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ORIGINAL ARTICLE

Latent class profile of psychiatric symptoms and treatment utilization in a sample of patients with co-occurring disorders

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Objective: To identify symptom-based subgroups within a sample of patients with co-occurring disorders (CODs) and to analyze intersubgroup differences in mental health services utilization.
Methods: Two hundred and fifteen patients with COD from an addiction clinic completed the Symptom Checklist 90-Revised. Subgroups were determined using latent class profile analysis. Services utilization data were collected from electronic records during a 3-year span.
Results: The five-class model obtained the best fit (Bayesian information criteria [BIC] = 3,546.95; adjusted BIC = 3,363.14; bootstrapped likelihood ratio test $p < 0.0001$). Differences between classes were quantitative, and groups were labeled according to severity: mild (26%), mild-moderate (28.8%), moderate (18.6%), moderate-severe (17.2%), and severe (9.3%). A significant time by class interaction was obtained (chi-square [$\chi^2_{[15]}$] = 30.05, $p = 0.012$); mild ($\chi^2_{[1]} = 243.90$, $p < 0.05$), mild-moderate ($\chi^2_{[1]} = 198.03$, $p < 0.05$), and moderate ($\chi^2_{[1]} = 526.77$, $p < 0.05$) classes displayed significantly higher treatment utilization.
Conclusion: The classes with more symptom severity (moderate-severe and severe) displayed lower utilization of services across time when compared to participants belonging to less severe groups. However, as pairwise differences in treatment utilization between classes were not significant between every subgroup, future studies should determine whether subgroup membership predicts other treatment outcomes.

Keywords: Co-occurring disorders; latent class profile; treatment utilization; psychiatric symptoms

Introduction

A large body of evidence suggests that psychiatric symptoms are very common in samples of patients with substance use disorders (SUDs).[1,2] This circumstance, known as co-occurring disorders (CODs), is linked to poor treatment response and worse overall clinical outcomes across the patient's lifespan.[3]

Current perspectives in psychiatry propose that the introduction of modern mental disorders classifications (ICD and DSM) has resulted in the appearance of conditions known as "subsyndromal" or "subthreshold" disorders. These are defined as psychiatric syndromes that do not endorse enough diagnostic criteria to be considered full-criteria mental disorders, and are frequently coded as "not otherwise specified" in current diagnostic systems.[4,5]

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As a response, the use of a dimensional or spectrum-based approach toward disease classification (understood as a continuum of the severity of psychiatric symptoms that ranges from the mildest to the most severe manifestation of the disorders) has been proposed to reduce uncertainty when assessing psychiatric comorbidities.[6,7]

The heterogeneity resulting from the possible combinations between CODs and psychiatric symptoms plays a major role in clinical decision making. Therefore, unveiling subtypes of such symptoms in patients with COD is imperative[8] and should be the first step toward developing tailored and adaptive interventions.[9]

The latent class profile (LCP) is a numerical extension of latent class analysis (LCA), a person-centered (rather than variable-centered) approach which has proven useful in testing whether meaningful subgroups exist within a population.[10] LCP is a finite mixture model that assumes the existence of two or more underlying subgroups within a population, where the subgroups are defined as the intersection of a manifest set of numerical indicators.[11]

Regardless of the amount of evidence pointing out that contact with mental health services in patients with COD is briefer when compared to SUD-only patients,[12] it is clear that the heterogeneity of this population hinders identification of predictors of treatment attendance.[13]

The objective of this study was twofold: to use LCP to determine whether subgroups based on psychiatric symptoms exist and, if so, to analyze differences in mental health services utilization between these subgroups.

Methods

Setting

Data collection was carried out at Clínica de Trastornos Adictivos, Instituto Nacional de Psiquiatría Ramón de la Fuente Muñiz (CTA-INPRFM), Mexico City, Mexico, between January 2012 and November 2014. The CTA-INPRFM is an outpatient treatment program specialized in pharmacological and psychological treatment of patients with COD.

Participants

Consecutive patients were recruited at treatment intake in CTA-INPRFM. Patients were eligible for participation if they endorsed criteria for COD (defined as endorsing any SUD and any non-addictive psychiatric disorder simultaneously) and were at least 18 years old. Patients for whom data were missing were excluded from the analyses. Figure 1 displays participant flow during the study.

