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Should Substance Use Disorders be Considered as Categorical or Dimensional?

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## Abstract

This paper discusses the representation of diagnostic criteria using categorical and dimensional modeling. Conventional modeling using categorical or continuous latent variables has limitations for the analysis of diagnostic criteria. New hybrid models are discussed which provide both categorical and dimensional representations in the same model. Conventional and new models are applied and compared using recent data for DSM-IV alcohol dependence and abuse criteria from the National Epidemiologic Survey on Alcohol and Related Conditions. Implications for DSM-V are discussed.

## Introduction

This paper discusses the representation of diagnostic criteria using categorical and dimensional modeling. The choice between categorical and dimensional views of disorders has created a long-standing debate in psychiatry. In the context of traditional DSM diagnosis, the categorical view dominates, because it meets clinical needs and the needs of reporting for healthcare planners and insurance companies. Recent interest, however, focuses on the possibility of dimensional approaches where a quantitative score, or scores, can be used at least for research purposes such as genetic analysis. This raises questions about which approach is most suitable for a particular domain of disorders and for which particular purpose, as well as if and how one can translate between categorical and continuous representations.

To be able to answer the question posed in the title of this paper, it is important to bring together critical thinking both in areas of psychiatric measurement and statistical analysis. This paper aims to contribute to statistical analysis, presenting the research frontier in terms of psychometric modeling. To give subject-matter experts a chance to understand the current analytic possibilities, it is necessary to give an overview of relevant methods, including particularly promising novel approaches that combine categorical and dimensional representations.

The current psychiatric debate about categorical and dimensional views has a counterpart in psychometrics and statistics in general, where the corresponding choice is between using categorical and continuous latent variables. Categorical latent variables (also called

latent class variables and finite mixture components) are used to find homogeneous groups of individuals using latent class analysis or, with longitudinal data, to describe across-time changes in group membership using latent transition analysis. Continuous latent variables (also called traits, factors, and random effects) are used to study underlying dimensions by explaining correlations among outcomes in item response theory and factor analysis or, with longitudinal data, to describe individual differences in development in growth modeling (also called repeated measures analysis, multilevel analysis).

Conventional modeling using categorical or continuous latent variables has limitations for the analysis of diagnostic criteria and symptom items. In latent class analysis, which uses categorical latent variables, the latent classes ignore possible within-class heterogeneity such as individual differences in severity, and the categorical nature of the latent variable causes relatively low power for genetic analysis such as linkage analysis. In factor analysis, which uses continuous latent variables, there is no model-based classification and it may be difficult to find natural cut points or thresholds for diagnostic purposes. Novel psychometric developments, using hybrids of categorical and continuous latent variable models, aim to circumvent these limitations and provide a useful bridge between the two modeling traditions. One such hybrid will be discussed here: latent class factor analysis.

This paper begins with a brief, non-technical overview of the two conventional models of latent class analysis and factor analysis from the perspective of analyzing diagnostic criteria and symptom items. In the context of factor analysis, a brief description is also

given of a reporting system used for educational achievement testing, where issues of categories and dimensions similar to those in psychiatry have been discussed. Section 3 introduces the hybrid model of latent class factor analysis. Section 4 provides some general considerations for the analysis of diagnostic criteria. Section 5 applies the various models to recent data on DSM-IV alcohol dependence and abuse criteria in the NESARC (National Epidemiologic Survey on Alcohol and Related Conditions). Section 6 concludes with a summary of the assets and liabilities of the different analytic approaches.

#### Conventional Latent Variable Analysis Applied to Diagnostic Criteria

This section gives a brief overview of latent class analysis (LCA) and factor analysis (FA). LCA uses categorical latent variables and FA uses continuous latent variables. The presentation is non-technical using model diagrams and examples. References to literature with both technical and application focus are provided for further studies.

