**Misbegotten Methodologies and Forgotten Lessons from Tom Swift's Electric Factor
Analysis Machine: A Demonstration with Competing Structural
Models of Psychopathology**

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Abstract

Confirmatory factor analysis (CFA) and its bifactor models are popular in empirical investigations of the factor structure of psychological constructs. CFA offers straightforward hypothesis testing but has notable pitfalls, such as the imposition of strict assumptions (i.e., simple structure) that obscure unmodeled complexity. Due to the limitations of bifactor CFAs, they have yielded anomalous results across samples and studies that suggest model misspecification (e.g., evaporating specific factors and unexpected loadings). We propose the use of exploratory factor analysis (EFA) to evaluate the structural validity of CFA solutions—either before or after the estimation of more restrictive CFA models—to (1) identify model misspecifications that may drive anomalous estimates and (2) confirm CFA models by examining whether hypothesized structures emerge with limited researcher input. We evaluated the degree to which predominant factor structures were invariant across contexts along the exploratory-confirmatory continuum and demonstrate how poor methodological choices can distort results and impede theory development. All models fit well, but there were numerous differences in replicability and substantive interpretability. Several similarities emerged between bifactor CFA and EFA models, including evidence of overextraction, the collapse of specific factors onto the general factor, and subsequent shifts in how the general factor was defined. We situate these methodological shortcomings within the broader literature on structural models of psychopathology, articulate implications for theories (such as the *p*-factor) that are borne out of factor analysis, outline several remedies for problems encountered when performing exploratory bifactor analysis, and propose alternative specifications for confirmatory bifactor models.

Keywords: bifactor model; general factor; confirmatory factor analysis; exploratory factor analysis; rotation criteria

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Analysis Machine: A Demonstration with Competing Structural

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“In these fields [the biological and social sciences] we are like the crew of a ship approaching some strange coast through a fog. It is easy to seize on some arbitrary, transient point of visibility and still easier to convince ourselves that it proves the existence of structures created by our own imagination on the basis of pretentious hypotheses.” (Cattell, 1952, p.16).

The utility of factor analysis for theory development is fundamentally intertwined with the manner in which it is applied. Recent debates on how best to characterize the structure of psychopathology are typically framed around competing *types of latent variable models*, such as those that include a general factor and those that do not. Much less attention is devoted to the methodological differences between various *types of factor analysis*. Confirmatory factor analysis (CFA) is the most common technique for estimating and comparing alternative structures of psychopathology. While CFA offers numerous benefits, there are potential pitfalls, such as imposing strict pre-specified structures onto the data and the risk of model overparameterization (Asparouhov & Muthén, 2009; Schmitt et al., 2018). Exploratory factor analysis (EFA) helps reveal the structure of a particular dataset, before estimating more restrictive CFA models to confirm good model fit (Sass & Schmitt, 2010; Schmitt & Sass, 2011). Perhaps counterintuitively, EFA can also be used after CFA to identify model misspecifications and examine whether the hypothesized structure emerges with fewer *a priori* restrictions on the data (Schmitt et al., 2018). In what follows, to demonstrate the utility of EFA in the context of model testing, we conduct an in-depth comparison of competing models of psychopathology using both exploratory and confirmatory analytic techniques. Although we use psychopathology structural models and *p*-

factor studies in particular as case examples, our arguments are applicable to factor analytic studies of any latent psychological construct.

