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Modelling Predictors of Gambling Harms with Stochastic Search Variable Selection (SSVS)

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ABSTRACT

The purpose of the present study was to introduce stochastic search variable selection (SSVS) as a procedure to identify a subset of important predictors of gambling harm. The target set of predictors were dimensions of trait impulsivity, gambling cognitions, and gambling motivations. Five types of gambling harm (feeling one has a personal problem; social criticism; feeling guilt; health; and, financial) were measured by the Problem Gambling Severity Index. Casino patrons completed the measures. As a first step, we identified the significant predictors that would be included in modelling an aggregate harm score. The most important predictors, the cognition that one is not able to stop gambling, and the motivation to escape or avoid life stressors, were positively associated with overall harm. Two weaker, but statistically significant, predictors were negatively associated with harm: sensation-seeking and illusion of control. Although a perceived inability to stop gambling was the most important predictor of each individual harm, the pattern of predictors varied across harms. For example, sensation-seeking was an important predictor only for the belief that one has a gambling problem, and escape/avoidance motivation was strongly predictive of financial harm. The results suggest that primary interventions designed to mitigate harm should address the belief that the gambler is unable to stop gambling, and motivations related to escape/avoid life stressors. Other interventions would be tailored to the specific harms experience by the gambler.

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Introduction

Although the prevalence of gambling is high, the incidence of problem gambling is low [1; 2]. However, non-problem gamblers may experience negative outcomes such that at the population level there are more harms from non-problem gamblers than problem gamblers [3]. Recent research has focused on trait impulsivity, gambling cognitions, and gambling motivations in categorizing types of gamblers who may experience harms [4; 5]. Standard measures of impulsivity [6], gambling cognitions [7], and gambling motivations [8] recognize the multi-dimensional nature of those constructs. The aim of the present study was to identify the dimensions among those factors that best predict gambling harms. Identifying the best set of predictors of gambling harms among multi-dimensional constructs poses a statistical challenge.

One common method for selecting the best subset of predictors from a large number of predictors is stepwise regression. However, stepwise regression methods have been criticized due to their lack of replicability and the fact that they may select nuisance variables [9]. Another popular method for subset selection is to select the predictors which have the highest bivariate correlations with the criterion. However, bivariate tests may select a set of predictors that are redundant due to the predictors being highly intercorrelated. Furthermore, subset models based on bivariate correlations may include predictors that are meaningfully related to the criterion only when the model controls for one or more other predictors [10].

One statistical procedure that identifies important predictors is stochastic search variable selection (SSVS). SSVS has not been commonly implemented in psychological research but offers a method that is not subject to the limitations of methods that rely on bivariate relationships or stepwise regression [10]. SSVS samples thousands of high probability regression models made up of subsets of the predictors and returns the proportion of models that include each predictor, otherwise known as the marginal inclusion probabilities (MIPs) of the predictors. The parameters of the regression models in SSVS are estimated using a Bayesian framework via Markov-Chain Monte-Carlo (MCMC) estimation, which takes samples from the posterior distribution. The relative importance of predictors may be indexed by their MIPs. A relatively high MIP indicates that the predictor was included in more SSVS models than a predictor with a relatively low MIP. That is, the higher the MIP the more reliable is that variable as a predictor of the criterion. SSVS overcomes the redundancy of the bivariate correlation approach because it selects predictors while accounting for the other predictors potentially being in the model.

We carried out an SSVS analysis to identify a subset of predictors of gambling harms. Gambling harms were measured with items from the Problem Gambling Severity Index (PGSI[11]). The PGSI, considered the gold standard of problem gambling screening instruments [12], comprises items that may be categorized as either behaviors or adverse consequences. Harm was indexed by the scores on the adverse consequence items. We conducted the SSVS analysis first on an aggregate score of all harms. Given that a practical implication of identifying the best predictors of gambling harms is to tailor interventions in accordance with specific harms, we also conducted SSVS analyses separately for each harm.

