 4 games played on average vs. 4.64). Instead, Cluster 4 reported a much higher level of involvement (6.52 vs. 4.64). The results of the ANOVA indicated that the PGSI score and the number of games played differ significantly across clusters (Table 3). Cluster 1 shown the lowest proportion of males (86% vs. 92–96% in the other clusters), while Cluster 4 reported the lowest average age (32 years old vs. 37–39 years old in the other clusters). Clusters 1 and 3 were characterized by lower proportions of singles (44% and 48%, respectively) when compared to Clusters 2 and 4 (57% and 59%,

Table 3. Total sample and clusters gambling behavior and socio-demographic characteristics

Variable	Total sample ($n = 669$)	Clusters 1 ($n = 180$)	2 ($n = 98$)	3 ($n = 198$)	4 ($n = 193$)	χ^2 test	ANOVA
Gambling behavior variables							
Lotteries, scratch cards, and bingo	79% (527)	76% (137)	0% (0)	100% (198)	99% (192)	$\chi^2 = 467.31$***	–
Gambling over the Internet or over the phone	61% (409)	87% (157)	35% (34)	43% (85)	69% (133)	$\chi^2 = 112.93$***	–
Betting at bookmakers or at sports events	65% (436)	59% (107)	61% (60)	65% (129)	73% (140)	$\chi^2 = 7.89$*	–
Gaming machines inside and outside casino	54% (363)	27% (49)	47% (46)	62% (122)	76% (146)	$\chi^2 = 95.03$***	–
Casino tables	42% (280)	34% (62)	38% (37)	0% (0)	94% (181)	$\chi^2 = 361.11$***	–
FOBT	66% (442)	0% (0)	86% (84)	87% (173)	96% (185)	$\chi^2 = 483.83$***	–
Other gambling activities	13% (86)	16% (28)	6% (6)	0% (0)	27% (52)	$\chi^2 = 68.54$***	–
PGSI score and number of games played							
PGSI average score (st. dev.)	19.91 (4.73)	19.28 (4.59)	19.60 (4.93)	19.93 (4.84)	20.63 (4.58)	–	$F = 2.71$*
Average number of games played (st. dev.)	4.64 (2.08)	3.94 (1.63)	3.20 (1.73)	4.14 (1.47)	6.52 (1.87)	–	$F = 122.04$***
Socio-demographic variables							
Gender: male	92% (617)	86% (155)	96% (94)	92% (182)	96% (186)	$\chi^2 = 15.91$**	–
Average age in years (st. dev.)	35.92 (11.38)	37.27 (10.87)	38.71 (10.63)	37.26 (12.04)	31.84 (10.60)	–	$F = 11.57$***
Ethnicity ($n = 649$)							
White	74% (480)	75% (132)	73% (68)	78% (151)	69% (129)	$\chi^2 = 15.53$	–
Black	8% (49)	5% (9)	9% (8)	10% (20)	6% (12)		
Asian	11% (75)	14% (24)	10% (9)	7% (13)	16% (29)		
Other	7% (45)	6% (11)	9% (8)	5% (9)	9% (17)		
Marital status ($n = 627$)							
Single	51% (322)	44% (74)	57% (53)	48% (89)	59% (106)	$\chi^2 = 15.59$*	–
Married/cohabiting	38% (239)	40% (78)	28% (26)	40% (73)	35% (62)		
Divorced/separated/widowed	11% (66)	16% (18)	15% (14)	12% (22)	6% (12)		
Employment status ($n = 647$)							
Employed	68% (438)	72% (123)	51% (44)	71% (138)	69% (129)	$\chi^2 = 34.50$***	–
Unemployed	17% (111)	13% (22)	23% (22)	12% (24)	23% (43)		
Permanently unable to work	7% (46)	4% (7)	13% (12)	10% (19)	4% (8)		
Other	8% (52)	11% (19)	13% (12)	7% (14)	4% (7)		

Note. FOBT = fixed-odds betting terminal; PGSI = Problem Gambling Severity Index.
*$p < .05$, **$p < .01$, ***$p < .001$.

respectively), while it is the opposite for the proportion of married/cohabiting patients (40% for Clusters 1 and 3 against 28% and 35% for Clusters 2 and 4, respectively). Cluster 2 reported by far the lowest proportion of employed patients (51% against 68–71% in the other clusters) and, together with Cluster 4, the highest proportion of unemployed patients (23% against 12–13% in the other two clusters). The results of the χ^2 tests and of the ANOVA showed that all the socio-demographic characteristics differ significantly across clusters with the exception of ethnicity (Table 3).