Extending Tom Swift's Electric Factor Analysis Machine to Quantitative Nosology

Factor analysis is a branch of sophisticated statistical techniques whose history is uniquely situated within psychology (Bartholomew, 1995; Kendall, 1950; Smith, 1950). Following Spearman's (1904) introduction of the first factor model in history, further development of factor analysis was delayed and deterred by developers' clashing personalities, their debates on general-factor versus multifactorial views of human abilities and traits, and the long wait for user-friendly statistical software (Bartholomew, 1995; Beaujean & Benson, 2019). Inadequate computer capabilities prevented factor analysis from becoming a fully established scientific tool well into the late 60s, but, even then, factor analysis retained its reputation for being too subjective and arbitrary to be scientific (Bartholomew, 1995; Creasy, 1959; Kendall, 1950). For instance, Armstrong (1967) demonstrated in his article, "Derivation of Theory by Means of Factor Analysis or Tom Swift and His Electric Factor Analysis Machine," that factor analyses can produce misleading conclusions, especially in the absence of *a priori* theory. He maintained that factor analysis may be better suited for evaluating theories than for generating new ones (for an example of using EFA as an abductive method of theory development see Haig, 2005). Nevertheless, Preacher and MacCallum (2003) pointed out in "Repairing Tom Swift's Electric Factor Analysis Machine," that Armstrong actually demonstrated how poor methodological choices (e.g., confusing PCA with EFA, indefensible use of orthogonal varimax rotation, etc.) can lead to erroneous results.

Each version of Tom Swift's mistakes is writ large within the applied psychological literature: poor methodological choices have led to an overproduction of ambiguous results, which,

in turn, have paved the way for the derivation of theories by means of factor analysis. Some of the misbegotten methodologies underlying this problem are: (1) overreliance on goodness of fit indices for judging model superiority, (2) masking of important structural limitations, such as factor collapse and overextraction, and (3) a limited approach to model building and rote factor structure confirmation. We discuss each of these shortcomings within the context of the present study's combined use of exploratory and confirmatory approaches.

Combining Exploratory and Confirmatory Analyses

Exploration and confirmation are both encouraged when the aim is to identify latent factor structures of psychopathology that are statistically justifiable, generalizable, and clinically relevant (Schmitt et al., 2018). We outline a broad methodological approach in the flowchart presented in Figure 1 (adapted from Schmitt et al., 2018), which we used to guide the implementation of the present study's analytic strategy. As depicted in Figure 1, it is useful to begin the process of investigating factor structures by addressing the question of whether or not the factor structure is reasonably known, followed by questions regarding prior theory (e.g., none versus sparse) and expectations of how complex the resulting factor structure might be (e.g., simple vs. complex structure). By answering these questions first, researchers are able to match their theoretical and practical purposes with the specific types of exploratory and/or confirmatory methods to be used, and the order in which they are applied. To illustrate, we will now review these questions within the context of structural work on psychopathology and elaborate on the subsequent flow of procedures.

Questions 1 and 2: Is the factor structure of the data reasonably known, and how complex is the structure?

We used data from a large nationally representative sample, the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC), because it has been used for many other confirmatory structural studies on psychopathology (e.g., Blanco et al., 2013; Eaton et al., 2012; Eaton et al., 2011; Forbes et al., 2021; Greene & Eaton, 2016, 2017; Kim & Eaton, 2015; Lahey et al., 2012). These studies have focused on three confirmatory models in particular—correlated factor, higher-order, and bifactor models (see Figure 2)—that tend to fit diagnostic data well. These models are also conceptually similar, with each including a number of dimensions reflecting tendencies towards externalizing (i.e., poor emotional and behavioral control), and internalizing (i.e., negative emotionality); internalizing can also be split into dimensions of distress (i.e., anxious misery), and fear (i.e., sensitivity to imminent threat; Krueger, 1999). The latter two dimensions reflect narrower forms of internalizing, so we tested two separate sets of models with (1) externalizing and internalizing factors and (2) with externalizing, distress, and fears factors. The bifactor and higher-order models additionally incorporate a broader dimension, a general factor of psychopathology that notionally corresponds to the theoretical *p*-factor, which intends to account for the covariation among narrower psychopathology dimensions (e.g., externalizing, distress, and fears). The general factor in the bifactor model explains the covariation among all *items* in the model, whereas the general factor in the higher-order model explains the covariation among *lower-order factors*. In the case of conceptual models with three lower-order factors, the higher-order model is just-identified, making it a direct reparametrization of the interfactor correlations in the correlated factor model; both of these more restricted models may be nested within the bifactor model (Yung et al., 1999; Zhang et al., 2020).