Method

Participants

This research project received ethics approval from the Research Ethics Board at the authors' university. Participants were recruited at a racetrack-slots facility in Ontario, Canada with a poster stating that a research team was on the premises to study "the characteristics of gamblers" and that participants would receive $30 in compensation. There were 271 (161 females) participants whose ages ranged from 21 to 71 (M = 46.61, SD = 13.01). Participants completed a survey containing a series of standardized scales measuring trait impulsivity, gambling related cognitions, gambling motivation, and problem gambling severity in a room adjacent to the casino area.

Measurement instruments

Problem gambling: The Problem Gambling Severity Index (PGSI[11]) comprises nine items: How often have you bet more than you could really afford to lose? How often have you needed to gamble with larger amounts of money to get the same feeling of excitement? How often have you gone back another day to try to win back the money you lost? How often have you borrowed money or sold anything to get money to gamble? How often have you felt that you might have a problem with gambling? How often have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true? How often have you felt guilty about the way you gamble or what happens when you gamble? How often has your gambling caused you any health problems, including stress or anxiety? How often has your gambling caused any financial problems for you or your household? Respondents are asked to think about the past year and to indicate the frequency for each item using a 4-point scale: 0 = never; 1 = sometimes; 2 = most of the time; 3 = almost always.

Whereas the first four PGSI items refer to problem gambling behaviors, the final five items refer to adverse consequences [13]. The original scoring of the PGSI classified four gambling subtypes indexed by the sum of the responses across the nine items: 0 = non-problem gambler; 1-2 = low-risk gambler; 3-7 = moderate-risk gambler; 8 or more = problem gambler. For the current sample, Cronbach's alpha for the 9-item PGSI (M = 2.34; SD = 3.09) was 0.82 Cronbach's alpha for the 5-item Harm scale comprising the adverse consequences items (M = 1.07; SD = 1.73) was 0.74.

Impulsivity: The impulsivity scale [6] contains 59 items for which respondents indicate their level of agreement using a 4-point scale from 1 = agree strongly to 4 = disagree strongly. The scale [6] comprises five dimensions: lack of planning; lack of perseverance; sensation seeking; negative urgency; and, positive urgency. The latter two dimensions refer to lack of control in either a negative or positive affective state. Cronbach's alpha for the separate dimensions ranged from .85 (lack of perseverance) to .96 (positive urgency).

Gambling Cognitions: The Gambling Related Cognition Scale (GRCS[7]) comprises 23 items for which participants indicate their level of agreement on a 7-point scale (1 = strongly disagree; 7 = strongly agree). The GRCS identifies five cognitive factors related to gambling: expectancies (e.g., "gambling makes the future brighter"); illusion of control (e.g., "specific numbers and colors can help increase my chances of winning"); predictive control (e.g., "losses when gambling are bound to be followed by a series of wins"); inability to stop (e.g., "I can't function without gambling"); and, interpretive bias (e.g., "relating my losses to probability makes me continue gambling"). Cronbach's alpha ranged from .77 (predictive control) to .87 (inability to stop).

Gambling Motivation: The Gambling Motivation Scale[8] asks respondents to indicate their level of agreement with 27 statements using a 5-point scale where 1 = strongly disagree, 3 = neutral, and 5 = strongly agree. The scale identifies five dimensions: excitement; monetary; escape/avoidance; socialization; and, amusement. Cronbach's alpha ranged from .72 (amusement) to .91 (excitement).

