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ORIGINAL PAPER

Testing the Validity of the Pathways Model: A Latent Class Analysis of Potential Pathological Gambling Subtypes in a Non-Treatment Sample

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Abstract

Latent class analysis (LCA) was used to test the validity of the Pathways Model in 285 subjects with DSM-IV pathological gambling (PG). In addition to identifying three subtypes that roughly correspond with those described in the model (Behaviorally Conditioned, or BC, Emotionally Vulnerable, or EV, Antisocial-Impulsivist, or AI), LCA identified a fourth class, termed the Antisocial Drinker, or AD, characterized by high rates of antisociality, conduct disorder, and alcohol use disorder. BC gamblers comprised 45% of the sample, followed by EV (24%), AD (22%), and AI (9%) gamblers. Women were more likely to be EV gamblers (OR = 1.89) and less likely to be AD gamblers (OR = 0.46). Those who had attempted suicide were more likely to be EV (OR = 3.06) or AI (OR = 3.05) gamblers and less likely to be BC (OR = 0.37) or AD gamblers (OR = 0.50). Greater childhood maltreatment was associated with AD (standardized OR = 1.81) and AI (standardized OR = 1.43) gamblers. Individuals with later PG onset were less likely to be AI gamblers (standardized OR = 0.48). Individuals who preferred slots were more likely to be EV gamblers (OR = 1.83) and less likely to be AD gamblers (OR = 0.33). The BC subtype was associated with better health outcomes, better social functioning, less childhood maltreatment, and less severe PG. The AI subtype was associated with worse health outcomes, worse social functioning, and higher PG severity. The findings provide a better understanding PG heterogeneity that could be relevant to clinical management.

Keywords Pathways model · Gambling · Subtypes · Latent class analysis

Introduction

Pathological gambling (PG) is characterized by the presence of persistent and recurrent maladaptive gambling behavior the person is unable to adequately control (American Psychiatric Association, 1994). PG has a general population prevalence of 1–2% and is

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associated with depresion, substance misuse, domestic violence, and suicide (Black, in press; Kessler et al., 2008). PG was moved to DSM-5's chapter on substance-related and addictive disorders and renamed gambling disorder (American Psychiatric Association, 2013), but because our study protocol predates DSM-5, we use the term *pathological gambling*, or *PG*, in this communication. We also use the term *disordered gambling*, which includes both PG and its lesser variant, problem gambling.

Experts have generally agreed that PG is heterogeneous, and some investigators have defined potential subgroups by age at onset, gender, game preference, comorbidity, gambling-related cognitions, antisociality, impulsivity, urge, and other features associated with the disorder (Black et al., 2015; Blaszczynski & McConaghy, 1989; Blaszczynski and Steel, 1996; Kim et al., 2001; Moran, 1970; Winters & Rich, 1998). Aasved (2002) concluded that research on potential subtypes was "inconsistent and often contradictory" (p.101), and that proposed schemes lacked validity.

In an early effort to describe subtypes, Moran (1970) delineated five based mainly on clinical characteristics including psychiatric comorbidity, antisociality, and impulsivity. Blaszczynski and McConaghy (1989) later described gamblers as "escape-seekers" or "sensation-seekers;" the former were older persons, often women, who gambled to relieve depression, anxiety, or loneliness, often choosing slots, while the latter included persons, generally men, who seek stimulation and arousal to alleviate boredom or hyperarousal. Following on the heels of this work, Steel and Blaszczynski (1996) used principle components analysis to identify four factors: psychological distress, sensation-seeking, crime and liveliness, and impulsive-antisocial gambling, groups that partially overlap with Moran's categories, as well as the escape-seeker and sensation-seeker typology.

This body of work foreshadowed the Pathways Model proposed by Blaszczynski and Nower (2002), unique for its integration of biological, developmental, cognitive, and other determinants of disordered gambling. Three subtypes of disordered gamblers were described: (a) the Behaviorally Conditioned (BC); (b) the Emotionally Vulnerable (EV); and (c) the Antisocial-Impulsivist (AI). BC gamblers were hypothesized to have no specific predisposing psychopathology and to develop PG as a result of distorted cognitions and poor judgment. EV gamblers were hypothesized to experience depression or anxiety, frequent life events, and childhood maltreatment, with gambling serving to modulate their affective states or meet other psychological needs. Finally, AI gamblers were hypothesized to display antisociality and impulsivity, features that could suggest neurobiological dysfunction. For these individuals, gambling was thought to begin early in life and escalate rapidly. Nower and Blaszczynski (2017) have since validated a 48-item questionnaire that can be used to assign problem and pathological gamblers to one of these groups.