Because we expected approximate simple structures with good fit based on prior work in these data, the first step of the analyses was to conduct the CFAs shown in Figure 2. The purpose

of this step was to investigate differences in the robustness of parameters estimates across the various structural representations derived by CFA. For all bifactor models, we tested models with both oblique and orthogonal specific factors. The latter follows the original instantiation of the bifactor model's definition of specific factors that capture residual common variance that is orthogonal to the general factor (Holzinger & Swineford, 1937), while the presence of correlated specific factors in the former complicates interpretations of both the interfactor correlations and latent factors (Eid et al., 2017; Markon, 2019). Despite this shortcoming of oblique specific factors in bifactor models, we allowed for interfactor correlations so that results could be compared to similar models in other studies (Caspi et al., 2014; Castellanos-Ryan et al., 2016). There is also a reasonable theoretical justification for correlated specific factors in certain cases. For instance, distress and fears are thought to reflect two forms of internalizing and are more highly correlated with each other than they are with externalizing, suggesting a higher-order internalizing dimension. Were one to extract distress, fears, and externalizing specific factors, they might expect that general psychopathology variance might entirely explain distress and fears' associations with externalizing, but not the entirety of the variance shared between distress and fears.

Questions 3 and 4: Is there evidence of anomalous parameter estimates, and do models derived by CFA also emerge through EFA?

Next, we conducted a series of EFAs to probe evidence of anomalous results in previous work and to test whether the models derived by CFA would also emerge with limited input from the researcher (Watts, Boness, et al., 2020). Confirmatory approaches are clearly valuable given a strong theory about the latent structure of a set of observed variables, but contemporary CFA model comparisons typically proceed in a covertly exploratory manner (Asparouhov & Muthén, 2009;

Brown, 2015; Browne, 2001; MacCallum et al., 1992; Schmitt et al., 2018). Thus, the “C” in “CFA” may therefore be somewhat of a misnomer.

Resulting from these exploratory CFAs is an overabundance of theoretically contradictory factor structures, producing a largely piecemeal literature that is difficult to synthesize (e.g., Watts, Lane, et al., 2020). Exploratory factor analysis provides a special advantage in the case of previous applications of confirmatory bifactor models of psychopathology, which have yielded results that are misaligned with theoretical expectations. For instance, some models report irregular patterns of loadings on specific factors such that they are either weakly or negatively indicated by their components (e.g., Lahey et al., 2012; Martel et al., 2017; Watts et al., 2019). Relatedly, other studies report “vanishing” specific factors whereby a specific factor is dropped from the model due to anomalous patterns of loadings (e.g., Brandes et al., 2019; Caspi et al., 2014; Tackett et al., 2013). Almost certainly, in each of these cases, the specific factors do not reflect the conceptual definition of the construct of interest. For instance, a distress specific factor that is weakly indicated by depression and is negatively indicated by generalized anxiety (e.g., Watts et al., 2019)—both of which are thought to typify distress—is likely mislabeled. These contradictory results might be hinting at model misspecifications that lurk in the strict assumptions CFAs impose onto the data, increasing the risk of obscuring unmodeled complexity (Eid et al., 2017; Heinrich et al., preprint). Perhaps contrary to factor analysts’ intuitions, exploratory techniques are particularly valuable follow-up analyses to probe anomalous estimates (Schmitt et al., 2018; Watts, Smith, et al., 2019), because EFAs allow for direct identification of model misspecifications that may drive anomalous estimates in CFAs (e.g., illuminating meaningful cross-loadings). EFAs are considered a useful alternative to post hoc inspections of modification indices in CFAs (Asparouhov & Muthén, 2009;

Browne, 2001; McDonald, 1999; Schmitt et al., 2018) and can serve as a guide for estimating more restrictive CFA models (Haig, 2005; Reise, 2012; Schmitt, 2011).