Measures

The Spanish version of the Symptom Checklist 90-Revised version (SCL-90-R) was used to assess psychiatric symptoms.[14] The psychometric properties of this scale have been published elsewhere.[15] The SCL-90-R is composed of 90 items distributed across nine subscales: somatization (SOM), obsessive-compulsive (O-C), interpersonal sensitivity (I-S), depression (DEP), anxiety (ANX), hostility (HOS), phobic anxiety (PHOB), paranoid ideation (PAR), and psychoticism (PSY). Responses are given on a five-point Likert scale, and the score of each subscale is the mean of the responses to its items. For this study, the subscale scores were taken as observable indicators of psychiatric symptoms.

Mental health services utilization was measured as the number of visits to CTA-INPRFM for psychiatric or behavioral treatment over 6-month periods. Participants' records were tracked during a span of 3 years.

Psychiatric disorders and SUDs were assessed by a fully trained psychiatrist from the CTA-INPRFM team based on the DSM-IV-TR criteria. Diagnoses were grouped into the following broad categories: depressive disorders (including major depressive disorders and dysthymia); anxiety disorders (including social phobia, agoraphobia, generalized anxiety disorders, and post-traumatic stress disorder); bipolar disorders (including bipolar I and II disorders); psychotic disorders (including schizophrenia, brief psychotic disorders, and substance-induced disorders); attention deficit/hyperactivity disorder (ADHD); eating disorders (including anorexia, bulimia nervosa, and non-specific eating disorders); any somatoform disorder; personality disorders from clusters A, B, and C; and alcohol, cannabis, cocaine, inhalants, and other SUDs (including substances with lower prevalence, such as benzodiazepines, opiates, hallucinogens, and MDMA).

Procedures

At intake, the CTA-INPRFM on-site research team evaluated all patients for eligibility. Within the following week, eligible patients returned for clinical assessment. During this assessment session, an on-site researcher provided information on the study's aims and procedures and, after obtaining written informed consent from the patient, collected data on demographic characteristics and administered the SCL-90-R. Participants' visits at the CTA-INPRFM and psychiatric/SUD diagnoses were extracted from their electronic records.

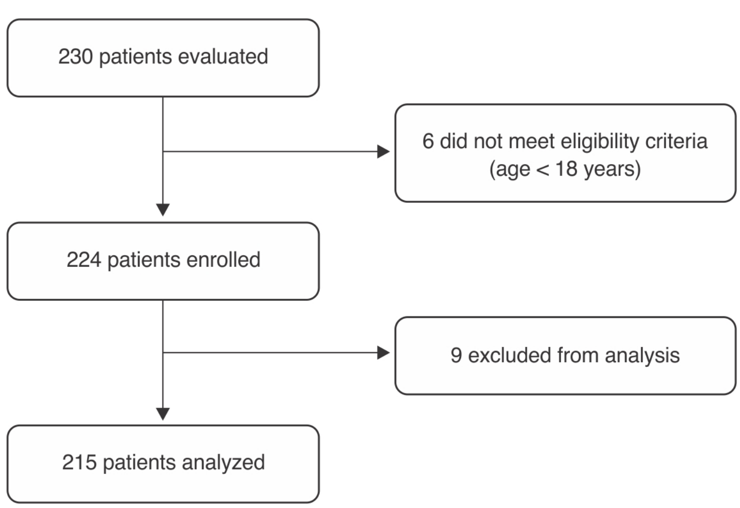

Figure 1 Flow diagram of study sample.

Statistical analysis

The nine SCL-90-R composite scores were included as numerical indicators in the LCP. Two- to eight-class LCP models were evaluated. Bayesian information criteria (BIC), sample-adjusted BIC (aBIC), class entropy, and the bootstrapped likelihood ratio test (BLRT) were estimated for every class. To determine which model obtained the best comparative fit, we used the recommendations of Nylund et al.,[16] considering the best-fitting model as that with the lowest BIC, aBIC, and a significant BLRT ($p < 0.05$). To prevent local solutions, every model was estimated with 1,000 random starts and 10 optimizations. We operationalized a global solution as the replication of the best log-likelihood in eight of 10 optimizations. This analysis was performed in the M*plus* 6 statistical software package[17] using maximum likelihood estimation with standard errors. Missing data were assumed to be completely at random (MCAR); therefore, we used the full information maximum likelihood approach to handle missing data, as it has shown better results in Monte Carlo simulation studies.[18] For this purpose, we tested the MCAR assumption using a method based on estimation of multivariate normality and homoscedasticity.[19] Differences in psychiatric disorders and SUDs between classes were tested using the chi-square statistic. To compare differences in mental health services utilization between the classes, we used generalized estimating equations (GEEs) for negative binomial distribution and a logit link function to analyze the time by class interaction, using SPSS version 19.0. GEE, a repeated-measures statistical analysis for count and categorical variables, is useful when the structure of the covariance matrix is unknown.[20] The significance level was set at $p < 0.05$.