The Pathways Model has garnered growing empirical support in the nearly two decades since its description. Three class solutions have been reported by Ledgerwood and Petry (2010) for a sample of 229 treatment-seeking subjects with PG; Nower et al. (2013) in 581 adults with problem gambling or PG enrolled in the National Epidemiological Survey of Alcohol and Related Conditions; Valleur et al. (2016) in 372 adults with problem gambling or PG enrolled in a five-year longitudinal cohort study of gamblers in France; Moon et al. (2017) in 150 non-treatment seeking subjects with PG; Dowd et al. (2019) in 566 young adult problem gamblers; and Mader et al. (2019) in 125 adults with problem gambling or PG enrolled in the Quinte Longitudinal study. Four class solutions were proposed by Turner et al. (2008) in a sample of 141 adults with problem gambling or PG (emotional vulnerability, impulsivity, erroneous beliefs, experiences of wins), and Allami et al. (2017) in a sample of 172 youth with problem gambling or PG (three classes resembling the Pathways Model typology and a fourth combining features of AI and EV gamblers).

Last, Gupta et al. (2013) reported a five class solution in a sample of 109 youth with problem gambling or probable PG; in addition to three Pathways Model subtypes, they found evidence for a depression only subtype and a subtype for those having both internalizing and externalizing disorders).

While all studies appear to fully or partially validate the Pathways Model, they vary widely in sample size and ascertainment method, statistical methods used, number and variety of variables examined, and population characteristics. Two studies (Ledgerwood & Petry, 2010; Moon et al., 2017) focused on subjects with PG; all other studies included a mixed group of subjects with either problem gambling or PG. Three studies focused on youth rather than adults (Allami et al., 2017; Dowd et al., 2019; Gupta et al., 2013). Several studies used epidemiologic samples (Allami et al., 2017; Mader et al., 2019; Nower et al., 2013; Valleur et al., 2016), and one used a treatment-seeking sample (Ledgerwood & Petry, 2010). Lack of consistency among studies complicates any interpretation of their results. In combining both problem gambling and PG, investigators may have missed important differences between the groups since not all problem gamblers advance to PG (Black et al., 2017), and disordered gambling in youth populations and adults might represent different constructs (Winters et al., 1993). Treatment seeking subjects with PG may not fully correspond to those with PG in the community, or in epidemiologic samples. Also, there is wide variation in research assessments. Several studies focused mainly on diagnostic data (Allami et al., 2017; Ledgerwood & Petry, 2010; Mader et al., 2019; Moon et al., 2017; Valleur et al., 2016), while none specifically assessed childhood maltreatment. Studies of disordered gamblers limited to diagnostic data cannot fully test the validity of the Pathways Model, which calls for data on gambling severity and preferences, personality characteristics, impulsiveness, childhood maltreatment, and other important variables.

With these concerns in mind, we aimed to test the validity of the Pathways Model using latent class analyses while correcting for the deficiencies of other studies. All subjects had PG and had participated in one of two NIH-funded studies that did not involve treatment (Black et al., 2014, 2017). All subjects were systematically assessed for a comprehensive range of variables germane to the Pathways Model.

Based on the literature, and our own experience, we expected to identify three classes corresponding to the BC, EV, and AI subtypes. More specifically, we expected BC gamblers to be the most psychologically healthy of the gamblers, and to have low rates of mental health conditions. We expected EV gamblers to have high rates of mood or anxiety disorders and childhood maltreatment, and to prefer slots. AI gamblers were expected to be the most psychologically disturbed of the gamblers, to prefer action gamblers, and to have high rates of antisociality and impulsiveness.

Methods

Subjects

Subjects were recruited from the community and had participated in either the Iowa Family Study of PG (Black et al., 2014) or the Iowa Longitudinal Study of PG (Black et al., 2017). All had South Oaks Gambling Scores (Lesieur & Blume, 1987) and National Opinion Research Center (NORC) DSM Screen for Gambling Problems (NODS; NORC, 1999) scores ≥ 5. Subjects met DSM-IV PG criteria (APA, 1994). Subjects were 18 years or older, spoke English, and lacked psychotic, cognitive, or chronic neurological disorders.

Exclusions included a history of adoption (because biological family history would be unavailable) or use of dopamine agonists because these agents have been reported to be associated with the onset or worsening of PG (Lader, 2008). No one was in fact excluded for these reasons.

In-person interviews were conducted from February 2005 to June 2010 for the family study and from March 2011 to September 2014 for the longitudinal study. Both studies were approved by the University of Iowa Institutional Review Board. Written informed consent was required of all subjects.

Assessments

In addition to collecting sociodemographic data on age, sex, marital status, race, education, and PG age at onset, we used the following instruments to assess DSM and non-DSM disorders of interest: the Structured Clinical Interview for DSM-IV, Non-Patient Version (SCID-IV; Spitzer et al., 1994); the Structured Interview for DSM-IV Personality (SIDP-IV; Pfohl et al., 1997); the Minnesota Impulsive Disorders Interview (MIDI; Christenson et al., 1994); and the Mini International Neuropsychiatric Interview-Attention Deficit Hyperactivity Disorder Module (MINI; Sheehan et al., 1998). The Barratt Impulsiveness Scale (BIS; Barratt, 1959) assessed impulsiveness. The Medical Outcome Study Short Form-36 (MOS; Ware, 1993) was used to assess physical and emotional health status. The NORC (1999) gambling self-administered questionnaire was used to gambling attitudes and behaviors. Gambling severity was assessed using the Gambling Symptom Assessment Scale (GSAS; Kim et al., 2009). Childhood maltreatment was assessed with the Revised Childhood Experiences Questionnaire (Zanarini, 1992).