In the field of assessment, a renewed appreciation of exploratory techniques has led to a sharp increase in technological advances in exploratory methods (Abad et al., 2017; Asparouhov & Muthén, 2009; Giordano & Waller, 2019; Marsh et al., 2014), such as exploratory bifactor analysis (EBFA; Jennrich & Bentler, 2011; Jennrich & Bentler, 2012), but classification researchers in clinical psychology have been surprisingly slow to adopt these methods.¹ Thus, the question of whether pre-specified structures generated through CFA can also be derived freely through EFA seems to be forgotten, if not discounted (c.f., Watts, Smith, et al., 2019). Numerous exploratory and confirmatory studies of the correlated factor models of psychopathology have demonstrated that these structures are highly replicable in terms of conceptual structure and model fit (e.g., Blanco et al., 2013; Blanco et al., 2015; Eaton et al., 2011; Forbush & Watson, 2013; Greene & Eaton, 2016), and across clinical and non-clinical samples (e.g., Eaton et al., 2012; Krueger, 1999; Miller et al., 2008). However, the same is not true of confirmatory bifactor models of psychopathology (Watts, Lane, et al., 2020), and EBFA investigations are sparse in psychopathology literature (Murray et al., 2019; Sharp et al., 2015). This is surprising, and perhaps concerning, given the notable increase in the number of reported bifactor models of psychopathology to date (see Greene et al., 2019, for review of the psychopathology literature, and Rodriguez et al., 2016a, for a review of psychological measures more generally). Thus, we aimed to assess whether the same bifactor models put forth by CFA in these data would emerge using

¹ Some attribute the renewed interest in bifactor modeling to the recent development of exploratory bifactor modeling approaches (Giordano & Waller, 2019). In this light, there is some irony in the fact that so few studies have included exploratory bifactor analysis in studies of the general factor of psychopathology.

EBFA—a test of the confirmatory bifactor model’s replicability and invariance in meaning along the exploratory-confirmatory continuum.

Based on prior work that used these data to derive CFA models (Forbes et al., 2021), we anticipated the following outcomes: (1) in oblique EFAs (i.e., non-bifactor models; see Figure 3), interfactor correlations were expected to decrease and meaningful cross-loadings were expected to appear; (2) in all EBFAs (see Figure 3), internalizing disorders were expected to load higher on the general factor than on their respective specific factors, while externalizing disorders were expected to produce strong specific factors; (4) estimation problems for EBFAs were expected given previous demonstrations (Mansolf & Reise, 2016).

Question 5: How do traditional bifactor model CFAs compare to re-specified bifactor CFAs?

Given that traditional confirmatory bifactor models often result in estimation problems and anomalous parameter estimates, they might be inadequate for modeling multidimensionality (for a review of problematic results in the *p*-factor literature see Heinrich et al., preprint). Eid and colleagues (2017) proposed a solution for the anomalous results generated by the traditional bifactor model, the *bifactor S-1 model* (Eid et al., 2017). The bifactor S-1 model extracts all but one specific factor included in the traditional bifactor, in turn converting the general factor into a reference indicator marked by high degrees of whatever form(s) of psychopathology are included in the specific factor that is dropped from the model. In contrast with the traditional bifactor model, the bifactor S-1 model tends to produce more interpretable, theoretically consistent specific factors (Burns et al., 2019, 2020; Eid, 2020; Eid et al., 2017; Heinrich et al., 2018). It should be noted, though, that the bifactor S-1 model converts the general factor into a referent index of whatever specific factor is dropped, which effectively equates the general factor with a subset of indicators in the model.

For the last step in this study, we respecified the traditional bifactor model and compared results from the restricted bifactor S-1 models to the other CFA and EFA models in terms of structural validity (i.e., model fit, robustness of parameter estimates, factor loading patterns). Technically, the confirmatory bifactor S-1 model requires an *a priori* decision regarding which specific factor to exclude when it is extracted. Based on previous analyses of the structure of psychopathology in these data (Greene & Eaton, 2017; Forbes et al., 2021; Lahey et al., 2012), we began by testing a bifactor S-1 model with externalizing and fears specific factors, in turn dropping the distress specific factor so that distress indicators only loaded on the general factor. We did so because the general factor in this specific sample tends to be marked most strongly by distress-related disorders. Nevertheless, because what defines a general factor of psychopathology in a given model varies from study to study (Watts, Lane, et al., 2020), we extracted additional bifactor S-1 models in an exploratory manner to test models that excluded the fear and externalizing specific factors.