Linear regression analysis

We fitted two different models, one with all the available observations (the initial model) and the other without the potentially problematic observations detected (the final model).

Outliers detection. We used the leverage-versus-residual-squared plot to visually identify the potential outliers. The initial model plot (Figure 1) allowed identifying 13 points with high leverage values, high residual values, or high leverage and residual values. We fitted

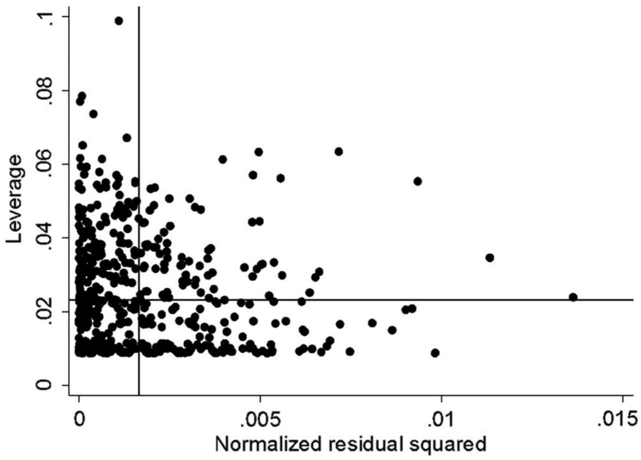

Figure 1. Leverage-versus-residual-squared plot for the initial model

another model without these 13 observations, and the second leverage-versus-residual-squared plot (not shown here) allowed discovering eight additional potential outliers. We fitted a third regression model (the final model) also excluding these eight observations (without 21 observations in total); the third leverage-versus-residual-squared plot (Figure 2) did not highlight any other problematic point. The estimate results of the initial and of the final model are very similar, which confirms the robustness of the initial models' findings.

Regression assumptions. The skewness–kurtosis test indicated that the residuals were normally distributed for both the initial and the final models (initial model p-value = .1052 and final model p-value = .1134). No multicollinearity problem was detected in the two models (initial model mean variance influence factor = 1.25 and final model mean variance influence factor = 1.24). The Cook–Weisberg test indicated that both models were characterized by heteroskedasticity: (initial model p-value = .0348 and final model p-value = .0240); to overcome this problem, we

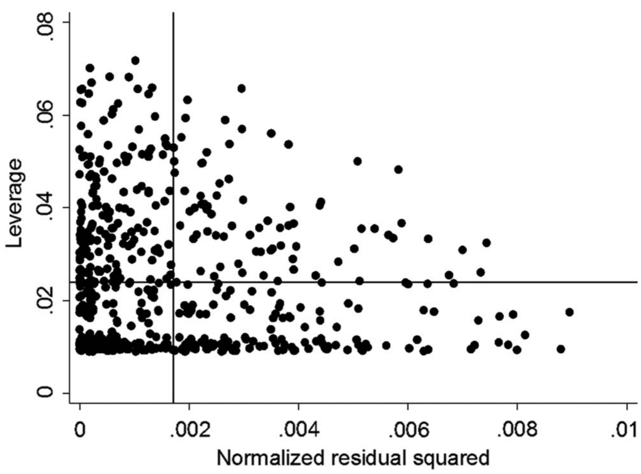

Figure 2. Leverage-versus-residual-squared plot for the final model

Table 4. Linear regression analysis results

Independent variable	Dependent variable: PGSI (initial model, unstandardized coefficients)	Dependent variable: PGSI (final model without the outliers detected, unstandardized coefficients)
Cluster 2	−0.0854 (0.629)	−1.981 (0.639)
Cluster 3	0.997* (0.506)	1.252* (0.507)
Cluster 4	1.314** (0.494)	1.692*** (0.477)
Gender: female	2.243** (0.692)	2.247** (0.714)
Age	−0.0163 (0.0202)	−0.0087 (0.0203)
Ethnicity		
Black	−1.009 (0.778)	−0.820 (0.697)
Asian	1.195* (0.583)	1.366* (0.561)
Other	0.399 (0.759)	0.624 (0.726)
Marital status		
Married/cohabiting	−0.478 (0.446)	−0.435 (0.434)
Divorced/separated/widowed	1.043 (0.669)	1.307 (0.675)
Employment status		
Unemployed	2.142*** (0.522)	1.951*** (0.509)
Permanently unable to work	1.529 (0.759)	1.233 (0.741)
Other	−0.0797 (0.687)	−0.3371 (0.679)
Constant	19.22*** (0.765)	18.92*** (0.767)
R^2	0.0824	0.0940
Observations	605	584

Note. Robust standard errors in parentheses. PGSI = Problem Gambling Severity Index.
$*p < .05$, $**p < .01$, $***p < .001$.

estimated robust standard errors using the Huber–White sandwich estimators.