#### Categorical Representation: Latent Class Analysis (LCA)

Figure 1 describes LCA. Figure 1a considers analysis results in terms of profiles for the four items listed along the x-axis. Here, the example of dichotomous diagnostic criteria for ADHD is used with the first two items representing inattentiveness and the next two items representing hyperactivity. The picture shows four latent classes (unobserved groups) of individuals who are homogeneous within classes and different across classes. In this sense, LCA has the same aim as cluster analysis. Class 1 consists of individuals

who have a high probability of endorsing both types of items (“combined class”), class 2 consists of individuals who show low inattentiveness and high hyperactivity probability (“hyperactive-only class”), class 3 consists of individuals who show high inattentiveness and low hyperactivity probability (“inattentiveness-only class”), and class 4 consists of individuals who have low probabilities for types of items (“unaffected class”). It is seen that the item profiles are distinct and even show two classes with crossing profiles. In a general population sample, the prevalence is the largest for the normative class 4, whereas it is typically found that the hyperactive-only class is the least prevalent in that hyperactivity is most often observed in conjunction with inattentiveness. The class probability may be regressed on background variables (covariates) such as family history of ADHD to estimate how elevated the prevalence is for each of the affected classes 1-3 for individuals with a positive family history as compared to having no such family history.

Figure 1b shows a corresponding model diagram. The boxes at the top represent the four observed items, the circle in the middle represents the categorical latent variable  $c$  with four classes, and the box at the bottom represents a covariate  $x$  such as family history.

LCA with covariates has four key sets of parameters: (1) The influence of  $c$  on each of the items (as shown in the left-most picture); (2) the prevalence for the classes of  $c$ ; (3) the influence of  $x$  on  $c$ ; and (4) the direct influence of  $x$  on an item. The fourth type of parameter is useful to study measurement non-invariance. As an example, consider a covariate such as gender or age. It is often the case that males and females and old and young differ in their responses on certain items even when they belong to the same latent class. A proper model needs to allow for such partial measurement non-invariance.

When the covariate has a genetic content, such item non-invariance may be of particular interest in that certain criteria may show especially strong heritability. A fifth type of parameter is also possible, allowing for correlations between items within class, e.g. due to similar question wording. Such relaxation of the independence of the items within class can affect the class formation. Given an estimated model, each individual's probability of class membership can be estimated and the person may be classified into his/her most likely class.

For an overview of LCA methods and applications, see e.g. Hagenaars and McCutcheon (2002). In terms of statistical specifications for LCA, both the influence of  $c$  on an item and the influence of  $x$  on  $c$  are modeled using logistic regression and can therefore be expressed in common terms of odds, odds ratios, probabilities, and logits. The decision on the number of classes to be used in the analysis is perhaps the most difficult part of LCA, but a combination of statistical and substantive consideration is usually satisfactory. Muthén (2001) put LCA in a broader latent variable modeling framework. Muthén and Muthén (2000) discussed several applications including LCA of antisocial behavior items in the National Longitudinal Survey of Youth (NLSY), a survey of individuals in early adulthood, where in addition to a normative class they found three classes of individuals with clearly different profiles of antisocial acts: property offense, person offense, and drug offense. Rasmussen et al. (2002) applied LCA to DSM-IV ADHD symptoms in Australian twin data and found an 8-class solution where only some classes were congruent with DSM-IV subtypes. While these studies did not show parallel profiles for all classes, the parallel profiles outcome is often seen in LCA with alcohol use disorder criteria, see, e.g., Bucholz et al. (1996) for COGA data and Muthén (2001)

for NLSY data, but has also been found in other cases such as with schizophrenia (Nestadt et al., 1994).

#### Dimensional Representation: Factor Analysis (FA)

Consider a different version of Figure 1a where the profiles are parallel. Parallel profiles obtained by LCA may be seen as an indication that the construct under study is unidimensional. This view would suggest a factor analysis (latent trait) representation instead of LCA. Factor analysis is discussed next.

Figure 2 describes FA. This analysis is often referred to as latent trait analysis, or IRT (item response theory) modeling, particularly when a single factor is used. For this situation, Figure 2a shows how the probability of endorsing an item increases as a function of the factor  $f$ . Different items have different functions, represented by logistic regressions with different intercepts and slopes. Below the  $f$  axis is shown the distribution of the factor, typically assumed to follow a normal distribution.