Statistical Analysis

Statistical Model for Identifying Classes of PGs

Latent class analysis (LCA) is a statistical technique for identifying and characterizing groups of individuals based on a set of observed categorical (dichotomous or nominal) variables. LCA uses the observed variables ("manifest variables") to identify unobserved latent groups. LCA attempts to eliminate confounding between the manifest variables, such that the manifest variables are assumed to be independent within each latent group (Linzer & Lewis, 2011).

LCA does not automatically determine the appropriate number of latent classes (groups). Instead, researchers must select the number of latent classes using goodness of fit statistics, theory, and judgment. For each latent class, LCA estimates the distribution of each manifest variable, allowing the researcher to interpret the meaning of each latent class. We used the *poLCA* R software package (Linzer & Lewis, 2013) to fit the LCA model using the sample of 285 individuals with PG. In addition to fitting the model to characterize the latent classes, *poLCA* can be used to predict latent class membership. While the manifest variables must be categorical, the predictor variables can be continuous, dichotomous, or categorical.

The *poLCA* package was used to fit 3-class and 4-class models. The 3-class model is consistent with the Pathways Model, while fitting the 4-class model allows us to test the adequacy of the 3-class model and potentially identify an additional class of PGs. The statistical output includes model fit statistics, estimates of class size (the proportion of individuals belonging to each class), distributions of each manifest variable (mental health disorders that predated the subjects PG) within each class, and the probability of membership in each class for each individual in the sample. We used the probabilities of class membership, along with a large set of predictor variables, to examine predictors of class membership.

The LCA model was fit using dichotomous indicator variables for nine mental health conditions and one indicator for having high impulsivity. The nine mental health conditions included: meeting ≥ 2 criteria for antisocial personality disorder (ASPD), having a conduct disorder, having an impulse control disorder, having a drug use disorder, having an alcohol use disorder, having posttraumatic stress disorder, having attention deficit hyperactivity disorder (ADHD), having a mood disorder, or having an anxiety disorder. High impulsiveness was defined as a BIS score ≥ 75.

By comparing age of onset for each mental health condition to PG age of onset, we were able to determine whether each diagnosis occurred before the onset of PG. However, age of onset was not collected for ASPD criteria, conduct disorder, or ADHD. Therefore, we could not determine if these conditions occurred before or after PG onset. Similarly, high impulsiveness scores may have manifested before or after PG onset.

Analysis of Predictors of PG Class Membership

A large set of predictors of latent class membership were examined using variables collected in the two studies. Predictors included PG age of onset, age, sex, race, childhood maltreatment, and several other background and clinical measures (Table 1). We included an indicator for study (1, data collected in the Iowa Family Study of PG, 0, data collected in the Iowa Longitudinal Study of PG). Childhood maltreatment was coded dimensionally (0–5, based on the number of types of maltreatment experienced, including emotional, verbal, physical, or sexual abuse, and negligence).

Logistic regression was used to examine the relationship between each predictor variable and the probability of membership in each PG class. Logistic regression models produce odds ratio (OR) estimates, confidence intervals (CIs), and *p*-values. For dichotomous and categorical predictors, each OR measures the odds of membership in each PG class associated with the predictor group. For example, for gender and the three class model, the odds ratio for "Class 1" represents the odds of being in Class 1 for females, relative to the odds of being in Classes 2 or 3. For continuous predictors (e.g., age of PG onset, General Health score from the MOS), the OR represents the increase in the odds of membership in each PG class associated with each standard deviation increase in the predictor.

Prior to fitting the statistical models, missing data was imputed using the *MICE* R software package (van Buuren & Groothuis-Oudshoorn, 2011). Five imputed data sets were created, and the study's results were obtained by averaging results across the data sets. To facilitate interpretation of effect sizes, continuous predictor variables were standardized to have mean 0 and standard deviation 1.

Table 1 Sociodemographic and Clinical Characteristics of the Sample

Category	Variable	%	Mean	SD
Sociodemographic	Age		47.06	17.73
	Female	45.3		
	Minority race	13.7		
	Years of education		14.00	2.35
	Ever arrested	42.1		
	Prior suicide attempt	20.7		
	Childhood maltreatment		1.95	1.82
	Family study participant	56.1		
	PG age of onset		34.92	15.40
	Marital status			
	Divorced/separated	22.0		
	Married	26.7		
	Single	32.7		
	Widowed	18.6		
PG variables	Gaming preference			
	Action games	36.8		
	Other games	24.1		
	Slots	39.1		
PG severity	NODS score		7.86	2.00
	GSAS score		16.51	10.93
Mental health condition	ASPD ($\geq$ 2 criteria)	38.1		
	Conduct disorder	38.0		
	Impulsive (BIS $\geq$ 75)	27.5		
	Impulse control disorder	20.7		
	ADHD	14.2		
	Drug use disorder	21.1		
	Alcohol use disorder	42.9		
	PTSD	9.8		
	Mood disorder	40.6		
	Anxiety disorder	31.4		
MOS scores	Bodily pain		70.16	26.04
	General health		62.13	22.59
	Mental health		66.46	20.35
	Physical function		75.28	26.73
	Emotional role		62.29	43.24
	Physical role		64.61	40.70
	Social		72.89	27.00
	Vitality		49.89	20.11

