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ADHD and the externalizing spectrum: direct comparison of categorical, continuous, and hybrid models of liability in a nationally representative sample

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Abstract

Purpose—Alcohol use disorders, substance use disorders, and antisocial personality disorder share a common externalizing liability, which may also include attention-deficit hyperactivity disorder (ADHD). However, few studies have compared formal quantitative models of

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externalizing liability, with the aim of delineating the categorical and/or continuous nature of this liability in the community. This study compares categorical, continuous, and hybrid models of externalizing liability.

Method—Data were derived from the 2004–2005 National Epidemiologic Survey on Alcohol and Related Conditions (N = 34,653). Seven disorders were modeled: childhood ADHD and lifetime diagnoses of antisocial personality disorder (ASPD), nicotine dependence, alcohol dependence, marijuana dependence, cocaine dependence, and other substance dependence.

Results—The continuous latent trait model provided the best fit to the data. Measurement invariance analyses supported the fit of the model across genders, with females displaying a significantly lower probability of experiencing externalizing disorders. Cocaine dependence, marijuana dependence, other substance dependence, alcohol dependence, ASPD, nicotine dependence, and ADHD provided the greatest information, respectively, about the underlying externalizing continuum.

Conclusions—Liability to externalizing disorders is continuous and dimensional in severity. The findings have important implications for the organizational structure of externalizing psychopathology in psychiatric nomenclatures.

Keywords

Externalizing; Comorbidity; ADHD; Classification; DSM-5

Introduction

Common mental disorders co-occur more often than expected by chance [1, 2] and some disorders exhibit greater comorbidity among themselves than with other disorders, such as antisocial behavior disorders, alcohol use disorders, and drug use disorders [3]. Krueger and colleagues [4, 5] suggest that patterns of co-occurrence among these disorders indicate a coherent underlying externalizing spectrum. The externalizing spectrum conceptualization has been robustly supported [6–8] and its phenotypic coherence is undergirded by genetic correlations among its constituent disorders [9]. Recent commentators in the literature have suggested that the externalizing spectrum may also include a broader range of psychopathology than has been shown to date [10]. This may include attention-deficit hyperactivity disorder (ADHD), which shares common etiological influences, including similar genetic factors [11] and neural underpinnings [12], with other externalizing disorders and an elevated risk of experiencing nicotine dependence, alcohol, and other substance use disorders [13, 14]. A small number of studies have formally tested the fit of ADHD in the externalizing spectrum [15–20]. However, these studies were largely based on a priori assumptions about underlying latent structure; i.e., they assumed an underlying latent trait [15–18] or a combination of latent traits and latent classes [19]. This is a significant limitation in the literature. To adequately characterize the structure of externalizing syndromes it is necessary to compare the relative fit of continuous (i.e., latent trait), categorical (i.e., latent class), and hybrid (i.e., factor mixture) models. Only one study has compared alternative latent variable models of externalizing liability including ADHD [20]. The present study adds to the scant international literature incorporating ADHD into the externalizing spectrum and directly compares alternative quantitative models of externalizing liability. We also examined gender invariance using nationally representative data from the largest psychiatric epidemiologic survey conducted to date in the US. Evidence of invariance suggests that any observed gender differences in prevalence rates arise from differences in means on latent externalizing liability.

Method

Sample

Data were drawn from the 2004–2005 Wave 2 National Epidemiologic Survey on Alcohol and Related Conditions (NESARC), a follow-up of the Wave 1 NESARC which was conducted in 2001–2002. In brief, the NESARC Wave 1 was a nationally representative, face-to-face survey of the civilian, non-institutionalized US population aged 18 years and over. Interviews were conducted with 43,093 respondents, with oversampling of African-Americans, Hispanics, and young adults aged 18–24 years. The response rate was 81 %.

In NESARC Wave 2, efforts were made to conduct interviews with all respondents in Wave 1. Interviews were completed with 34,653 individuals. The NESARC Wave 2 data were carefully weighted to reflect design characteristics, adjustments for non-response, and attrition between Wave 1 and Wave 2. In particular, adjustment for non-response across sociodemographic characteristics and the presence of any lifetime Wave 1 substance use disorder or psychiatric disorder was performed at the household and person levels to ensure that the sample approximates the target population. This took into account the original sample minus attrition between the two waves due to death, institutionalization or incapacitation, as well as deportation or permanent departure from the US, and being in the military for the full length of the Wave 2 interviewing period. The cumulative response rate of Wave 2 as a national sample was 70.2 %, incorporating non-response in both Waves 1 and 2.