Coefficient interpretation. The initial and final linear regression models shown that the coefficients of Clusters 3 and 4 membership were positive and statistically significant; after controlling for gender, age, ethnicity, marital status, and employment status of the patients, the average PGSI score was, on average and depending on the model considered, 1–1.25 points higher in Cluster 3 with respect to Cluster 1 (i.e., the baseline category), as well as 1.3–1.7 points higher in Cluster 4 (Table 4).

DISCUSSION

In this study, we have examined the extent to which particular forms of gambling were associated with problem gambling symptoms in a treatment-seeking population. First, we analyzed the frequencies of different types of gambling. This study supports the previous observations of problem gamblers frequenting more venues (Phillips & Ogeil, 2011) and engaging in a wider range of gambling activities, both online and offline (Afifi, LaPlante, Taillieu, Dowd, & Shaffer, 2013; LaPlante et al., 2011, 2013; Welte et al., 2009). Results from the BPGS estimated that, in the general population, the most popular types of gambling were poker, dog races, slot machines, and casino games (Wardle et al., 2010), while problem gamblers were mostly involved in poker at a pub/club (12.8%), followed by online slot machine-style games (9.1%), and fixed-odds betting terminals (8.8%). In our treatment-seeking population sample, we noted several differences between the frequency rates of the past year and 30 days gambling. While some forms of gambling were widely practiced in the previous year, they were not as practiced in the 30 days prior to the assessment. These were lottery, scratch card, or bingo (78.8% vs. 54.5%) and casino table games (41.5% vs. 19.2%). On the other hand, the rates of gambling on FOBT, sport betting at bookmakers or at events, and gaming machine did not show a marked decrease (65.8% vs. 58.6%, 65.3% vs. 52.6%, and 53.9% vs. 40.0%). This finding might suggest that people who play lottery, scratch cards, or bingo, and casino table games are less likely to consider their behavior as a problem or that they have low gambling-related harm; therefore, they are less motivated to seek treatment.

The second step of our analysis was to evaluate whether some forms of gambling were correlated with a higher PGSI score, that is, higher gambling severity. Our data confirmed the previous research concerning the gaming machine gambling (Breen & Zimmerman, 2002; Cantinotti & Ladouceur, 2008; Chóliz, 2010; LaPlante et al., 2011; Lund, 2006; Petry, 2003); moreover, we found that the engagement in FOBT was associated with higher PGSI score, and that such relationship became even more significant in the analysis of data from the 30 days prior to the assessment. Indeed, gambling on casino table games had a positive correlation with PGSI score; however, this was only true when considering 30 days data. The association between the aforementioned types of gambling and high PGSI scores may reflect that they cause more harm than others, and this hypothesis could be further supported by a few differences in gaming frequency rates between the past year and the past 30 days. Our results concerning the casino table games suggest that, although it was not one other most popular gambling activities among pathological gamblers, it could cause more problems than others, when regularly practiced. In the linear regression analysis, the positivity and statistical significance of Cluster 4 membership coefficient showed the importance of gambling involvement. The higher gambling addiction severity found in the fourth cluster with respect to the first one was probably mainly due to the overall involvement level (the coefficient is likely to reflect essentially the involvement effect). Indeed, the patients belonging to the fourth cluster were much more involved in all the gambling activities considered (6.52 games played on average vs. 3.94 in Cluster 1), with the exception of interactive gambling. The relation between gambling addiction severity and gambling involvement has been highlighted by some studies based on general population surveys (Afifi et al., 2013; LaPlante et al., 2011). The results of the current cluster analysis indicate that, even in a treatment-seeking population, gambling addiction severity is related to gambling involvement. Moreover, the average age of pathological gamblers belong to Cluster 4 is lower than other clusters. This may suggest that younger are more likely to gamble in a harmful manner.