Figure 2b shows the corresponding model diagram. The factor  $f$  is assumed to describe all the correlations among the items. The model has a set of four key types of parameters similar to those of LCA: (1) the two measurement parameters for the influence of  $f$  on each item; (2) the mean and variance of the factor distribution (typically standardized to 0, 1); (3) the influence of the covariate  $x$  on  $f$ ; and (4) the direct influence of  $x$  on an item. The interpretations of the parameters are similar to those of LCA although for the influence of  $x$  on  $f$  a regular linear regression specification is used, not a logistic regression. A fifth type of parameter is also possible, allowing for correlations between

items within class. Given an estimated factor model, each individual's factor score can be estimated. The estimated precision of this estimate, typically referred to as information functions, can also be assessed.

Analysis and reporting of national general population surveys is one important area of interest for DSM-V considerations. In this context it is interesting to note that FA is routinely used for reporting on national trends in educational achievement in the NAEP survey (National Assessment of Educational Progress; Beaton & Zwick, 1992). The basis for the reporting is a dimensional model such as the one shown in Figure 2b, where the items in a particular domain such as mathematics are assumed to follow a unidimensional factor model. Different sets of students are randomly given different test forms in order to cover more content domains, which implies that for a given content domain any one student responds to a limited set of items. Because the limited set of items does not produce sufficiently precise factor score estimates, it is necessary to bring in more information in the form of a large set of covariates. Although Figure 2b shows only one covariate, NAEP achievement analysis uses over 100 covariates including detailed demographic information. The dissemination of information to the public as seen in newspaper reports, however, is not in terms of scores on the factor, but in terms of regions of proficiency that are easier to understand: Basic, Proficient, and Advanced. In this way, a categorization is made of the dimensional factor. The regions are related to the percentiles of the estimated factor distribution with current choices levels being approximately the 30<sup>th</sup>, 80<sup>th</sup>, and 95<sup>th</sup> percentiles (Mislevy, personal communication). The factor percentiles are anchored to performance on items discriminating well at the percentile. The choice of relevant percentiles is made in special standard setting sessions

with panels of judges basing their judgment on what might be expected of students at a given grade level and subject domain. In sum, NAEP reporting has a dimensional foundation augmented by substantively-based categories. This is in contrast with analyses providing model-based categories to be discussed later.

It is interesting to consider a procedure similar to that of NAEP to be used for analysis and reporting of national trends with respect to substance use disorders. If support for dimensional modeling of substance use disorder criteria is found, it might be possible to track national trends using categories such as Unaffected, Abuse, and Dependence, where those category boundaries are anchored in FA scores.

For an overview of methods for FA in the form of unidimensional traits, see, e.g., the item response theory text of Hambleton and Swaminathan (1985). Muthén (1989a) discusses general multi-factorial FA including the use of covariates. FA in the form of both unidimensional and multidimensional models has been suggested in mental health applications at many points in time: neuroticism in Duncan-Jones, Grayson, and Moran (1986); depression in Muthén (1989a, b) and Gallo, Anthony and Muthén (1994); and alcohol in Muthén (1992, 1996), Muthén, Grant and Hasin (1993), Harford and Muthén (2001), and Krueger et al. (2004). The experience with latent trait modeling in education has been very positive, but it remains to be seen if this methodology is the most suitable or the only one needed for mental health applications.

## Hybrid Latent Variable Analysis Applied to Diagnostic Criteria

Recent methodological developments have made efforts to use a combination of categorical and continuous latent variables to better understand various substantive phenomena. Two key models are latent class factor analysis and factor mixture modeling. Following is a brief description of these analyses and how they relate to the conventional techniques.

### Latent Class Factor Analysis (LCFA)

With parallel item profiles, the notion of a dimension influencing the item responses can be formalized into a latent class factor analysis model. This modeling is described in pictorial form in Figure 3. Figure 3a shows a distribution for a factor (latent trait)  $f$  and Figure 3b shows a model diagram. The distribution of the factor is shown as a histogram in Figure 3a, indicating a strongly non-normal distribution where most individuals are at the unaffected point. The discrete distribution makes for a very flexible description of the factor distribution and is referred to as a non-parametric representation in that it does not assume a specific statistical distribution such as the normal. Although the points of the distribution are occupied by individuals in different latent classes, it is up to the analysis interpretations in light of auxiliary variables (correlates) and substantive theory to decide if these classes can be seen as substantively different categories or simply representing a single, non-normal distribution.