Comparison of Wave 2 respondents with the target population that comprised Wave 2 respondents plus eligible non-respondents in terms of baseline (Wave 1) sociodemographic and diagnostic measures indicated no significant differences between Wave 2 respondents and the target population with respect to age, race-ethnicity, sex, socioeconomic status, or the presence of any lifetime substance use, mood, anxiety, or personality disorder (each examined separately). Subsequently, the weighted Wave 2 data were adjusted to be representative of the US population on socioeconomic variables including region, age, race-ethnicity and sex, based on the 2000 Decennial Census [21]. In summary, attrition and/or non-response is likely to have minimal impact on the current findings with regard to externalizing diagnosis prevalence or latent structure.

The research protocol, including informed consent procedures, received full ethical review and approval from the US Census Bureau and the US Office of Management and Budget. Further details regarding the survey methodology [22] and Wave II demographic characteristics are reported elsewhere [7]. The mean age of respondents was 49.06 years.

Assessment

The NIAAA's Alcohol Use Disorder and Associated Disabilities Interview Schedule-DSM-IV Version (AUDADIS-IV) was used to generate diagnoses. This is a structured interview designed for use by non-clinician interviewers. The reliability of AUDADIS diagnoses has been extensively documented elsewhere [22–25]. Seven disorders were included in the present analyses: ADHD, antisocial personality disorder, nicotine dependence, alcohol dependence, marijuana dependence, cocaine dependence, and other substance dependence. Other substance dependence included heroin, amphetamines, sedatives, tranquilizers, opioids, hallucinogens, inhalants or solvents, or other substances not specified a priori. Respondents were considered to meet criteria for other substance dependence if they met full dependence criteria for at least one of these substances.

Analyses were conducted on lifetime diagnoses, comprising lifetime diagnostic assessments from Wave 1 and 'since last interview' diagnostic assessments from Wave 2. In other words, if a respondent met lifetime diagnostic criteria for a given disorder at Wave 1 or in the interval between Waves 1 and 2, they were considered to have a lifetime diagnosis at Wave 2. Exceptions included ADHD, which was assessed only at Wave 2. An extensive list of questions queried ADHD symptom onset before age 18 and subsequent course across the lifespan. We examined cases of ADHD with childhood onset.

The weighted lifetime prevalence estimates of the disorders were as follows: ADHD = 2.5 % (S.E. 0.06), antisocial personality disorder = 3.8 % (SE 0.07), nicotine dependence = 23.1 % (SE 0.14), alcohol dependence = 15.2 % (SE 0.15), marijuana dependence = 1.7 % (SE 0.03), cocaine dependence = 1.2 % (SE 0.04), and other substance dependence = 1.5 % (SE 0.05).

Statistical analyses

Analyses were conducted in Mplus version 6 using maximum likelihood estimation with robust standard errors (MLR). To accommodate the complex design features of the NESARC, all analyses were conducted using the Wave 2 stratification, clustering, and sampling weight variables. Model fit was evaluated using the Bayesian Information Criterion (BIC) [26], Akaike Information Criterion (AIC) [27], and the sample size adjusted BIC (SSABIC) [28]. These information-based criteria aim to strike a compromise between model fit and parsimony by imposing a penalty on overparameterized models or small sample sizes. Smaller values suggest better model fit.

Greater emphasis was placed herein on the BIC, which is a reliable index and has been used as a sole index of model fit in similar structural analyses of this kind [6, 8, 29–31]. Moreover, contrary to what is sometimes assumed in the literature, the BIC does not assume that the true model is among those being compared: as sample size increases, it will tend to choose the model that is closest to the true model (in a relative entropy sense) [32–34]. Finally, BIC has also been shown to perform well in choosing between different latent variable models of the sort examined in this paper [35]. A difference of more than 10 in BIC values between two models indicates support for the model with the lower BIC value [36]. For completeness, the number of free parameters and log likelihood values associated with each model are presented, though these criteria cannot be used solely to test differences in model fit. The smaller the number of freely estimated parameters, the less complex and more parsimonious the model.