Ethical considerations

All patients provided written informed consent for participation in the study. To maintain confidentiality, all data provided to the research team were anonymized. The study protocol, informed consent form, and assessment materials were approved by the Institutional Ethics Committee.

Results

Sample characteristics

Of the 231 enrolled participants, 215 (96.1%) completed all required data for analysis. Most participants were male, with a mean age of 30.85 years (standard deviation = 10.30 years). Most reported being currently employed, completed high school, and having never been married (Table 1).

Testing for the MCAR assumption

The first step was to conduct the Hawkins test, which yielded $p < 0.001$. This indicates rejection of the assumptions of multivariate normality and homoscedasticity. We then conducted a nonparametric analysis, which yielded p = 0.329. These results are consistent with insufficient evidence to reject the MCAR assumption.

Table 1 Patients' characteristics

	n (%)
Age* (years) (n=208)	
18-29	109 (50.70)
30-39	56 (26.00)
40-49	31 (14.40)
⩾ 50	12 (5.60)
Gender (n=215)	
Male	161 (74.90)
Female	54 (25.10)
Education† (n=213)	
Middle school or less	45 (20.90)
High school	89 (41.40)
College education	79 (36.70)
Marital status† (n=213)	
Married/cohabiting	52 (24.20)
Divorced	23 (10.70)
Never married	138 (64.20)
Employment‡ (n=206)	
Currently working	84 (39.10)
Student	60 (27.90)
Unemployed	62 (28.80)
Residential situation§ (n=195)	
Secure	190 (88.40)
Insecure	5 (2.30)

Missing values: * 7, † 2, ‡ 9, § 20.

Latent class model selection

When the LCP analysis was performed, six-, seven-, and eight-class models obtained the best results in goodness-of-fit measures (Table 2). However, after performing LCP with 1,000 random starts, these models failed to obtain global solutions, resulting in seven replications for the six-class model and two for the seven- and eight-class models. In the remaining models (two to five classes), the best log-likelihood was replicated 10 times in 10 optimizations. With regard to goodness-of-fit, the five-class model yielded the best BIC, aBIC, and BLRT results. Table 2 displays goodness-of-fit measures from two- to eight-class models.

Description of the five-class model

Figure 2 displays a plot representation of the subscale mean scores obtained in the five-class model. Taking into account that differences between classes are mostly quantitative, we decided to label the resulting classes based on relative severity, from mild (which was characterized by individuals with the lowest mean scores on all nine of the SCL-R dimensions) to severe (which had participants with the highest mean scores across all dimensions). Prevalence for each class was as follows: mild, 26%; mild-moderate, 28.8%; moderate, 18.6%; moderate-severe, 17.2%; and severe, 9.3%.

Table 2 Fit measures of latent profile analysis models

	Number of classes						
	2	3	4	5	6*	7*	8*
AIC	3,730.27	3,375.82	3,288.94	**3,207.92**	3,160.74	3,127.42	3,100.24
BIC	3,824.64	3,503.90	3,450.74	**3,403.42**	3,389.95	3,390.33	3,396.85
aBIC	3,735.92	3,383.49	3,298.63	**3,219.63**	3,174.48	3,143.17	3,118.00
Entropy	0.96	0.95	0.89	**0.90**	0.91	0.92	0.92
VLMR†	< 0.0001	< 0.0001	0.05	**0.39**	0.31	0.38	0.52
LMR†	< 0.0001	< 0.0001	0.06	**0.40**	0.32	0.38	0.52
BLRT†	< 0.0001	< 0.0001	< 0.0001	< **0.0001**	< 0.0001	< 0.0001	< 0.0001

aBIC = adjusted-Bayesian information criteria; AIC = Akaike information criterion; BIC = Bayesian information criteria; BLRT = bootstrapped likelihood ratio test; LMR = Lo-Mendell-Rubin test; VLMR = Vuong-Lo-Mendell-Rubin test.
* Failed to obtain a global solution.
† p-values.