LCFA has five key types of parameters: (1) The influence of  $f$  on the items is represented by logistic regressions like in the FA model so that each item has an intercept and a slope; in line with FA, these measurement parameters do not change across the classes; (2) the influence of  $c$  on  $f$  is analogous to regression with dummy variables so that the mean of  $f$  changes across the classes of  $c$ , giving rise to the distances between the histogram bars seen in Figure 3a; (3) the class probabilities give the height of the histogram bars in Figure 3a; (4) the influence of the covariate  $x$  on  $c$  indicates how the class probabilities change as a function of  $x$ , i.e. how the distribution of  $f$  is changed by  $x$ ; and (5) the influence of  $x$  on  $f$  indicates that  $f$  may have within-class variation as a function of  $x$ ; this within-class influence can be allowed to vary across class. In line with LCA and FA, LCFA can also have direct influence from  $x$  to items and items can have residual correlations. Given an estimated model, two types of individual estimates are obtained. First, probabilities for membership in each class are provided. Second, factor score estimates are obtained, both for the most likely class and mixed over all classes.

LCFA combines strengths of both LCA and FA, providing a categorical *and* dimensional representation. Unlike LCA, LCFA provides a factor-analytic interval-scaled dimension with quantitative scores on the factor  $f$ . The LCFA model is also considerably more parsimonious than LCA. Using the example of 11 dependence and abuse criteria, four classes, and no  $x$  variables, LCA uses 47 parameters (corresponding to  $11 \times 4$  item probabilities and 3 class probabilities) while LCFA uses only 27 parameters (corresponding to  $11 \times 2$  item intercepts and slopes, 4 factor means of which 2 are fixed to

set the metric, and 3 class probabilities). The relative parsimony of LCFA can make it more powerful in detecting the influence of covariates.

### Factor Mixture Analysis (FMA)

A second hybrid model, factor mixture analysis (FMA) allows for within-class variation around the means. FMA will not be discussed here for lack of space, but may be suitable for applications where there are reasons to believe that the items have a common source of influence within class, e.g. representing severity, causing a within-class correlation. There are two important variations of FMA. One variation is closely related to LCFA in that measurement parameters are invariant across classes, representing a dimensional model as in factor analysis. The other variation is closely related to LCA, specifying measurement non-invariance, and not producing a dimensional representation but instead a clustering of subjects.

LCFA and FMA have been developed in Muthén and Asparouhov (2004), drawing on statistical methods described in Asparouhov and Muthén (2004). For related modeling without covariates, see Wilson (1989), Heinen (1996), Vermunt (1997), and Formann and Kohlman (2002), with mental health applications in De Boeck, Wilson and Acton (in press), and Krueger et al. (in press). Even without covariates, LCFA and FMA do not seem to have been widely used and seems very worthwhile to explore further in mental health contexts.

## General Analysis Considerations

Although the discussion in this paper centers on dichotomous outcomes, it should be noted that the outcomes could be of any type: dichotomous (binary), ordinal (ordered polytomous), nominal (unordered polytomous), continuous, limited-dependent (censored-normal), counts, etc., and any combination of such outcomes. This holds true for both categorical and continuous latent variable models. In other words, the type of observed outcome does not necessarily affect the choice between categorical and continuous latent variables. The variety of observed outcome types that can be analyzed together makes it possible, for example, to combine information on dichotomous diagnostic criteria with different information such as quantitative biological measures. As one example, the Windle and Scheidt (2004) analysis could fruitfully be carried out by LCA.

Another consideration related to variables is exemplified by the choice between analyzing symptom items and aggregating their information into diagnostic criteria. An even higher level of aggregation is considered when analyzing diagnoses of dependence for several domains such as alcohol, tobacco, marijuana, and depression. Such different levels of aggregation may uncover different features related to categories and dimensions and the differences need to be understood.

In studying mental health phenomena, especially in general population samples, it is typically the case that a large proportion of the sample exhibits none of the symptoms. Proper modeling should include specifications that reflect this.