Latent trait models—Latent trait models account for patterns of co-occurrence among disorders with reference to an underlying dimension(s) (i.e., individuals are arrayed along a continuum ranging from very low pathology, mild, moderate, and severe pathology). According to this continuous perspective, diagnostic comorbidity is accounted for by population variation in the latent trait.

Response functions and information functions are useful for graphically depicting the latent trait model. Response functions are s-shaped curves representing the probability of disorder as a function of underlying liability. Similarly, information functions express the relative amount of statistical information each disorder provides about underlying liability. Generally, the maximum height of a given response or information function is relative to the slope parameter for the disorder. A steeper slope indicates a stronger relationship between underlying liability and the observed disorder, and suggests that the disorder provides greater information about liability. The location of a response or information function reflects the severity of a disorder, and shifts from left to right along the *x*-axis as the disorder increases in severity.

Latent class models—In latent class models, patterns of comorbidity are explained by a finite number of mutually exclusive classes. We fitted a series of latent class models ranging from two to seven classes (given that there were seven observed disorders, it was not possible to fit latent class models having more than seven classes). If a latent class model provided the best fit to the data it would suggest that there are distinct groups of individuals differing in liability for externalizing syndromes. Groups may differ qualitatively (i.e., differences in patterns of liability based on those externalizing disorders endorsed) or quantitatively (i.e., differences in the extent of externalizing liability). This categorical approach assumes that there is no diagnostic covariance amongst individuals in the same latent class.

Factor mixture models—We also estimated models that reflect a conceptual midpoint between categorical and continuous models. These hybrid models are considered categorical insofar as they group individuals into categories and considered dimensional because once individuals have been assigned to liability classes, differences in severity between classes are modeled through the use of continuous latent variables. These hybrid models facilitate meaningful distinctions between homogeneous groups whilst also allowing for different levels of severity within a given class.

Following guidelines in the literature [37], we estimated factor mixture models in which the factor means were the only parameters allowed to vary across classes. Item thresholds and factor loadings were held invariant across the latent classes, and the factor covariance matrix was fixed to zero. Similar to latent class models, we fitted a series of factor mixture models, ranging from two to seven latent values. Class membership is based on each individual's location on the factor (i.e., arrayed along a dimension), as represented by the varying factor means. If one of these models provided the best fit to the data it would suggest that groups of individuals in the population differ according to the amount (or severity) of the disorders they experience.

Invariance analyses—In addition to analyses comparing the relative fit of categorical, dimensional and hybrid models, we conducted invariance analyses to determine whether parameter estimates of the best-fitting model were similar across males and females. Models in which parameter estimates were constrained to be equal across gender were compared with models in which parameter estimates were allowed to vary across gender.

Results

Evaluation of model fit in the entire NESARC sample

In the full sample, we tested latent trait, latent class, and factor mixture models. We regard to the latent trait models, the number of latent dimensions specified was guided by the extant literature [5, 6] and examined using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The EFA specified up to two latent dimensions. The statistical fit indices indicated minimal difference in model fit between the one-factor EFA model (AIC = 93,497.118; BIC = 93,615.462; SSABIC = 93,570.970) and the two-factor model EFA model (AIC = 93,442.352; BIC = 93,611.415; SSABIC = 93,547.855). The difference in BIC values was less than 10 indicating support for the one-factor model. In the two-factor model, high factor correlations (r = 0.80) were observed indicating multi-collinearity and casting doubt on the discriminant validity of two factors [38].

In summary, the high factor correlation and minimal improvement in fit based on the BIC suggested that the one-factor model provided a more parsimonious fit to the data. Accordingly, a one-factor model was selected and specified in a CFA framework (AIC = 93,499.783; BIC = 93,618.127; SSABIC = 93,573.635).