Summary. In sum, EFA can be viewed as a confirmatory approach for evaluating hypotheses about unmodeled complexity and model replicability, while model comparison studies using CFA can be viewed as exploratory endeavors where data are analyzed several different ways. No prior study has characterized these issues in quantitative nosology, and few have included EBFA techniques, so their use in applied settings is poorly understood. There are many excellent reviews on confirmatory and exploratory factor analytic procedures to guide researchers on issues of sample size, estimation procedures, selecting the optimal number of factors, rotations, rotation criteria, and so forth (e.g., Abad et al., 2017; Asparouhov & Muthén, 2009; Fabrigar et al., 1999; Giordano & Waller, 2019; Goldberg & Velicer, 2006; Mansolf & Reise, 2016; Markon, 2019; Marsh et al., 2014; Morin et al., 2016; Preacher & MacCallum, 2003; Reise, 2012; Sass & Schmitt,

2010; Schmitt, 2011; Schmitt & Sass, 2011; Schmitt et al., 2018; Zhang & Preacher, 2015). However, making informed decisions that are most appropriate to the circumstances is often difficult when information is inconsistent, outdated, or difficult for applied researchers to understand. The present study therefore aims to illustrate how exploratory and confirmatory factor analytic methods can be combined to provide a thorough characterization of the optimal latent variable model for a given dataset, and to ascertain factor structure stability across the exploratory-confirmatory continuum as well as across exploratory rotation criteria.

Method

Sample and Procedure

This study used diagnostic data from the first wave of the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC). The NESARC sample is a civilian, noninstitutionalized adult population, with complex survey design variables that weight age, racial/ethnic, and gender distributions to be representative of the 2000 United States Census (for a full description of the sampling frame, see Grant & Dawson, 2006). Participants initially assessed at Wave 1 (W1 N = 43,093; fielded 2001–2002; response rate: 81% of eligible individuals; Grant & Dawson, 2006) ranged in age from 18 to 98 years. Women comprised 57% of the sample; self-identified non-Hispanic White participants comprised 56.9%, Hispanic or Latinx 19.3%, African-American 19.1%, Asian or Pacific Islander 3.1%, and American Indian or Alaska Native 1.6% (Grant, Kaplan, Shepard, & Moore, 2005). The research protocol, including written informed consent, received full review and approval from the United States Census Bureau and Office of Management and Budget.

Assessment

We analyzed lifetime DSM-IV diagnoses, assessed with the Alcohol Use Disorder and Associated Disabilities Interview Schedule-*DSM-IV* Version (AUDADIS- IV; Grant et al., 2003). The AUDADIS-IV is a structured interview designed for highly trained lay interviewers. The 11 common diagnoses examined were major depressive disorder (MDD), dysthymia, generalized anxiety disorder (GAD), social phobia, specific phobia, panic disorder with agoraphobia (PD/AG; Greene & Eaton, 2016), alcohol dependence, nicotine dependence, marijuana dependence, other drug dependence, and a 12-month diagnosis was used for antisocial personality disorder (ASPD). The other drug dependence variable was created by combining rarer forms of substance use (e.g., stimulants, cocaine, sedatives, opioids, tranquilizers, solvents, hallucinogens, heroin, and any other drug not assessed), with variance sufficient for covariance structure modeling. Internal consistency of this variable was good ($\alpha=.77$; Eaton et al., 2012). The AUDADIS-IV diagnostic reliabilities for mood, anxiety, and ASPD were fair to good (kappas = .40 to .67), and good to excellent for substance use disorders (kappas = .54 to .76; Grant et al., 2003; Hasin et al., 2005). We selected these diagnoses due to their inclusion in several structural studies using these data (Blanco et al., 2013; Greene & Eaton, 2016, 2017; Kim & Eaton, 2015; Lahey et al., 2012). Test-retest estimates for the AUDADIS-IV are strong and comparable to other structured interviews (Grant et al., 2004; Wittchen, 1994), and has advantages over other such measures, including assessment of clinically significant distress and impairment once a disorder is fully characterized (Hasin et al., 2005).