Many of the models discussed here cannot be chosen between based on only statistical criteria. For example, it is well-known that LCA and FA models often fit the data similarly (Bartholomew & Knott, 1999). Subject-matter considerations play an important role in choosing among models used for different purposes, including considering auxiliary variables in the form of antecedents, concurrent events, and distal events (predictive validity; Muthén, 2004). Typically with these models maximum-likelihood estimation is used, where the log likelihood (logL) can be seen as an overall assessment of the fit between the model and the data when comparing models. LogL can however be made larger simply by adding more parameters to the model and therefore BIC and ABIC statistics are used to combine logL with a penalty for using many parameters. A good model has both a high logL value and low BIC and ABIC values. A likelihood ratio test referred to as LMR (Lo, Mendell & Rubin, 2001) provides testing of  $k-1$  versus  $k$  classes, and bootstrapped likelihood ratio tests are also possible. In models with categorical latent variables, the entropy (with a 0-1 range, 1 being optimal) gives a measure of how well the latent classes can be distinguished. This is based on individual posterior class probabilities, which can be used for classification into most likely class. The Mplus program (Muthén & Muthén, 1998-2004) provides a very general latent variable modeling framework for maximum-likelihood estimation where the models discussed are special cases. Some of the new models draw on techniques in Asparouhov and Muthén (2004).

This method overview by necessity leaves out a host of related developments. This includes the longitudinal data models of latent transition analysis and growth mixture modeling (for an overview, see Muthén, 2004) as well as the work by Meehl and

colleagues (Waller & Meehl, 1998; Beauchaine, 2003) on techniques for distinguishing between categories and dimensions.

### Application to NESARC Alcohol Dependence and Abuse

This section illustrates the different modeling techniques presented above using data on alcohol dependence and abuse from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC; Grant et al., 2004). NESARC is a nationally representative face-to-face survey of 43,093 respondents carried out in 2001-2002. NESARC uses a complex survey design with stratification, 435 PSUs, and oversampling of Black and Hispanic households. Within each household, one person was randomly selected for interview with young adults (18 to 24) oversampled at the rate of 2.25. The analyses to be presented concern a subsample of 13,067 male current drinkers (respondents who reported drinking five or more drinks on a single occasion one or more times in the past year). The analyses focus on the 7 alcohol dependence criteria and the 4 alcohol abuse criteria, which were derived from a set of 32 past year symptom item questions designed to operationalize DSM-IV.

The analysis steps will correspond to the order in which the methods were presented: LCA, FA, and LCFA. All analyses were carried out using the Mplus program (Muthén & Muthén, 1998-2004). The estimation takes into account the NESARC complex survey features of stratification, clustering, and sampling weights (Asparouhov, 2005). Mplus setups are available on request from the author.

## Results for LCA

As a first step, the 11 alcohol criteria in NESARC were explored in the male current drinker sample using LCA with 2 – 5 classes. Table 2 shows model fit in terms of the maximum log likelihood value (logL), BIC, sample-size adjusted BIC (ABIC), and LMR. The regular LCA results at the top part of the table suggest that a 4-class solution is preferred. The increase in logL levels off when going from 4 to 5 classes and BIC is at its optimum at 4 classes. Although ABIC suggests 5 classes, LMR points to 4 classes.

Figure 4 shows the item profiles of the regular 4-class LCA model. It is seen that this is an example of parallel profiles, suggesting an ordering among the classes from low to high. The estimated class percentages are (going from class 1 with the highest endorsement probabilities to class 4 with the lowest endorsement probabilities): 1%, 5%, 17%, 77%. The entropy for this model is 0.83, suggesting good classification qualities.

## Results for FA

The model fitting results for FA are given in Table 1, both for a single factor and for two factors. The 2-factor solution is an exploratory factor analysis solution with minimum restrictions on the factor loadings. The fit statistics of Table 1 indicate that little is gained by adding a second factor. The second factor is measured by the last two abuse criteria, but the two factors are highly correlated (0.95) and it appears that it is not meaningful to consider two separate factors. The item slopes for the factor indicate how well an item discriminates between different levels of the factor. The 1-factor model shows similar

slopes for most criteria, but has lower slopes for the dependence criterion “Persistent desire or unsuccessful effort to cut down or control drinking” and the two abuse criteria “Recurrent drinking in situations where alcohol use is physically hazardous” and “Recurrent alcohol-related legal problems.”