Overall, the continuous latent trait provided the best fit to the data (see Table 1). This model had the lowest BIC value (BIC = 93,618.127), suggesting that it provided the optimal account of comorbidity patterns among the seven externalizing disorders. These findings were robust even when nicotine dependence, cocaine dependence, marijuana dependence, alcohol dependence, and other drug dependence were combined into a composite substance use dependence syndrome (for further details please contact the corresponding author). Thereafter, the 3-, 4-, 5-, and 6-value factor mixture models exhibited superior fit compared to the majority of the latent class models. Among the latent class models, the 3-class model provided the best fit to the data. This general pattern of results was consistent across males and females (see Table 1). In particular, among females the best-fitting model was the latent trait model, followed by the 3-, 4-, and 5-value factor mixture models, followed by the 3-class model. Among males, the latent trait model provided the best fit to the data, followed by the 3-, 4-, 5-, 6-, and 7-value factor mixture models, followed by the 3-class model.

Evaluation of model fit by gender

Multiple-group CFA tested whether the latent trait model was equivalent across genders (see Table 2).

Following recommendations in the literature [39], we fitted a model in which thresholds and factor loadings were freed across both genders; scale factors were fixed at one in both genders; and factor means were fixed at zero in both genders (unconstrained model; Model 1). This was compared to a second model in which thresholds and factor loadings were held equal across genders; scale factors were fixed at one in men and freed in women; factor means were fixed at zero in men and freed to vary in women (constrained model; Model 2). Model 2 represents the gender invariant model. Model fit was evaluated using the root mean square error of approximation (RMSEA) [40], the Comparative fit index (CFI) [41], and the Tucker–Lewis index (TLI) [42]. Recommendations in the literature suggest that RMSEA values less than 0.05 indicate close model fit; values up to 0.08 suggest a reasonable error of approximation in the population, and values exceeding 0.10 indicate poor fit [43]. CFI and the TLI values ≥0.90 indicate acceptable fit and values ≥0.95 imply very good fit [44].

The CFI (0.994), TLI (0.992), and RMSEA (0.010) values associated with the constrained model (Model 2) demonstrated excellent fit and nearly identical fit to the unconstrained model (Model 1), suggesting that the latent trait model was invariant between males and females. The difference in CFI values did not exceed 0.01 [45], indicating that invariance is supported and lending further support for the constrained model. Comparison of latent mean differences indicated that, compared to males, females had a significantly lower probability of experiencing externalizing disorders (−0.574, i.e., roughly half of a standard deviation lower, $p < 0.001$). The constrained model is presented in Fig. 1.

Parameter estimates under the invariant latent trait model (Model 2) provide important details about the relative information and severity of the seven disorders arrayed along the externalizing continuum. The response and information functions are presented in Figs. 2 and 3, respectively. In general, cocaine dependence, marijuana dependence, and other substance dependence provided the greatest information about the underlying externalizing continuum relative to the other disorders; ADHD provided the least information. The response functions for ADHD and cocaine dependence were placed on the extreme end of the liability continuum, suggesting that across males and females these disorders tapped the more severe end of the externalizing continuum, compared to alcohol dependence and nicotine dependence.

Across genders, the response and information functions for alcohol dependence and nicotine dependence were located at the negative end of the liability continuum, suggesting that these disorders provided information about less severe forms of externalizing pathology (see Figs. 2 and 3). Across males and females, the response and information functions for ADHD and cocaine dependence were placed on the extreme end of the liability continuum, suggesting that these disorders provided more information about more severe forms of externalizing pathology.

Discussion

Externalizing structure

This study compared the relative fit of continuous, categorical, and hybrid models of externalizing liability, including ADHD. In the entire sample, as well as males and females separately, the continuous latent trait model provided the best fit to the data. In the entire sample as well as the gender-stratified groups, the next best-fitting models were the factor mixture models, providing further evidence that continuous conceptualizations of externalizing liability provide superior fit over categorical conceptualizations of liability, as represented by latent class models. Measurement invariance analyses highlighted that the latent trait model was invariant across genders, with females displaying a significantly lower probability of experiencing externalizing disorders compared to males.

This study extends earlier work by Markon and Krueger [6] who modeled the externalizing spectrum using comorbidity data on six DSM-IV syndromes (past-year and lifetime diagnoses) from Wave I of the NESARC. This paper extended this work in two important ways: firstly, this paper expanded the empirically based externalizing spectrum by including ADHD, which was not assessed at Wave 1, but was assessed at Wave 2 of the NESARC. Using this follow-up wave, we modeled the same six externalizing disorders as Markon and Krueger [6] in addition to ADHD; secondly, Markon and Krueger [6] limited analyses to only testing categorical and continuous models. Clarifying the exact nature of externalizing liability has important clinical, theoretical, and practical implications. Accordingly, we extended previous structural analyses of the externalizing spectrum (including ADHD) by modeling categorical, continuous, and hybrid models of liability. To our knowledge, this is only the second study of this kind to do so.