Analytic Approach

Model estimation. We performed all confirmatory and exploratory factor analyses in *Mplus* 8 (Muthén & Muthén, 1998-2017). Latent variables were standardized to have a mean of 0 and a variance of 1, with factor loadings freely estimated. The *Mplus* type=complex option was used to incorporate the complex survey variables. For the sake of comprehensiveness, we

estimated models with both weighted least square mean and variance adjusted (WLSMV) and maximum likelihood with robust standard errors (MLR), allowing for adequate handling of missing data and the ability to treat diagnoses as dichotomous. Researchers are encouraged to use these robust estimators with binary indicators (i.e., present/absent diagnoses) since the assumption of multivariable normality is violated (i.e., asymmetrical thresholds with most of the responses falling into diagnoses absent category), which can bias parameter estimates (Beauducel & Herzberg, 2006; Flora & Curran, 2004; Rhemtulla et al., 2012). Instances in which these estimators produced diverging results are noted.

Model fit. The root mean square error of approximation (RMSEA) quantified absolute fit, with values $< .05$ indicating close fit. Incremental fit indices, the comparative fit index and Tucker Lewis index (CFI and TLI; Bentler, 1990; Hu & Bentler, 1999), were used to evaluate improvements in fit by comparing the hypothesized model to a null model, with values $> .95$ indicating close fit. Gignac's (2007) practical difference criterion of $\Delta TLI \geq .010$ was used to guide comparisons. Together, these fit indices moved model evaluation beyond the global model evaluation method of the χ^2 test due to its well-known tendency to reject models with irrelevant misspecifications in large sample sizes (Saris et al., 2009). Relative fit indices that were used to directly compare models' fit included the Akaike information criterion (AIC; Akaike, 1987), Bayesian information criterion (BIC; Raftery, 1995), and the sample-size adjusted BIC (SABIC; Sclove, 1987), with lower values being superior (e.g., $\Delta AIC/BIC$ of 10 points strongly favour the model with a lower value; Raftery, 1995).

Traditional confirmatory factor analyses. We extracted an initial set of eight confirmatory factor models (see Figure 2): 1) a correlated two-factor internalizing-externalizing model, 2) a correlated three-factor distress-fear-externalizing model, 3) a higher-order

internalizing-externalizing-general psychopathology model, 4) a higher-order distress-fear-externalizing-general psychopathology model, 5) an orthogonal bifactor internalizing-externalizing-general psychopathology model, 6) an orthogonal bifactor distress-fear-externalizing-general psychopathology model, 7) an oblique version of Model 5, and 8) an oblique version of Model 6. All cross-loadings were constrained to zero in both the correlated factors and higher-order models, and all interfactor correlations were constrained to zero for the bifactor models with orthogonal specific factors, whereas interfactor correlations were freely estimated in the bifactor model with oblique specific factors. The eight CFA models were each estimated using WLSMV and MLR estimators, amounting to a total of 16 CFAs.

Exploratory factor analyses. Estimation of exploratory models proceeds in two phases: extraction of an initial set of common factors, followed by factor rotation to transform the initial factor loadings into more parsimonious and interpretable solutions. While there are several available methods for selecting the appropriate number of factors (Fabrigar et al., 1999; Finch, 2020; Hayton et al., 2004; Schmitt, 2011), the decision to extract two-, three-, and four-factor solutions was based the present study's aims of ascertaining factor structure stability across the exploratory-confirmatory continuum, as well as across exploratory rotation criteria. That is, we extracted exploratory solutions that we deemed conceptually compatible with our confirmatory models to compare them (see also Watts et al., in press). The choice of rotation methods was guided by the expectation that the 11 diagnostic indicators from NESARC would yield factor structures with only a few meaningful cross-loadings. Thus, the geomin (Yates, 1988) and cf-quartimax rotation criteria (Crawford, 1975; Crawford & Ferguson, 1970) were most suitable given that both aim for approximate simple structure and have options for rotating factors to oblique and orthogonal orientations. An added benefit of these two rotation criteria is their