The positivity and statistical significance of Cluster 3 membership coefficient might have a different meaning. Indeed, Clusters 1 and 3 had similar levels of gambling involvement in terms of average number of games played (4.14 in Cluster 3 vs. 3.94 in Cluster 1), but they were very different in terms of gambling behavior structure: the gambling habits of Cluster 3 patients were clearly more oriented toward gaming machines and, especially, FOBT, while Cluster 1 patients were much more oriented toward interactive gambling. Moreover, Cluster 1 was composed of one-third of casino table gamblers and 16% of gamblers involved in other gambling activities, while Cluster 3 was not. Both clusters had high proportions of lotteries, scratch cards, and bingo gamblers. The positivity and statistical significance of Cluster 3 membership coefficient suggests that, for a similar level of gambling involvement in terms of number of games played, gambling habits oriented toward gaming machines and (especially) FOBT were associated with higher gambling addiction severity (i.e., a higher PGSI score). The delay in obtaining the result may be one of the most important features in the development of gambling disorder, although the association between the speed of a subject's habitual gambling activities and problem gambling severity seems to be indirect (Challet-Bouju et al., 2014).

Therefore, although some studies suggested that involvement is a better gambling disorder predictor, compared to the individual types of game (LaPlante et al., 2013, 2014, 2011; Lloyd et al., 2010; Phillips et al., 2013; Welte et al., 2009), this might not be true for machine gambling and especially for higher speed and higher stake machine gambling. Such finding is in accordance with a previous study by LaPlante et al. (2011), which had shown that controlling for gambling involvement reduced or eliminated all statistically significant relationships between the type of gambling and disordered gambling, with the only exception being FOBT, which maintained a significant relationship to disordered gambling, even after adjusting for involvement (LaPlante et al., 2011). Thus, it might be hypothesized that both involvement and type of gambling activity could contribute to causing higher harm in some categories of gamblers.

This study had some limitations. First, our sample was a voluntary treatment-seeking population, and may differ from not treatment-seeking gamblers in the general population. Second, the results concerning the gambling behavior in the 30 days prior to the assessment have to be interpreted with caution since, as already mentioned above, many patients ask for help after a period of "gambling abstinence" that can last more than 1 month. More precisely, 158 of the 685 patients who gambled during the year before did not gamble in the 30 days prior to the assessment, which means that in considering the 30 days data, 23% of the initial subjects were excluded from further analysis. This substantial "loss" of patients might have greatly affected these results; for this reason, analysis based on the past-year gambling behavior was preferred in this study. Third, we used a conservative approach to assess the type of gambling without distinguishing multiple types of games within a category (e.g., casino table games, Internet gambling, etc.); thus, we could not investigate the effects of subtypes of games on gambling-related problems. Finally, we defined involvement as the number of gambling activities in which the subject was engaged, and did not consider the frequency with which individuals gambled, whereas some research has highlighted how this measure of involvement might also predict gambling disorder (Nelson et al., 2008). Despite these limitations, the results of our analysis are of particular interest for two reasons. First, the findings concern a treatment-seeking population of pathological gamblers only; the fact of having found significant relations without a control group of "healthy" gamblers suggests their robustness. Second, cluster analysis allowed accounting for the complex structure of gambling behavior, providing a synthetic index useful for regression analysis. This is an important consideration because regression analysis in this field usually employs models that include binary indicators of participation in gambling activities separately with one or a couple of two-way interactions. These regression analyses may therefore not account for the complexity characterizing gambling behavior structure. The clustering methodology represents an interesting way to deal with the complex interactions between gambling activities, and should therefore be included in further research. Moreover, the possibility of an automatic determination of the final number of clusters based on empirical data is one of the greatest advantages of the clustering techniques we used; indeed, other clustering algorithms usually require the indication of the final number of clusters before performing the procedure.

The clinical implications of this research are important. Focusing only on specific games, as predictors of risk for developing gambling disorders, rather than on overall play patterns, might erroneously over- or under-ascribe risk for developing a gambling-related disorder, therefore it is important for clinicians to inquire about gambling frequency and the number of games played as a gauge for possible gambling problems. Furthermore, although the involvement has shown to be an important predictor factor of gambling disorder, there are some forms of gambling that are more associated with a higher severity of gambling-related problems, namely, FOBT and gaming machines. Recognizing the heterogeneity of gambling behaviors, and whether different subtypes of pathological gamblers exist, has a potential importance for treatment implementation, in keeping with previous research (Blaszczynski & Nower, 2002; Milosevic & Ledgerwood, 2010). These findings can guide the activity of policy makers, who are currently under pressure to implement harm-prevention measures. Further research on gambling subtypes are necessary for a better understanding and recognition of different patient groups, according to their gambling behavior, which, in turn, may be helpful in pinpointing risk and protective factors, and improving prevention and treatment strategies (Toneatto & Rihs-Middel, 2004).

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