The present study is congruent with previous findings by Markon and Krueger [6] and Krueger [46] suggesting that externalizing liability is best conceptualized as a continuum rather than a set of discrete risk groups. The seven disorders were arrayed along a continuum of graded severity, with nicotine dependence and alcohol dependence less severe than ADHD and cocaine dependence. Marijuana dependence, cocaine dependence, and other substance dependence provided the greatest information regarding externalizing liability. Only one previous study examined alternative categorical, continuous, and hybrid latent variable conceptualizations of externalizing liability, including ADHD. The authors [20] found that a continuous, two-factor model provided the best fit to the data. Divergence between these findings and the current study may relate to the inclusion of different externalizing syndromes. Witkiewitz et al. [20] did not include nicotine or cocaine dependence, hallmarks of externalizing liability [6], and we did not include conduct disorder and oppositional defiant disorder in the present analyses. Due to practical constraints involved in conducting a national survey, the NESARC could not include all DSM-IV disorders; oppositional defiant disorder was one such disorder that was omitted. We excluded conduct disorder because it was assessed at Wave 1 only. We limited the disorders analyzed to only those assessed at Wave 2 to avoid any potential bias due to the wave at which the disorder was assessed. However, as an exploratory step (and in response to a reviewer's request), we re-ran the latent trait models to incorporate Wave I conduct disorder. The findings indicated minimal improvement in fit based on the BIC, providing convergent support for a one-factor model. Finally, a further noteworthy difference between the study by Witkiewitz et al. [20] and the present analyses relates to the examination of gender differences in this paper.

Implications

By drawing on data from a large-scale epidemiological survey and by investigating a wider panoply of competing measurement models than hitherto, this paper informs the literature on the empirical structure of externalizing psychopathology. These findings should ultimately inform the organizational structure of future editions of the DSM and other nomenclatures. Indeed, acknowledging the utility of the internalizing–externalizing framework in explaining "much of the systematic comorbidities seen in both clinical and community samples" [3], the recently released DSM-5 places internalizing disorders adjacent to one another and externalizing disorders next to one another. This new organizational structure marks efforts to develop a more valid foundation for classifying mental disorders [47] and to provide a bridge to new diagnostic approaches [3].

It should be noted that though ADHD loaded significantly on the externalizing factor in the present study, relatively speaking it was the weakest indicator of the seven syndromes examined. This suggests that ADHD may crossload onto another liability. As part of the DSM-5 revision process, ADHD has been speculated to load onto neurodevelopmental liability [48]. Future structural research should investigate whether ADHD loads onto other latent factors in addition to externalizing liability.

This paper found evidence for a continuous model of externalizing liability. Continuous models resolve inherent problems with the extant psychiatric classification system, such as extensive comorbidity and within-category heterogeneity, and offer flexibility to identify cut-off points to facilitate research and clinical decision-making [49]. From a research perspective, representing disorders as quantitative scores increases reliability, yields greater statistical power, and provides more comprehensive clinical information [50]. From a clinical perspective, some authors have found that dimensional models predict better clinical course, treatment needs, social and occupational functioning than their categorical counterparts [51–53]. In addition, a dimensional perspective provides a meaningful framework for informing our understanding of the specificity of biomarkers, putative endophenotypes, and genetic factors linked to liability.

The identification of a unitary continuum underlying externalizing liability, however, does not preclude the identification of thresholds [47]. Even if externalizing liability varies continuously in the general population, beyond a particular level, externalizing behaviors become problematic for the individual and/or those around them. It is unlikely that a uniform diagnostic threshold exists; as Widiger and Mullins-Sweatt [54] point out, a continuous model offers the flexibility to identify different thresholds to suit different social and clinical decisions. Indeed, a similar situation is evident in clinical medicine where, for instance, blood pressure is continuous yet a threshold signaling hypertension (i.e., systolic blood pressure $\geq$140 mmHg or diastolic blood pressure $\geq$90 mmHg) is used to aid clinical decision-making [55]. Future research could be directed towards identifying meaningful thresholds of externalizing liability according to external validators, such as measures of social and occupational impairment, and functional disability. These cut-offs could then be used to ensure individual treatments match the level of externalizing liability.