ASPD antisocial personality disorder; *BIS* Barratt Impulsiveness Scale; *ADHD* attention deficit/hyperactivity disorder; *PTSD* posttraumatic stress disorder. *NODS* National Opinion Research Center (NORC) DSM Screen for Gambling Problems; *SOGS* South Oaks Gambling Screen

Table 2 Model Fit Statistics for Sample

Model Fit Statistic	Number of Classes	
	3	4
AIC	2968.65	2938.98
BIC	3002.33	2984.23
Log likelihood	– 1477.93	– 1460.89

Table 3 Probabilities for Mental Health Conditions for 3-Class Latent Class Analysis, Combined Sample

Mental health condition	Class 1: behaviorally conditioned		Class 2: antisocial drinker		Class 3: antisocial-impulsivist/emotionally vulnerable	
	EST	SE	EST	SE	EST	SE
ASPD	0.109	0.045	1.000	0.000	0.483	0.078
Conduct disorder	0.166	0.034	0.812	0.077	0.517	0.078
Impulsive (BIS ≥ 75)	0.113	0.030	0.394	0.072	0.591	0.088
Impulse control disorder	0.128	0.030	0.171	0.054	0.458	0.080
ADHD	0.043	0.019	0.152	0.054	0.402	0.085
Drug use disorder	0.129	0.030	0.210	0.063	0.432	0.081
Alcohol use disorder	0.313	0.040	0.592	0.072	0.578	0.079
PTSD	0.036	0.018	0.000	0.000	0.367	0.077
Mood disorder	0.268	0.039	0.184	0.056	0.713	0.073
Anxiety disorder	0.211	0.039	0.000	0.000	0.912	0.064

ASPD antisocial personality disorder; *BIS* Barratt Impulsiveness Scale; *ADHD* attention deficit/hyperactivity disorder; *PTSD* posttraumatic stress disorder

Results

The study included 285 subjects with DSM-IV PG who had participated in either the Iowa Family Study of PG (N = 160) or the Iowa Longitudinal Study of PG (N = 125) (Black et al., 2014, 2017). Forty-five percent of the subjects were female, and 86% were European-Caucasian. Mean (SD) age was 47.1 (17.7) years. Sociodemographic and clinical characteristics of the sample are presented in Table 1.

Model Fit

With LCA, the Bayesian information criterion (BIC; Schwartz, 1978) and Akaike information criterion (AIC; Akaike, 1973) are often used to determine the best-fitting and most parsimonious model. Preferred models are those that minimize the BIC and/or AIC. Table 2 shows the model fit statistics for the 3- and 4-class models. Using the

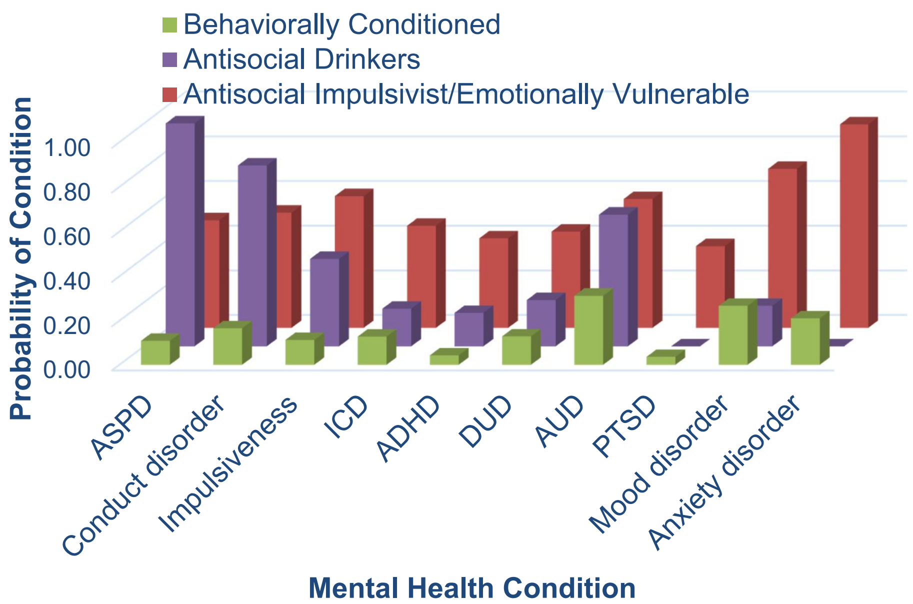

Fig. 1 Probabilities of Mental Health Disorders for 3 Class LCA, Combined Sample. ASPD = antisocial personality disorder; ICD = impulse control disorder; ADHD = attention deficit/hyperactivity disorder; DUD = drug use disorder; AUD = alcohol use disorder; PTSD = posttraumatic stress disorder

likelihood ratio test, the improvement in model fit for the four class is statistically significant (Chi-square = 34.1, df = 11, $p < 0.001$).

Because both the BIC and AIC are larger for the 4-class model and the improvement is statistically significant, the 4-class model is preferred based on statistical criteria. We proceed by fitting both 3- and 4-class models to contrast results and permit substantive interpretations of model differences.