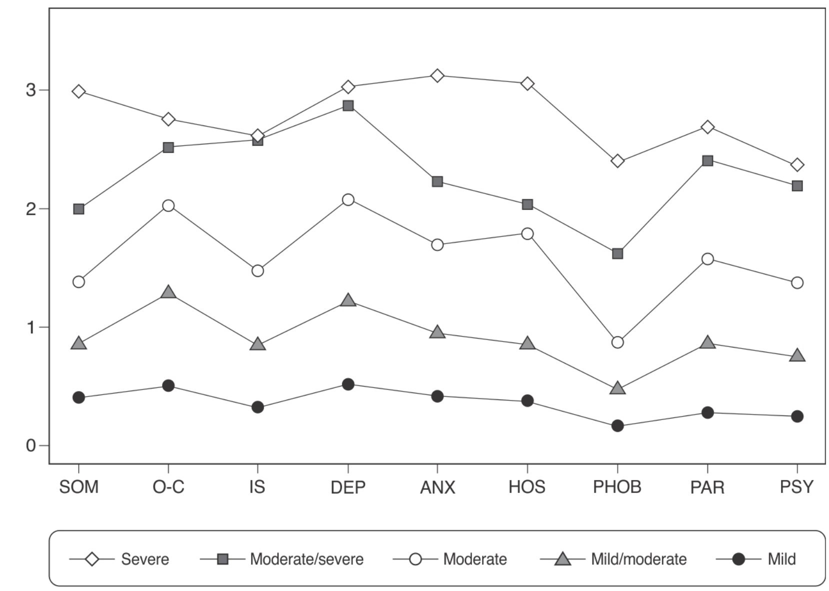

Figure 2 Symptom Checklist 90-Revised version subscale means in the five-class model. ANX = anxiety; DEP = depression; HOS = hostility; I-S = interpersonal sensitivity; O-C = obsessive-compulsive; PAR = paranoid ideation; PHOB = phobic anxiety; PSY = psychoticism; SOM = somatization.

On between-class comparison of demographic characteristics, only gender was significantly different ($\chi^2_{[4]} = 12.504$, $p < 0.05$). The most prevalent psychiatric disorders were depressive (67.1%) and cluster B personality disorders (41%), while the most common SUDs were alcohol (66.6%), cannabis (44.8%), and cocaine (44.3%) use disorders. When comparing differences in psychiatric and SUDs in the five-class model, only depression was found to be significant ($\chi^2_{[4]} = 10.107$, $p < 0.05$). These results imply that distribution for most disorders was class-independent (Table 3).

Differences in mental health service utilization by class

Before estimating the association of each class with number of service visits, we tested the effects of demographic variables on this outcome. No significant variable by time interactions were found for gender ($\chi^2_{[4]} = 8.20$, $p = 0.084$), age ($\chi^2_{[5]} = 0.78$, $p = 0.37$), marital status ($\chi^2_{[5]} = 6.45$, $p = 0.26$), or education ($\chi^2_{[15]} = 5.57$, $p = 0.35$).

A significant time effect was found ($\chi^2_{[5]} = 323.25$, $p < 0.001$), indicating that the amount of visits decreased significantly over time. While no significant main effects of the classes where found ($\chi^2_{[5]} = 2.34$, $p = 0.67$), a significant time by class interaction was obtained ($\chi^2_{[15]} = 30.05$ $p = 0.01$), indicating differences between the classes across time. When analyzing results across classes, significant differences were found between classes with lower severity (mild, mild/moderate, and moderate) when compared to the more severe (moderate/severe) (Table 4).