Although we did not find evidence that a hybrid model provided the best fit to the data, this paper adds to the sparse literature comparing the fit of hybrid models to traditional categorical and continuous models of psychopathology. Hybrid models capitalize on the merits of continuous and categorical approaches. Clinically speaking, this model supports the interpretation that a subgroup in the population has an elevated risk for experiencing externalizing syndromes and that, within this subgroup, symptoms are graded in severity.

Limitations

The present findings should be tempered by a number of caveats. First, structured interviews were conducted by non-clinicians who were unable to access independent sources of information or probe respondents for further information. Moreover, information was gathered through retrospective self-report. These survey design features, though common in psychiatric epidemiology and indeed clinical evaluation, have particular relevance for the assessment of childhood ADHD. Respondents were asked an extensive list of items enquiring about ADHD symptom onset before age 18; however, because significant others from childhood/adolescence and objective measures like report cards were not available to corroborate reports, the only source of information about symptoms and behaviors was the respondent. Recall bias therefore cannot be ruled out. Empirical research on the validity of retrospectively reported ADHD is mixed [56]. Relatedly, whilst it would be preferable to include a diagnosis of ADHD capturing childhood and adult symptom manifestations, the NESARC data set only comprises a childhood diagnosis which necessarily limits the focus of the present study. Nevertheless, ADHD functioned as a reliable indicator of overall externalizing level in the present study and demonstrated reliability in psychometric tests of the AUDADIS [22].

Second, analyses were based on lifetime diagnoses (with the exception of childhood ADHD). Analyses of past-year diagnoses herein were precluded due to low prevalence estimates of some disorders (e.g., cocaine dependence and other substance dependence). Third, the study was limited to data collected at a single point in time. Longitudinal data facilitates insights about stability and changes in externalizing symptomatology and behaviors over time, and has demonstrated utility in refining our understanding of liability to other forms of psychopathology [57]. In the context of a population genetic framework, longitudinal data holds promise of informing our understanding of whether the externalizing liability continuum is activated early in the developmental process to set in motion a chain reaction of disorders, or is present relatively constant throughout development as a predisposition towards externalizing disorders. Although the NESARC is a longitudinal design, since ADHD was only assessed at Wave 2 it was not possible to conduct longitudinal analyses to ascertain which of these accounts of the externalizing spectrum is most accurate.

Closing remarks

In closing, this study highlighted that liability to externalizing spectrum disorders is continuous in nature and dimensional in severity. Moreover, this study adds to a small body of research demonstrating that externalizing liability encompasses childhood ADHD. Congruent with longitudinal and genetic findings highlighted earlier, this observation suggests a degree of developmental continuity such that a childhood diagnosis of ADHD predicts the later development of other externalizing disorders in adulthood. Accurate identification, intervention, and treatment of childhood ADHD are therefore crucial.

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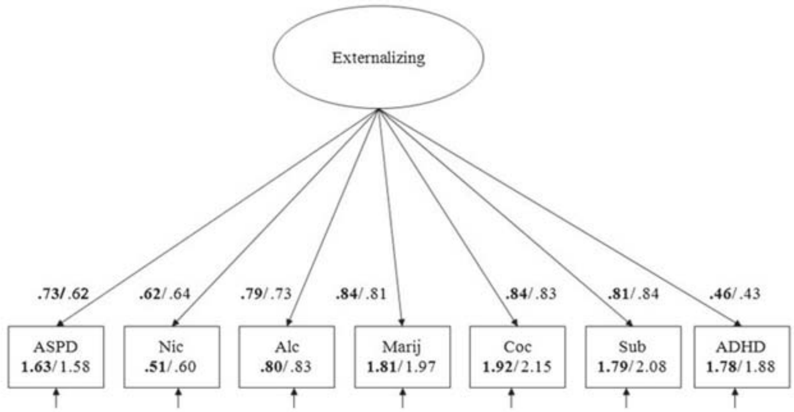

Fig. 1.