#### Results for LCFA

Given the parallel profiles found for the 4-class LCA, as well as the unidimensionality of the FA, it is natural to fit a 4-class LCFA. This model adds a factor to the regular LCA in line with Figure 4. The model fit statistics for this model are given at the bottom of Table 1. Although logL is worse than for the regular 4-class LCA, this difference is not large and the parsimony of the LCFA relative to the LCA is reflected by LCFA having considerably better BIC and ABIC values. It is interesting to note that the LCFA model fits better in terms of logL than the 1-factor FA, although the difference is not large and BIC and ABIC values are rather close. LCFA does, however, have clear advantages to FA in terms of practical utility as described earlier in that it provides not only dimensional information but also classification. The LCFA slopes in the regression of the items on the dimension have values close to those of the FA.

The LCFA estimated class percentages and entropy remain the same as for LCA. The dimensional aspect of the model is reflected in the estimated class-varying factor means, i.e. the quantitative scores on the single dimension (in the order of class 4, class 3, class 2, class 1): 0, 1, 1.5, and 1.9 (the first two values are fixed to set the metric of the scale). The 11 criteria gives rise to 2,048 possible outcome patterns of which 50 had a frequency

of at least 10 in the analysis sample. The LCFA implies that the large number of response patterns for the 11 criteria has been reduced to only four significantly different types of patterns and these types of patterns can be given these quantitative scores along a single dimension. These scores are well estimated in terms of having small standard errors. Their relative difference indicates that the last two steps are smaller than the first one.

The interpretation of the classes is aided by using the individual estimated class probabilities to classify each individual into his most likely class. For class 1, the response patterns have all dependence criteria met and have most abuse criteria met. Class 2 has mainly one abuse criterion met, Recurrent drinking in situations where alcohol use is physically hazardous (Hazard), and this may have to do with the high prevalence of drunken driving. Class 3 is quite heterogeneous. The unaffected class, class 4, consists of those meeting none of the criteria as well as responses with only one criterion met.

#### Alternative Classifications: LCFA versus Number of Criteria Met

Because a unidimensional model has been found for the 11 criteria, it is of interest to consider a classification based on the sum of all 11 criteria instead of a division into dependence and abuse criteria. Table 2 shows how this alternative classification relates to the LCFA classification. It is seen that given the LCFA model, the number of criteria met is only a crude approximation. For example, the class 1 diagnosis should be made if at least 8 of the 11 criteria are met, but 31 (8 + 23) individuals would be misclassified.

The class 2 diagnosis should be made if between 5 and 7 of the 11 criteria are met and the class 3 diagnosis should be made if between 2 and 4 of the 11 criteria are met, but both classifications would involve a large degree of misclassification relative to LCFA. The class 4 diagnosis should be made if 0 or 1 criteria are met, but this would include 524 individuals who are in class 3. Although a classification based on number of criteria met is possible and transparent, the classification based on the LCFA model uses more information than merely the sum of criteria and also has a statistical modeling rationale.

#### Result for FMA

Table 2 shows model fitting results for a 2-class FMA model with measurement non-invariance. This model appears to fit the data better than the previous ones. The FMA version reported here is the one that provides a clustering of subjects, not a representation with a single dimension for all individuals. The non-invariance implies that the items measure a different construct for the two classes. Within each class, however, a separate dimensional representation is obtained. A class with very low probabilities of endorsing items contains 75% of the subjects. This is close to the 70% who do not endorse any of the 11 criteria, but the class also contains individuals who endorse 1 or 2 criteria. The high 25% class contains individuals who have varying degrees of problematic alcohol involvement. The factor dimension for this high class may be useful to create severity scores for this group of individuals.

## Conclusions

This paper describes several powerful latent variable approaches to investigating categories and dimensions of substance abuse and other mental disorders. These should be very useful techniques for investigating psychiatric measurement instruments in the process of formulating the DSM-V. Some techniques have been in use for a long time and have been much explored in mental health settings, such as latent class analysis (LCA) and factor analysis (FA; latent trait analysis) for cross-sectional data and latent transition analysis (LTA) and growth modeling for longitudinal data. Methods that combine categories and dimensions are more recent developments that have seen little application to mental health: latent class factor analysis (LCFA), factor mixture analysis (FMA), and, with longitudinal data, growth mixture analysis (GMA; Muthén & Shedden, 1999; Muthén & Muthén, 2000; Muthén et al., 2002a, b). LCA and LTA fit well with the need to provide categories of individuals, but cannot supply dimensional assessment. FA supplies dimensional assessment but no categories. In contrast, the newer hybrid models of LCFA, FMA and GMA provide both categories and dimensions. These techniques may be particularly promising for applications to substance use disorders in that such disorders have often been found to have dimensional aspects (see, e.g., Muthén, 1996; Krueger et al., 2004). As shown by the hybrid models, the fact that dimensions are found does not imply that categories cannot be provided as well. In sum, the answer to the question in the title of the paper is that one does not have to choose categories *or* dimensions, but can consider categories *and* dimensions.