Results

PGSI Analyses

The distribution of participants across gambling severity categories was as follows: non-problem gambler, 92 (34%); low-risk gambler, 89 (33%); moderate-risk gambler, 72 (27%); and, problem gambler, 18 (7%). PGSI scores were significantly skewed, Shapiro-Wilk = 0.74, p <.001. Non-parametric tests showed that difference between male (M = 2.54, SD = 3.22) and female (M =2.19, SD = 2.99) scores was not statistically significant, U = 8.11, p = .23, and the correlation between age and PGSI also was not statistically significant, rho = .09, p =.11. Similar patterns occurred for the Harm scores (the final five items on the PGSI scale) where skewness was statistically significant, Shapiro-Wilk = 0.65, p < .001. Non-parametric tests showed that the difference between Harm scores for males (M = 1.13, SD = 1.89) and females (M =1.02, SD = 1.62) was not statistically significant, U = 8403, p = .44, and the correlation between age and Harm was not statistically significant, *rho* = .08, p =.18.

Table 1 Summary of regression analysis with total harm as the dependent variable.

Predictor	Bivariate correlation (*rho*)	Inclusion Probability (MIP)	Coefficient ($\hat{\beta}$) in the SSVS selection model (R^2 = 0.418)
Age	0.083	0.00	-0.002 (-0.016, 0.011)
Gender	-0.029	0.05	0.003 (-0.366, 0.371)
Impulsivity			
Sensation-seeking	-0.143	0.47	-0.321* (-0.621, -0.021)
Perseverance	-0.030	0.05	0.052 (-0.332, 0.436)
Planning	0.002	0.06	-0.008 (-0.427, 0.411)
Positive urgency	0.182*	0.06	0.003 (-0.373, 0.378)
Negative urgency	0.247**	0.07	0.154 (-0.229, 0.537)
Gambling Motivations			
Excitement	0.109	0.06	-0.165 (-0.443, 0.113)
Money	0.362**	0.20	0.206 (-0.039, 0.450)
Escape/Avoidance	0.328**	0.86	0.315* (0.059, 0.571)
Socialization	-0.123	0.04	-
Amusement	0.301**	0.05	0.116 (-0.143, 0.375)
Gambling Cognitions			
Inability to stop	0.509**	1.00	1.066** (0.848, 1.283)
Illusion of control	0.273**	0.34	-0.206* (-0.385, -0.027)
Predictive control	0.321**	0.04	-
Interpretive bias	0.347**	0.04	-
Expectancies	0.401**	0.04	-

** indicates p < .001, * indicates p <.01

Table 2 Summary of SSVS inclusion probabilities (MIP) and Spearman's rho for each dimension and harm.

Dimension	Harm 1		Harm 2		Harm 3		Harm 4		Harm 5	
	MIP	*rho*	*MIP*	*Rho*	*MIP*	*rho*	*MIP*	*rho*	*MIP*	*rho*
Impulsivity										
Sensation Seeking	0.22	-0.151	0.04	-0.087	0.13	-0.176*	0.03	-0.035	0.02	-0.035
Perseverance	0.02	0.029	0.02	-0.067	0.03	0.013	0.02	-0.014	0.04	-0.032
Planning	0.02	-0.055	0.02	-0.042	0.01	-0.019	0.02	-0.084	0.03	0.040
Positive Urgency	0.02	0.144	0.02	0.151	0.01	0.122	0.02	0.139	0.02	0.084
Negative Urgency	0.01	0.174*	0.06	0.212**	0.03	0.066	0.02	0.139	0.07	0.207*
Motivations										
Excitement	0.01	0.152	0.01	0.108	0.01	0.099	0.01	0.088	0.06	0.064
Money	0.13	0.312**	0.03	0.247**	0.02	0.224**	0.03	0.252**	0.03	0.237**
Escape/ Avoidance	0.03	0.241**	0.20	0.229**	0.01	0.142	0.20	0.256**	0.81	0.273**
Socialization	0.02	0.062	0.02	0.065	0.02	0.152	0.04	-0.002	0.02	0.145
Amusement	0.01	0.192*	0.01	0.201*	0.01	0.143	0.02	0.201*	0.10	0.297**
Cognitions										
Inability to Stop	1.00	0.485**	0.99	0.281**	1.00	0.421**	1.00	0.299**	1.00	0.379**
Illusion of Control	0.09	0.208*	0.01	0.181	0.01	0.184*	0.21	0.088	0.03	0.181*
Predictive Control	0.01	0.258**	0.01	0.224**	0.01	0.173*	0.01	0.135	0.02	0.211**
Interpretive Bias	0.01	0.274**	0.01	0.227**	0.01	0.163*	0.01	0.149	0.02	0.265**
Expectancies	0.01	0.365**	0.01	0.225**	0.01	0.290**	0.01	0.214**	0.03	0.308**