Identification and Characterization of PG Classes

For the 3-class model, Table 3 and Fig. 1 provide the distribution of each manifest variable (premorbid mental health disorder) for each latent class. Based on the distributions, we assigned names to each latent class, using the Pathways Model as a theoretical framework: Class 1 is named Behaviorally Conditioned, or *BC*; Class 2 is named Antisocial Drinker or *AD*, and Class 3 is named Antisocial-Impulsivist/Emotionally Vulnerable, or *AI/EV*.

The AD class is characterized by having antisocial symptoms (100%), high rates of conduct disorder (81%), high rates of alcohol use disorder (59%), and moderate rates of high impulsiveness (i.e., BIS ≥ 75) (39%). Posttraumatic stress disorder and anxiety disorders did not appear prior to PG onset in the AD group.

The AI/EV class has a diagnostic profile that combines features of the EV and AI classes proposed by Blaszczynski and Nower (2002) and is characterized by moderately high rates of antisocial symptoms, conduct disorder, impulse control disorders, and high rates of impulsiveness. This group also has very high rates of mood (71%) and anxiety

Table 4 Probabilities for Mental Health Conditions for 4-Class Latent Class Analysis, Combined Sample

Mental health condition	Behaviorally conditioned		Emotionally vulnerable		Antisocial drinker		Antisocial-impulsivist	
	EST	SE	EST	SE	EST	SE	EST	SE
ASPD	0.091	0.055	0.282	0.077	1.000	0.000	0.621	0.124
Conduct disorder	0.141	0.038	0.339	0.077	0.813	0.079	0.664	0.120
Impulsiveness (BIS ≥ 75)	0.115	0.036	0.246	0.074	0.398	0.071	0.891	0.106
Impulse control disorder	0.098	0.035	0.282	0.077	0.171	0.054	0.667	0.118
ADHD	0.057	0.025	0.025	0.051	0.161	0.054	0.876	0.128
Drug use disorder	0.089	0.035	0.368	0.094	0.219	0.063	0.394	0.116
Alcohol use disorder	0.280	0.048	0.551	0.084	0.586	0.072	0.487	0.127
PTSD	0.000	0.000	0.262	0.081	0.000	0.000	0.411	0.122
Mood disorder	0.198	0.048	0.632	0.086	0.184	0.056	0.719	0.113
Anxiety disorder	0.148	0.048	0.669	0.094	0.000	0.000	1.000	0.000

ASPD antisocial personality disorder; *BIS* Barratt Impulsiveness Scale; *ADHD* attention deficit/hyperactivity disorder; *PTSD* posttraumatic stress disorder

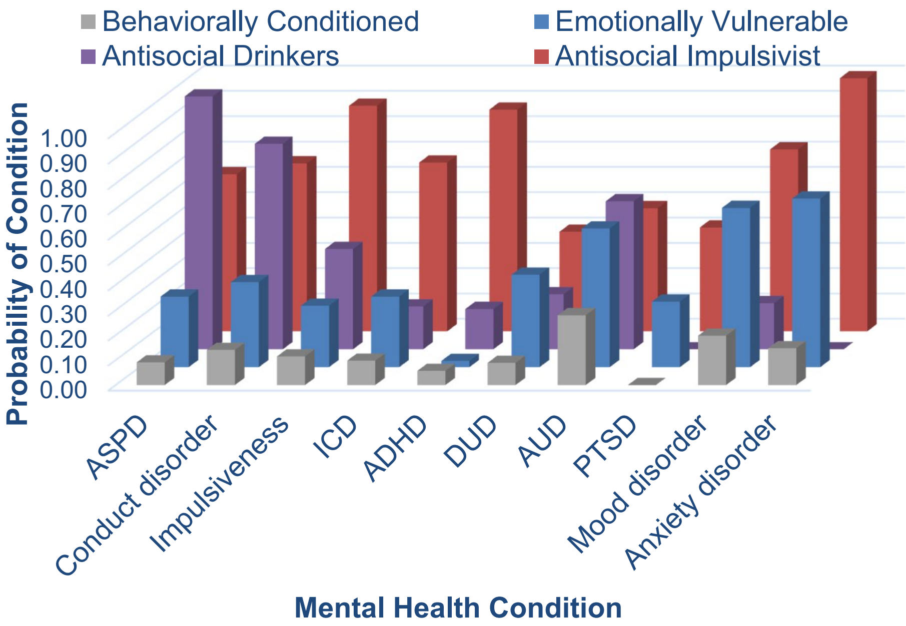

Fig. 2 Probabilities of Mental Health Disorders for 4-Class LCA, Combined Sample. ASPD = antisocial personality disorder; ICD = impulse control disorder; ADHD = attention deficit/hyperactivity disorder; DUD = drug use disorder; AUD = alcohol use disorder; PTSD = posttraumatic stress disorder

(91%) disorders, along with high rates of ADHD (40%), drug use disorder (43%), alcohol use disorder (58%), and posttraumatic stress disorder (37%).

The BC class is characterized by having low rates of premorbid mental health conditions but has a moderate rates of alcohol use disorder (31%).