correspondence to the only two available bifactor rotation criteria in *Mplus*, bi-geomin and bi-cf-quartimax (referred to as the JB rotations; Jennrich & Bentler, 2011, 2012). Each model was estimated separately using both orthogonal and oblique rotation criteria, as well as using both WLSMV and MLR estimators. In sum, the primary exploratory analyses included two-, three-, and four-factor solutions using oblique and orthogonal geomin, cf-quartimax, bi-geomin, and bi-cf-quartimax rotation criteria (i.e., 12 basic EFAs and 12 bifactor EFAs, resulting in a total of 48 models across WLSMV and MLR estimators).

Interpretative criteria. Before reviewing the properties and performances of each rotation criterion, we will first consider how factor loading patterns were interpreted. Criteria for factor adequacy were established *a priori* based on prior research (Cudeck & O'Dell, 1994; Schmitt & Sass, 2011): high factor loadings were defined as those $\geq .60$, moderate loadings were $\geq .30$, and those $\leq .30$ were ignored. The criterion of $.30$ was used to distinguish between statistical and meaningful significance—a difficult distinction when many cross-loadings increase as the result of constraining factors to orthogonality. For bifactor models, loadings $> .80$ on the general factor were interpreted as pure indicators (Robertson, 2019).

These criteria served as the basis for classifying structures into the following three types, assuming that factors were properly identified (i.e., defined by at least three indicators for orthogonal structures and by two indicators for oblique structures): 1) *independent clusters* refers to models in which indicators have no cross-loadings, 2) *independent cluster basis* refers to models in which cross-loadings are present (McDonald, 2000), and 3) *independent cluster pure* (Mansolf & Reise, 2016) refers to bifactor structures with pure indicators of the general factors (i.e., variables that only load on the general factor, resulting in partial or full collapse of a specific factor). Because the concepts of “no” or “zero” cross-loadings are misnomers in applied settings

(Zhang & Preacher, 2015), these guidelines were applied using the aforementioned cut-off criteria for factor loadings.

Basic rotation criteria. The key to understanding all exploratory methods is in how factors are rotated to a substantively interpretable solution (for equations and detailed reviews see Browne, 2001; Mansolf & Reise, 2016; Sass & Schmitt, 2010). Rotation criteria are mathematical functions that a rotation seeks to minimize, and all rely on an optimization algorithm as the technical method for minimizing a given rotation criterion function. The gradient projection algorithm (GPA; Bernaards & Jennrich, 2005) is used to minimize both the geomin and cf-quartimax rotation criteria, which each contain penalties for variable complexity (i.e., cross-loadings). Because the cf-quartimax criterion was designed to produce easily interpretable independent clusters, it seeks to identify solutions in which each indicator loads strongly on one single factor and near-zero on all others (Asparouhov & Muthén, 2009; Sass & Schmitt, 2010). Rotation criteria that seek to minimize variable complexity tend to break down in the presence of cross-loadings, but Yates' geomin is an exception (Browne, 2001). Instead, geomin searches for structures where each indicator has at least one near-zero loading, because it is based on Thurston's (1954) notion of approximate simple structure. Once this happens, the remaining factor loadings for a given indicator are not influenced by the minimization function, allowing for more complex structures to emerge.

Analytic bifactor rotations. Historically, researchers wishing to approximate a bifactor solution in EFA have turned to the Schmid-Leiman transformation (SLT; Schmid & Leiman, 1957). The SLT procedure begins with the extraction of k orthogonal common factors, where k is the number of specific factors, that are then obliquely rotated and expanded via a higher-order model into an orthogonal bifactor solution with $k+1$ factors (Mansolf & Reise, 2016, 2017; Yung