In the NESARC, data on the 11 alcohol dependence and abuse criteria were found to be fit equally well by a 4-class, 1-dimensional LCFA as by a 1-dimensional FA (latent trait model), but the LCFA model provides a richer representation of the data. A similar 4-class LCFA was also found for the 32 symptom items underlying the 11 criteria. Furthermore, 3-class LCFA models were found to fit NESARC data on marijuana dependence and abuse criteria as well as tobacco dependence criteria.

The NESARC data were used to compare the LCFA classification into dependence and abuse with the number of criteria met. Instead of the DSM-IV requirement of at least 3 out of 7 dependence criteria for a dependence diagnosis and at least 1 out of 4 abuse criteria for an abuse diagnosis, cut points based on the total number of criteria met were considered. They were found to provide only a crude approximation to the classification based on LCFA.

Hybrid models can be used in analyses with different aims. As opposed to FA, they can be used to produce model-based national prevalence rates in categories such as alcohol dependence and abuse. As opposed to LCA, they can be used for research analyses such as genetic linkage analysis to attain high power due to using a more parsimonious model with a dimensional character. Translations between categories and dimensions are achieved because the categories are formed on the dimensions. Hybrid modeling with longitudinal data appears particularly powerful in uncovering different pathways of problematic development.

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Table 1. Latent Class Analysis, Factor Analysis, Latent Class Factor Analysis Model Fit Statistics, NESARC, Male Current Drinkers, n = 13,067

Table 2. Total Number of Criteria Met Versus Latent Class Factor Analysis Diagnosis

# classes	log L	# par	BIC	ABIC	LMR
<b>Regular LCA</b>					
2	-25,887	23	51,993	51,590	0.0000
3	-25,100	35	50,532	50,420	0.0000
4	-24,989	47	50,424	50,274	0.0025
5	-24,947	59	50,452	50,265	0.1028
<b>LCA Adding a Zero Class</b>					
4	-25,043	36	50,428	50,314	0.0000
5	-24,985	48	50,426	50,273	0.0283
<b>FA</b>					
1	-25,033	22	50,274	50,204	--
2	-24,991	32	50,285	50,183	--
<b>LCFA</b>					
4	-25,012	27	50,279	50,193	0.0000
5	-25,006	29	50,287	50,195	0.1520
<b>FMA</b>					
2	-24,736	49	49,898	--	--

Total	<i>Class 1</i>	<i>Class 2</i>	<i>Class 3</i>	<i>Class 4</i>	<i>Total</i>
11	11.27	0	0	0	11.27
10	35.93	0	0	0	35.93
9	35.76	0	0	0	35.76
8	40.52	23.07	0	0	63.58
7	8.35	91.14	0	0	99.49
6	0	129.20	0	0	129.20
5	0	197.69	0	0	197.69
4	0	134.22	175.18	0	309.39
3	0	5.32	419.43	0	424.76
2	0	0	856.16	0	856.16
1	0	0	524.40	1195.78	1720.18
0	0	0	0	9183.59	9183.59
Sum	131.83	580.63	1975.17	10379.37	13,067