For the 4-class model, Table 4 and Fig. 2 provide the distribution of each premorbid psychiatric disorders for each latent class. Based on those results, class names were assigned as follows: Class 1 BC, Class 2 EV, Class 3 AD, and Class 4 AI. By moving from the 3-class model to the 4-class model, we found that the AI/EV group splits in two, forming groups more in keeping with the Pathways Model.

Individuals in the EV group have relatively low rates of antisocial symptoms, conduct disorder, and impulse control disorders. They have high rates of mood (63%) and anxiety (67%) disorders, and high rates of drug use disorders (37%) and alcohol use disorders (55%) disorders, but low rates of ADHD.

The AD group from the 4-class model is essentially the same as the group identified from the 3-class model. Again, individuals in this class have high rates of antisocial personality disorder symptoms, high rates of conduct disorder, moderate rates, high rates of impulsiveness, and high rates of alcohol use disorders.

The AI group has a diagnostic profile like that proposed in the Pathways Model and is characterized by high rates of antisocial symptoms (62%), conduct disorder (66%), impulse control disorders (67%), and impulsiveness (89%). This class also had high rates of ADHD (88%), and mood (72%) and anxiety (100%) disorders. The AI group differs from the AD group by having much higher rates of impulsiveness, ADHD, posttraumatic stress disorder, mood disorders, and anxiety disorders.

The BC group from the 4-class model is similar—but not identical—to the group identified from the 3-class model, again characterized by having relatively low rates of premorbid mental health conditions.

Size of PG Classes

Table 5 provides estimates of the probabilities of belonging to each latent class. For both 3- and 4-class models, a plurality of individuals with PG are BC (57% in the 3-class and 45% for 4-class models). Nearly 22% of the sample are ADs. For the 4-class model, relatively few individuals are AI (9%) and nearly one-quarter are EV (24%).

Predictors of PG Class Membership

To examine predictors of PG class membership, we focus on the results for the 4- class model because it had stronger statistical fit and represents an extension of the three class

Table 5 Probabilities of Class Membership, Combined Sample

Model	Name of class	Probability	
		Estimate	SE
3 class	Behaviorally conditioned	0.572	0.019
	Antisocial drinker	0.217	0.014
	Antisocial-impulsivist/emotionally vulnerable	0.212	0.015
4 class	Behaviorally conditioned	0.455	0.026
	Emotionally vulnerable	0.240	0.024
	Antisocial drinker	0.219	0.015
	Antisocial-impulsivist	0.086	0.010

Table 6 Significant Predictors of Class Membership for 4-Class Model

Variable	Behaviorally conditioned			Emotionally vulnerable			Antisocial drinker			Antisocial-impulsivist		
	OR	95% C.I	*p*-val	OR	95% C.I	*p*-val	OR	95% C.I	*p*-val	OR	95% C.I	*p*-val
Age	1.21	0.95, 1.53	0.115	0.98	0.75, 1.29	0.895	0.99	0.74, 1.31	0.927	0.57	0.36, 0.90	0.016
Female sex	0.92	0.57, 1.47	0.713	1.89	1.09, 3.29	0.024	0.46	0.25, 0.84	0.011	1.51	0.65, 3.47	0.335
Ever arrested	0.48	0.29, 0.77	0.003	1.19	0.69, 2.07	0.531	2.22	1.25, 3.94	0.007	1.15	0.50, 2.65	0.744
Prior suicide attempt	0.37	0.19, 0.69	0.002	3.06	1.65, 5.66	0.000	0.50	0.22, 1.12	0.092	3.05	1.28, 7.24	0.012
Childhood maltreatment	0.59	0.46, 0.76	0.000	0.96	0.73, 1.26	0.756	1.81	1.36, 2.42	0.000	1.43	0.95, 2.15	0.086
Family study participant	0.93	0.85, 1.02	0.134	0.63	0.57, 0.70	0.000	0.60	0.54, 0.67	0.000	0.39	0.33, 0.46	0.000
PG age of onset	1.25	0.99, 1.59	0.062	1.21	0.92, 1.58	0.165	0.76	0.56, 1.02	0.069	0.48	0.28, 0.83	0.009
Marital status												
Divorced/separated	0.98	0.56, 1.72	0.937	1.82	0.98, 3.38	0.058	0.53	0.24, 1.15	0.108	0.82	0.29, 2.36	0.713
Married	1.29	0.76, 2.19	0.343	0.95	0.51, 1.76	0.866	0.47	0.22, 0.97	0.041	2.02	0.86, 4.75	0.107
Single	0.98	0.60, 1.62	0.945	1.08	0.61, 1.92	0.794	0.80	0.43, 1.48	0.476	1.40	0.60, 3.28	0.439
Widowed	0.75	0.41, 1.39	0.363	0.40	0.17, 0.94	0.036	4.70	2.46, 8.97	0.000	0.02	0.00, 6.08	0.177
Game preference												
Action games	1.08	0.67, 1.76	0.747	0.62	0.34, 1.12	0.112	1.25	0.70, 2.23	0.446	1.37	0.59, 3.18	0.459
Other game	0.61	0.35, 1.07	0.087	0.80	0.41, 1.55	0.509	2.46	1.34, 4.53	0.004	0.86	0.31, 2.35	0.768
Slots	1.34	0.83, 2.16	0.234	1.83	1.05, 3.18	0.032	0.33	0.17, 0.65	0.001	0.81	0.34, 1.94	0.635
NODS score	0.60	0.46, 0.78	0.000	1.22	0.91, 1.63	0.187	1.21	0.90, 1.64	0.213	3.03	1.54, 5.96	0.001
GSAS score	0.68	0.53, 0.86	0.002	1.37	1.04, 1.81	0.024	1.04	0.79, 1.38	0.765	1.43	0.95, 2.17	0.087
MOS scores												
Bodily pain	1.40	1.10, 1.79	0.007	0.76	0.58, 0.99	0.044	1.03	0.78, 1.37	0.829	0.67	0.46, 0.99	0.043
General health	1.32	1.04, 1.68	0.023	0.81	0.62, 1.07	0.136	1.14	0.86, 1.52	0.359	0.52	0.34, 0.80	0.003
Mental health	1.53	1.19, 1.97	0.001	0.67	0.51, 0.87	0.003	1.44	1.05, 1.98	0.023	0.41	0.28, 0.62	0.000
Role function: emotional	1.76	1.37, 2.26	0.000	0.73	0.56, 0.96	0.023	0.92	0.70, 1.22	0.565	0.46	0.30, 0.72	0.001
Role function: physical	1.31	1.03, 1.66	0.028	0.94	0.72, 1.23	0.644	0.83	0.63, 1.10	0.199	0.77	0.51, 1.14	0.191