The constrained latent trait model in women and men (Model 2). Values presented on the structural paths from externalizing to the disorders are standardized factor loadings; values presented in *boxes* are thresholds (all significant $p < 0.001$). Values before the *slash* and in *bold* relate to women; values after the *slash* relate to men. *ASPD* antisocial personality disorder, *Nic* nicotine dependence, *Alc* alcohol dependence, *Marij* marijuana dependence, *Coc* cocaine dependence, *Sub* other substance dependence, *ADHD* attention-deficit hyperactiv-ity disorder. *Arrows* without numbers indicate unique variances, including error

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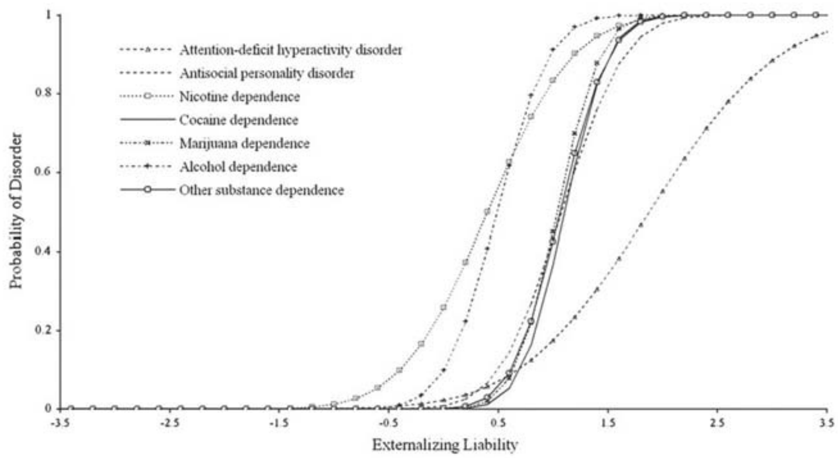

Fig. 2.

Response functions of externalizing disorders under a latent trait liability model (Model 2: constrained model)

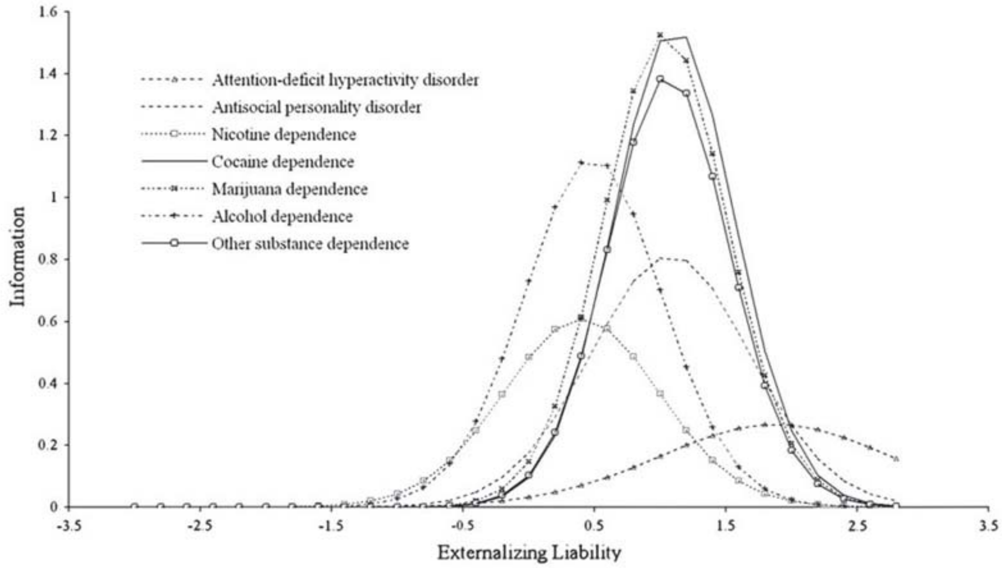

Fig. 3.