Discussion

The present study sought to determine the existence of psychiatric symptom subgroups in a sample of COD outpatients and to assess whether the resulting subgroups differed significantly in their utilization of mental health services. On LCP analysis, a five-class model based on levels of symptom severity obtained the best fit. Participants in the classes with higher symptom severity

Table 3 Psychiatric and substance use disorders (SUDs) by class (n=210)

	Mild (n=53)	Mild/moderate (n=60)	Moderate (n=40)	Moderate/severe (n=40)	Severe (n=20)	Total (n=210)	Difference between classes ($\chi^2_{[4]}$)
Depressive disorder	27 (50.9)	40 (66.7)	30 (75.0)	29 (78.4)	15 (75.0)	141 (67.1)	10.10*
Anxiety disorder	12 (22.6)	19 (31.7)	14 (35.0)	10 (27.0)	6 (30.0)	61 (29.0)	2.02
Bipolar disorder	4 (7.5)	1 (1.7)	1 (2.5)	0 (0.0)	2 (10.0)	8 (3.8)	6.51
Psychotic disorder	11 (20.8)	10 (16.7)	2 (5.0)	2 (5.4)	1 (5.0)	26 (12.4)	9.11
ADHD	6 (11.3)	7 (11.7)	5 (12.5)	5 (13.5)	1 (5.0)	24 (11.4)	1.02
Eating disorder	1 (1.9)	1 (1.7)	3 (7.5)	3 (8.1)	2 (10.0)	10 (4.8)	5.01
Somatoform disorder	0 (0.0)	0 (0.0)	2 (5.0)	0 (0.0)	1 (5.0)	3 (1.4)	7.60
Cluster A personality disorder	1 (1.9)	0 (0.0)	0 (0.0)	0 (0.0)	1 (5.0)	2 (1.0)	5.28
Cluster B personality disorder	21 (39.6)	21 (35.0)	17 (42.5)	18 (48.6)	9 (45.0)	86 (41.0)	1.99
Cluster C personality disorder	0 (0.0)	3 (5.0)	0 (0.0)	1 (2.7)	1 (5.0)	5 (2.4)	4.64
Alcohol use disorder	38 (71.7)	36 (60.0)	25 (62.5)	24 (64.9)	16 (80.0)	139 (66.2)	3.72
Cannabis use disorder	30 (56.6)	28 (46.7)	16 (40.0)	13 (35.1)	7 (35.0)	94 (44.8)	5.61
Cocaine use disorder	20 (37.7)	30 (50.0)	15 (37.5)	17 (45.9)	11 (55.0)	93 (44.3)	3.43
Inhalant use disorder	7 (13.2)	2 (3.3)	4 (10.0)	5 (13.5)	0 (0.0)	18 (8.6)	6.68
Other SUD	11 (20.8)	15 (25.0)	6 (15.0)	9 (24.3)	10 (50.0)	51 (24.3)	9.44

Data presented as n (%).
ADHD = attention deficit/hyperactivity disorder; χ^2 = chi-square.
Data from five participants was missing for this analysis.
* $p < 0.01$.

Table 4 Between-class differences in mental health services utilization

	Months since intake						Differences between classes ($\chi^2_{[1]}$)
	6	12	18	24	30	36	
Mild	14.33 (22.14)	3.69 (10.70)	2.08 (5.18)	0.49 (1.80)	0.37 (1.14)	0.10 (0.50)	243.90*
Mild/moderate	13.04 (13.97)	0.95 (1.69)	0.93 (2.74)	0.58 (1.98)	0.31 (1.27)	0.05 (0.40)	198.03*
Moderate	13.74 (15.38)	4.00 (9.18)	2.55 (7.71)	1.08 (3.43)	0.00 (0.00)	0.05 (0.32)	526.77*
Moderate/severe	17.26 (13.83)	2.24 (3.66)	1.35 (3.18)	0.47 (1.63)	0.00 (0.00)	0.00 (0.00)	0.947
Severe†	10.33 (9.41)	3.00 (6.09)	0.44 (0.85)	0.89 (3.77)	0.00 (0.00)	0.00 (0.00)	-
Total	13.99 (16.37)	2.66 (7.29)	1.57 (4.75)	0.66 (2.43)	0.18 (0.90)	0.05 (0.36)	-

Data presented as mean (standard deviation).
* $p < 0.01$.
† This class was set as the comparison category.

(moderate-severe and severe) displayed lower utilization of services across time when compared to participants belonging to less severe groups (mild, mild-moderate, and moderate).