Table 6 (continued)

Variable	Behaviorally conditioned			Emotionally vulnerable			Antisocial drinker			Antisocial-impulsivist		
	OR	95% C.I	*p*-val	OR	95% C.I	*p*-val	OR	95% C.I	*p*-val	OR	95% C.I	*p*-val
Social	1.88	1.43, 2.47	0.000	0.70	0.54, 0.91	0.009	1.07	0.80, 1.43	0.641	0.40	0.27, 0.59	0.000
Vitality	1.45	1.13, 1.85	0.003	0.69	0.52, 0.91	0.009	1.23	0.92, 1.65	0.153	0.48	0.31, 0.75	0.001

NODS National Opinion Research Center (NORC) DSM Screen for Gambling Problems; *SOGS* South Oaks Gambling Screen; *MOS* Medical Outcome Survey

Pathways Model. For each predictor variable and each PG class, Table 6 shows the OR estimate, 95% CI, and p-value for variables that were significant predictors of class membership.

If a variable predicts a higher probability of membership in one class, it necessarily predicts a lower probability of membership in another class because all individuals must belong to one class (the probabilities of class membership must sum to 1 for each subject). For example, older individuals with PG were less likely to be AI (OR = 0.57, $p = 0.016$) and relatively more likely to be BC (OR = 1.21, $p = 0.115$).

Variables predictive of EV membership included female sex (OR = 1.89), prior suicide attempt (OR = 3.06), being widowed (negatively predictive, OR = 0.40), preference of slots over other games (OR = 1.83), and gambling severity as measured by GSAS (standardized OR = 1.37). Multiple subscales from the MOS were predictive of being EV. Worse Bodily Pain, Mental Health, Emotional Role Functioning, Social Functioning, and Vitality were predictive of being EV.

Predictors of AD membership included male sex (female sex, OR = 0.46), having been arrested (OR = 2.22), more childhood maltreatment (OR = 1.81), being married (negatively predictive, OR = 0.47), being widowed (OR = 4.70), preferring games other than slots and action games (OR = 2.46), and higher Mental Health functioning as measured by the MOS (standardized OR = 1.44).

Predictors of AI membership included age (negatively predictive, OR = 0.57), prior suicide attempt (OR = 3.05), age of PG onset (negatively predictive, standardized OR = 0.48), and PG severity as measured by NODS score (standardized OR = 3.03). Contrary to our expectations, we did not find evidence that males were more likely to be AI. Several measures from the MOS were predictive of being in the AI group; in all cases, worse medical outcomes were related to a higher probability of being an AI.

The predictors of BC membership suggest that individuals in this group are generally less psychologically disturbed and have better health. Predictors of BC membership included no prior arrests, no prior suicide attempt, less childhood maltreatment, lower PG severity (as measured by both the NODS and GSAS), and higher scores on the MOS, indicating better overall health.

Discussion

Our hypotheses were largely confirmed, and the findings also provide partial confirmation of the Pathways Model. We identified three classes that strongly resemble the Pathway Model subtypes, but also found evidence of a fourth class, which we have termed the *Antisocial Drinker*, or *AD*. As initially described by Blaszczynski and Nower (2002), the Pathways Model's three subtypes integrate personality, developmental, cognitive, biologic, and other data. Mainly derived from the authors' clinical experience and contemporary research findings, the subtypes acknowledge the inherent heterogeneity of the disordered gambling population. Their conceptual framework delineates a "series of three discrete pathways leading to the development of distinct subgroups of pathological gambling" (p. 487).