Information functions of externalizing disorders under a latent trait liability model (Model 2: constrained model)

Table 1

Fit indices for latent class, latent trait, and factor mixture models of externalizing liability in the 2004–2005 National Epidemiologic Survey on Alcohol and Related Conditions

Model	*k*	LL	BIC	AIC	SSABIC
Entire sample (n = 34,653)					
Latent class models					
2 classes	15	−47,019.464	94,195.726	94,068.929	94,148.056
3 classes	23	−46,732.210	93,704.843	93,510.421	93,631.749
4 classes	31	−46,703.143	93,730.333	93,468.286	93,631.815
5 classes	39	−46,679.846	93,767.365	93,437.693	93,643.424
6 classes	47	−46,667.835	93,826.967	93,429.669	93,677.601
7 classes	55	−46,662.786	93,900.495	93,435.573	93,725.706
Latent trait model	**14**	**−46,735.891**	**93,618.127**	**93,499.783**	**93,573.635**
Factor mixture models					
2 values	16	−47,019.464	94,206.179	94,070.929	94,155.331
3 values	17	−46,736.789	93,651.282	93,507.578	93,597.256
4 values	19	−46,723.873	93,646.355	93,485.745	93,585.973
5 values	21	−46,723.916	93,667.348	93,489.832	93,600.610
6 values	23	−46,723.873	93,688.167	93,493.745	93,615.074
7 values	25	−46,723.889	93,709.106	93,497.778	93,629.657
Females (n = 20,089)					
Latent class models					
2 classes	15	−22,146.548	44,441.716	44,323.097	44,394.047
3 classes	23	−22,008.251	44,244.385	44,062.503	44,171.292
4 classes	31	−21,990.597	44,288.340	44,043.194	44,189.823
5 classes	39	−21,979.948	44,346.306	44,037.897	44,222.366
6 classes	47	−21,971.395	44,408.462	44,036.790	44,259.098
7 classes	55	−21,965.394	44,475.724	44,040.788	44,300.936
Latent trait model	**14**	**−22,022.086**	**44,182.883**	**44,072.172**	**44,138.931**
Factor mixture models					
2 values	16	−22,146.548	44,451.624	44,325.097	44,400.776

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Model	*k*	LL	BIC	AIC	SSABIC
3 values	17	−22,013.607	44,195.648	44,061.213	44,141.623
4 values	19	−22,011.636	44,211.523	44,061.272	44,151.142
5 values	21	−22,011.655	44,231.376	44,065.310	44,164.639
6 values	23	−22,011.672	44,251.227	44,069.344	44,178.134
7 values	25	−22,011.627	44,270.952	44,073.254	44,191.503
Males (n = 14,564)					
Latent class models					
2 classes	15	−23,284.280	46,712.354	46,598.559	46,664.685
3 classes	23	−23,140.588	46,501.661	46,327.176	46,428.569
4 classes	31	−23,121.160	46,539.495	46,304.319	46,440.979
5 classes	39	−23,102.310	46,578.486	46,282.619	46,454.547
6 classes	47	−23,090.158	46,630.872	46,274.316	46,481.510
7 classes	55	−23,086.152	46,699.552	46,282.305	46,524.766
Latent trait model	**14**	**−23,134.157**	**46,402.522**	**46,296.313**	**46,358.031**
Factor mixture models					
2 values	16	−23,284.280	46,721.940	46,600.559	46,671.094
3 values	17	−23,143.396	46,449.760	46,320.793	46,395. 735
4 values	19	−23,128.782	46,439.705	46,295.565	46,379.324
5 values	21	−23,128.782	46,458.877	46,299.565	46,392.141
6 values	23	−23,128.785	46,478.054	46,303.569	46,404.962
7 values	25	−23,128.788	46,497.234	46,307.577	46,417.786

Criterion. Bold type indicates the best-fitting model

k number of estimated parameters, *LL* Log likelihood, *BIC* Bayesian information, *AIC* Akaike information criterion, *SSABIC* sample size adjusted BIC

Table 2

Measurement invariance tests of the externalizing spectrum across gender: summary of fit indices

Model	Test	CFI	TLI	RMSEA	$\Delta\chi^2$
Model 1 (unconstrained model)		0.997	0.995	0.008	–
Model 2 (constrained model)	2–1	0.994	0.992	0.010	27.791**

CFI comparative fit index, *TLI* Tucker–Lewis index, *RMSEA* root mean square error of approximation

** $p < 0.0001$