These results are in line with a body of work which points toward the integration of both a categorical and a dimensional (understood as symptom severity, expressed by the score of a particular subscale item) approach to patient classification. For instance, studies seeking to find subgroups based on combinations of psychiatric comorbidities in adolescents,[21] patients with posttraumatic stress disorder (PTSD),[22] patients with schizophrenia,[23] and the general population[24-26] obtained solutions with quantitative and qualitative differences between classes, suggesting that subgroups are mostly based on combinations of specific disorders and symptom severity. In another study,[27] carried out with adults seeking treatment for substance use, the best fit was obtained by a three-class model with quantitative differences only (classes were labeled as SUD-only, co-occurring major depressive disorder, and multimorbidity). This implies that, similarly to our findings and despite methodological and sample differences (i.e., indicators were categorical), psychiatric symptoms in patients with COD might be distributed across distinctive levels of severity. A study performed in a sample of trauma-exposed soldiers,[28] which also used a dimensional approach to assess depression, anxiety, and PTSD symptoms, also reported that the best fit was obtained by a three-class model with only quantitative differences. This suggests that differences in psychiatric symptoms between COD patients might be attributable more to symptom severity than to combinations of disorders.

Taking into account that the dimensions of symptomatology measured by the SCL-90-R are only those within the internalizing spectrum and that previous studies assessing psychiatric symptom subgroups have obtained models with quantitative differences only,[28,29] our results may be explained by the existence of a hierarchical structure of emotional disorders,[30] which includes mood and anxiety disorders, assuming that such disorders are highly interrelated and dependent on a higher-order construct (labeled "emotional disorders"). These results indicate that the emotional disorders might encompass all possible "subthreshold" and "full-criteria" cases of comorbidity, e.g., from mild depressive symptoms to severe major depressive disorder). A similar pattern was also found on the SCL-90-R subscales related to psychotic symptoms (psychoticism and paranoid ideation), suggesting, at least partially, that such symptoms might be closely related to the emotional disorders construct.

It is important to note that significant time effects were found, implying that the probability of using mental health services in the overall sample decreased over time. In addition, a significant time by class interaction was found, indicating that the frequency of clinic visits decreased more steeply in classes with greater symptom severity. Research into mental health services utilization by patients with COD has yielded mixed findings; however, a major limitation of many studies focused on this subject is the exclusion of patients with acute and severe mental disorders.[31] Furthermore, previous studies analyzing the effect of psychiatric symptom severity on service utilization[32,33] have also found a direct association between these two variables. This may be explained by the increase in interpersonal difficulties at higher levels of disease severity, which may lead to difficulty receiving feedback and instructions from the clinician,[34] or by higher levels of self-stigma and internalized shame, which reduce overall participation in mental health services.[35]

The results of the present study stress the importance of using person-centered (rather than variable-centered) approaches, such as LCA and LCP, because the differences in treatment utilization found between classes imply that differential characteristics in this variable exist between subgroups, suggesting that the use of a categorization based on symptom severity might help achieve better patient classification. This, in turn, may be a useful tool for tailoring treatment.

Nevertheless, further studies are needed to analyze – through longitudinal models, such as latent growth mixture modeling or latent trajectories analysis – the stability of such latent class models and to link class membership to other variables of treatment response, promoting the development of adaptive treatment interventions for patients with CODs.

As mentioned before, the restriction to assessing internalizing symptoms with the SCL-90-R precluded inclusion of externalizing symptoms, such as those related to ADHD, antisocial behavior, and impulse control (highly prevalent in this sample), thus limiting the scope of our results regarding the whole spectrum of psychiatric symptoms. On the other hand, even though the sample size was not small in absolute terms, when dividing it into five subgroups, the power to find associations between disorders with low prevalence and class membership and our ability to control for covariates such as gender may have been compromised. Another potential limitation of this study is that pairwise differences in treatment utilization across time were not found between every subgroup; the mild, mild-moderate, and moderate groups displayed significant differences only when compared to the moderate-severe and severe classes, indicating that the model did not find complete validation for this distal variable and may exhibit better external validity for treatment outcomes (substance use or psychiatric severity).

Despite these limitations, our findings support the use of a dimensional approach for categorization of patients with COD in order to account for possible subtypes that may impact treatment outcomes. Further studies are needed to ascertain whether class membership predicts a differential response to treatment in outcomes such as psychiatric symptoms or days of substance use; to assess the replicability of the LCP model in samples with a higher level of severity, such as residential patients; and to determine whether gender-related differences exist within the model.

To the best of our knowledge, this was one of the first studies to use such an approach to analyze mental health services utilization on a sample of patients with COD and provide evidence of the importance of developing empirically derived subgroups for treatment planning in these patients.

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Disclosure

The authors report no conflicts of interest.

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