Since its initial description, investigators around the globe have attempted to validate the Pathways Model, efforts that have varied greatly in their methods and conclusions. While many investigations have at least partially validated the model, some have found evidence supporting four, or even five classes. Our study falls among the latter, as we found support for four classes. While the LCA produced 3-and 4-class models, the latter produced a better fit for the data.

Our BC and EV classes align remarkably well with the Pathways Model descriptions. BC gamblers are considered "essentially 'normal' in character" (Blaszczynski & Nower, 2002; p. 496) without premorbid psychological disturbance, and low severity, a description fully consistent with our findings. EV gamblers, on the other hand, combine poor coping with depression, anxiety and alcohol disorders, and, if female, prefer slots. Our EV class is characterized by all these traits, although we are unable to confirm the association with poor coping because that was not assessed.

The Pathways Model AI class differs somewhat from ours. Both involve early age at onset, severe PG symptoms, antisociality, impulsivity, and substance abuse, but our AI class also displayed high rates of mood and anxiety disorders. Our AD class exhibited moderate rates of antisociality and impulsivity, but also showed high rates of childhood maltreatment and alcohol use disorders, essentially combining features of the Pathways Model EV and AI classes. Like the Pathways Model subtypes, gamblers in the BC class were the least psychologically disturbed and had the best emotional and physical role functioning, while AI gamblers were the most psychologically disturbed and had the poorest emotional and physical role functioning.

The EV and AI subtypes have much in common with early—versus later—onset gamblers we have previously described (Black et al., 2015). We reported that later-onset gamblers were mostly women who preferred slots and had a history of sexual abuse, while in contrast early onset gamblers were mostly male, preferred action games, and had more antisociality and impulsivity. This dichotomy is reminiscent of the "escape seeking" versus the "sensation seeking" gamblers described by Blaszczynski and McConaghy (1989), discussed earlier.

The importance of recognizing distinctions among disordered gamblers is that different groups might benefit from different treatment approaches, although we are not at the point whereby a gambler can be matched to a treatment. It could be that those with high PG severity, such as those in the AD or AI groups, might benefit from medication shown to reduce gambling urges, for example an opioid antagonist such as naltrexone or nalmefene (Grant et al., 2006; Kim et al., 2001). Those in the BC group might preferentially benefit from a cognitive-behavioral approach that challenges disturbed gambling-related cognitions (Petry, 2005). Those in the EV group might benefit from antidepressant medications, such as one of the serotonin specific reuptake inhibitors to help relieve their comorbid depression or anxiety (Medeiros and Grant, 2019). Those with high rates of substance use disorders, including those in EV and AD groups, might benefit from treatment aimed at achieving abstinence.

There are several methodological limitations to acknowledge. First, an epidemiological sampling method would have been more desirable, but this was not feasible. Second, the low participation rate of minority subjects reduces the generalizability of our findings to these populations, and, because we focused on adults, the findings also cannot be generalized to youth populations. Third, latent class analysis requires methodological choices by researchers that can influence the study's results, including which variables to include as manifest variables, which variables to include as predictor variables, model choice (e.g., 3-class or 4-class), and how to interpret and name the resulting PG subtypes. Other researchers might make different choices which could lead to different conclusions.

Summary

In summary, we were able to partially confirm the three Pathways Model subtypes with some critical differences including the identification of a fourth class. Four classes were identified in our analysis:

(1) BC gamblers are unlikely to have psychiatric conditions, to report past suicide attempts or childhood maltreatment; they have better overall health;
(2) EV gamblers, mostly women, have histories of suicide attempts, and mood, anxiety and substance use disorders, but low rates of behavioral disturbances; they have worse overall health, and they prefer slots;
(3) AD gamblers are mostly men with high rates of behavioral disorders (antisociality, impulsive control disorders, arrests), alcohol use disorders, and childhood maltreatment; they prefer games other than slots, and are less likely to be married;
(4) AI gamblers are younger than individuals in other groups, have an early age of PG onset and high severity, and have high rates of externalizing disorders, mood and anxiety disorders, posttraumatic stress disorder, and poor physical and emotional role functioning.

Future investigations should continue testing Pathways Model subtypes, as well additional subtypes identified by us, or other research teams. It could be that four or five class solutions will work better than three class solutions and better capture the heterogeneity inherent in the PG population. Investigators should use large samples carefully assessed for a range of variables including gambling severity and behavior, psychiatric diagnoses, addictions, personality traits, antisociality, impulsiveness, and childhood maltreatment. In addition to giving the field a better understanding of disordered gambling, the goal of this work is to improve clinical care.

Authors contribution Dr. Black designed the study and contributed to preparing the manuscript. Dr. Allen analyzed the data and contributed to writing the manuscript. Both authors approved the final version.

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Data availability Data are available to researchers.

Declarations

Conflict of interest Dr. Black is a consultant to Otsuka and receives royalties from American Psychiatric Publishing, Oxford University Press, Merck, and Kluwer Wolters. Drs. Allen reports no conflicts.

Consent to participate All subjects gave written, informed consent.

Ethics approval The research was approved by the University of Iowa Intuitional Review Board.

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