** indicates $p < .001$, * indicates $p < .01$

Note. Harm 1 corresponds to "How often have you felt that you might have a problem with gambling?", Harm 2 corresponds to "How often have people criticized your betting or told you that you had a gambling problem, regardless of whether or not you thought it was true?", Harm 3 corresponds to "How often have you felt guilty about the way you gamble or what happens when you gamble?", Harm 4 corresponds to "How often has your gambling caused you any health problems, including stress or anxiety?", and Harm 5 corresponds to "How often has your gambling caused any financial problems for you or your household?"

SSVS Analysis

In order to identify the most influential predictors of the aggregate Harm score, the dimensions with the highest MIPs in an SSVS analysis were selected to be included in a multiple linear regression model. In addition, the 15 bivariate correlations of each dimension across the three scales with the Harm score were computed to assess which dimensions would have been selected for a model based on bivariate correlations. There were 10 statistically significant bivariate correlations at the 1% level of significance ($p < .01$). We planned to include as many predictors for the regression model as would have been selected based on bivariate correlations [10]. Therefore, for the regression model selected based on MIPs, the dimensions with the top 10 MIPs were to be included. However, two predictors tied for the 10th highest MIP, resulting in 11 dimensions being included in the model. Age and gender were additionally included as predictors in the regression model.

We conducted the SSVS analyses with the web application, SSVSforPysch [9] which is available at:https://ssvsforpsych.shinyapps.io/ssvsforpsych/. This package uses default prior distributions for the Bayesian estimates. The default of 0.5 was used so that each predictor had a 50% chance of being included in the SSVS models. Finally, a burn-in period of 10,000 iterations was selected when running the MCMC sampler to ensure convergence of results when using random starting values. Each of the SSVS analyses converged, as the lowest correlation between results when each analysis was run twice was 0.9982.

Aggregate Harm Analysis: A multivariate linear regression analysis with Harm score as the dependent variable was conducted. Table 1 summarizes the regression analysis along with the MIP and bivariate correlation of each candidate predictor. There was a significant, but imperfect positive correlation between the MIPs from the SSVS analysis and the bivariate correlations, $r(15) = 0.597$, $p = 0.011$. Therefore, predictors selected for inclusion in the model based on the SSVS MIPs would not be identical to those in a model where selection is based on bivariate correlations. The 11 dimensions with the highest inclusion probabilities included all five impulsivity dimensions, two gambling cognitions (inability to stop; illusion of control), and four gambling motivations (money; escape/avoidance; excitement; and, amusement). Age and gender were additionally included in the model.

The significant predictors of the overall harm score in this model were sensation seeking ($\hat{\beta} = -0.321$, $p = .036$), motivation through avoidance ($\hat{\beta} = 0.315$, $p = .016$), inability to stop ($\hat{\beta} = 1.066$, $p < .001$), and illusion of control ($\hat{\beta} = -0.206$, $p = .024$). Inability to stop and escape/avoidance motivation were positively related to harm. Sensation seeking and illusion of control were negatively related to harm. Together, the predictors in this model accounted for 41.8% of the variability in harm score.