Figure 1. Latent Class Analysis

Figure 2. One-Dimensional Factor Analysis

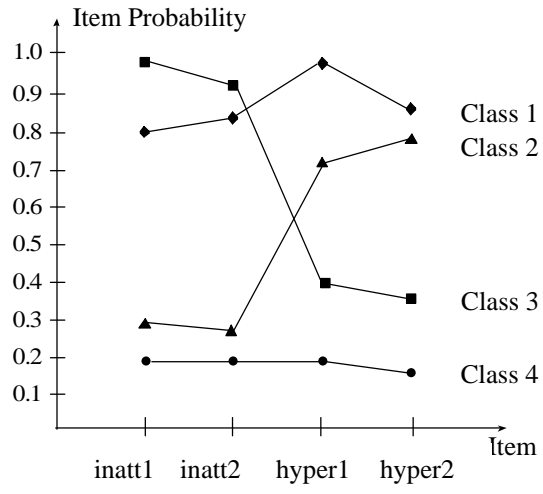
Figure 3. Latent Class Factor Analysis

Figure 4. Latent Class Analysis Profiles

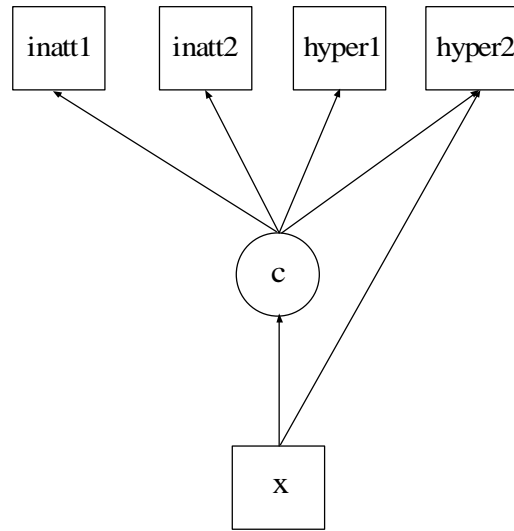
Legend for Figure 4:

- Class 1, 1.1%
- △— Class 2, 4.8%
- Class 3, 17.5%
- ◇— Class 4, 76.6%

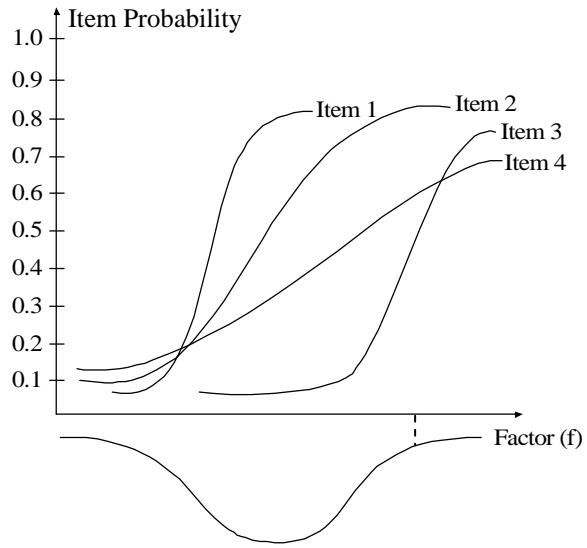
1a. Item Profiles



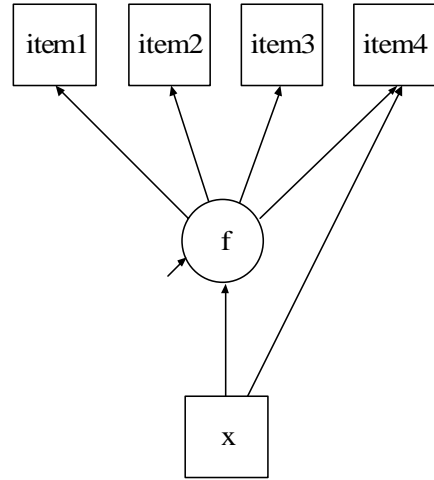
1b. Model Diagram



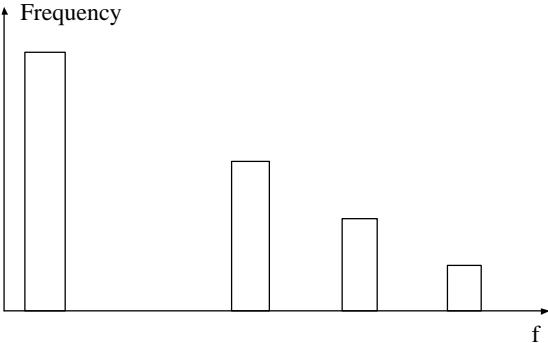
2a. Item Response Curves



2b. Model Diagram



3a. Factor Distribution



3b. Model Diagram