Individual Harm Analyses: Five additional SSVS analyses were conducted to identify which of the 15 dimensions of impulsivity, gambling cognitions, and gambling motivations were the important predictors of the individual harms. Harm 1 (personal problem) corresponds to the fifth question on the PGSI; Harm 2 (social criticism) corresponds to the sixth question; Harm 3 (guilt) corresponds to the seventh question; Harm 4 (health) corresponds to the eighth question; and, Harm 5 (financial) corresponds to the ninth question. To address the question of whether individual harms are linked to unique constellations of predictors, we present in Table 2 the MIP's and bivariate correlations of the predictor dimensions separately for each harm. The MIPs were used to determine relative dimension importance for the individual harms. Table 2 indicates that most dimensions had low MIPs (i.e., below 0.5). Given the low MIPs, it was decided to determine the most important predictors for each harm as those with an MIP greater than or equal to 0.2. As seen in Table 2, inability to stop was the most important predictor for each harm, with an MIP close to or equal to 1 for each harm. For personal problem, inability to stop ($MIP = 1.00$) and sensation seeking ($MIP = 0.22$) were the most important predictors. For social criticism, inability to stop ($MIP = 0.99$) and motivation through escape/avoidance ($MIP = 0.20$) were the two most important predictors. Inability to stop ($MIP = 1.00$) was the only important predictor for guilt. Inability to stop ($MIP = 1.00$) followed by illusion of control ($MIP = 0.21$) and motivation through escape/avoidance ($MIP = 0.20$) were the three most important predictors of health. Finally, inability to stop ($MIP = 1.00$) and motivation through escape/avoidance ($MIP = 0.81$) were the most important predictors of financial. For each harm, it was found that the dimensions which would be considered as important according to bivariate correlations differ from those that would be considered as important according to SSVS MIPs.

Discussion

Explanatory models of substance and behavioral addictions typically emphasize the contributions of three predictor domains: failure to regulate emotions; distorted cognitions related to control; and, motivations related to rewards and stress-reduction [4; 5; 14]. Identifying the relative importance of the dimensions of those factors as predictors of experiencing harm may lead to targeted interventions designed to attenuate the negative consequences. The purpose of the present study was to introduce stochastic search variable selection (SSVS) as a procedure to achieve that goal [10].

Five types of harm are measured by the PGSI: feeling one has a personal problem; social criticism; feeling guilt; health; and, financial. As a first step, we identified the significant predictors that would be included in modelling an aggregate harm score. The most important predictors, the cognition that one is not able to stop gambling, and the motivation to escape or avoid life stressors, were positively associated with harm. Two weaker, but statistically significant, predictors were negatively associated with harm: sensation-seeking and illusion of control. Although the cognition of an inability to stop gambling was the most important predictor of each individual harm, the pattern of important predictors varied across harms. For example, sensation-seeking was an important predictor for only the perception that one has a gambling problem, and escape/avoidance motivation was strongly predictive of financial harm. Interventions designed to mitigate harm might be tailored to address specific harms. The results suggest that primary interventions should address the belief that the gambler is unable to stop gambling, and motivations related to escape/avoid life stressors. Available techniques would include cognitive-behavior therapy approaches [15].

Broad generalizations from the current results are constrained by some limitations of sampling and measures in the current study. The participants were recruited at a casino where electronic gaming machines EMG's provided the only form of gambling. It is possible that the predictors of harm vary across gamblers who prefer other forms of gambling [16]. The dimensions of the predictors and their relative influence may vary across different measures of impulsivity [17], gambling cognitions [18], and gambling motivation [19]. Note that whereas the cognition and motivation measures were contextualized to gambling, impulsivity was measured as a context-free trait. Measures of impulsivity more directly attuned to gambling may increase its likelihood of selection as a variable predicting gambling harm.

Finally, advances in the quantification of gambling harm [20] have expanded the range of domains in which gambling harms may appear. Future developments [21] may lead to new standards for assessing gambling harms. Theoretically, it remains important to identify the critical dimensions of risk factors such as impulsivity, cognitions, and motivation as those factors may be central to other forms of addiction [14]. More practically, developing a model of important predictors of gambling harms may guide the scaffolding of interventions designed to ameliorate the negative consequences of this popular form of recreation.

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