et al., 1999). The SLT imposes proportionality constraints during the process of expanding the k correlated factors to a $k + 1$ factor space. These unique constraints imply that within each specific factor, the ratio of specific factor loadings (direct effects on observed variables) to general factor loadings (indirect effects) are constrained to equality (i.e., the partitioning of general and specific factor variance is perfectly proportional). Proportionality constraints are problematic in applied settings because they fail to hold when data depart from a perfect independent cluster structure (Brunner et al., 2012; Gignac, 2016; Mansolf & Reise, 2016; Molenaar, 2016; Yung et al., 1999). This is one reason for the common misconception that SLT factor loadings are functionally equivalent to those from a bifactor solution. Specifically, it is only when the proportionality constraints hold that the bifactor and higher-order models are equivalent and can both be perfectly re-expressed as a correlated factors model. Thus, when cross-loadings are present, SLT results will be biased. Although, the SLT method is noted as being suitable for descriptive purposes, or as a first step in determining patterns of (non-)salient loadings (Reise et al., 2010).

Jennrich and Bentler's (2011, 2012) bi-geomin and bi-cf-quartimax rotations offer a direct method for estimating a bifactor model in an exploratory framework. The JB rotations begin with the extraction of $k + 1$ orthogonal common factors, where the $(k + 1)$ th factor is the general factor, followed by a rotation to bifactor structure with orthogonal or oblique dimensions. Only the specific factors are rotated explicitly; the general factor is rotated implicitly. The two JB rotations require different conditions to perform optimally. Bi-cf-quartimax has been found to be most accurate for data with independent clusters structure or those that deviate only due to pure indicators of the general factor (Abad et al., 2017). Similar to the poor performance of the quartimax rotation criterion with cross-loadings (Asparouhov & Muthén, 2009), bi-cf-quartimax is extremely sensitive to cross-loadings, because it searches for structures where indicators have

very low or near zero cross-loadings on all specific factors (Mansolf & Reise, 2016). Bi-geomin is minimized for structures that contain at least one non-zero cross-loading. So, it has been found to perform best with more complex structures that contain cross-loadings (Mansolf & Reise, 2016), or those that combine cross-loadings and pure indicators (Abad et al., 2017).

Cautions in using analytic bifactor rotations. Because JB rotations directly extract $k + 1$ factors, they do not impose proportionality constraints, a distinct advantage when data are consistent with a bifactor structure. While the extraction of an additional factor is a non-issue when data are representative of a bifactor structure, problems arise when the data generating processes is a higher-order or non-hierarchical structure. That is, JB rotations perform poorly when the SL constraints hold or nearly hold (i.e., there is a perfect linear dependence between the general and specific factor loadings; Mansolf & Reise, 2016). In these cases, the JB rotations will produce overfactored or overparameterized models and other estimation problems (e.g., non-convergence). Overextraction occurs when the data carry an insufficient amount of information to estimate model parameters (Mansolf & Reise, 2016; Wood et al., 1996), resulting in nonsensical “junk” factors (e.g., single item factors) or Heywood cases (i.e., there is negative residual variance such that a model explains over 100% of the variance in one or more items). Beyond the issue of possible overextraction with JB rotations, there are two additional reasons for cautious implementation: (1) multiple random starting values need to be used and (2) specific factors are prone to collapsing onto the general factor (Asparouhov & Muthén, 2009; Jennrich & Bentler, 2011; Mansolf & Reise, 2016).

Although many exploratory rotation criteria are capable of producing multiple unique solutions in a single analysis (Asparouhov & Muthén, 2009; Browne, 2001; Rozeboom, 1992), including geomin, this is particularly true for the JB rotations (Dombrowski et al., 2019; Giordano

& Waller, 2019; Mansolf & Reise, 2016). This is known as the local minima problem whereby multiple solutions have similar rotation function values. A solution that converges to the same lowest function value with any combination of start values is referred to as the global minimum, while additional unique solutions are called local minima. In the presence of multiple local minima, an estimator may get “stuck” before reaching the global minimum and identify only one of many possible solutions, which may not be the most optimal if it is judged by the criterion of interpretability. Thus, local minima are not problematic, but using a model identified from local minima may not be the best solution (Asparouhov & Muthén, 2009). This issue tends to go unrecognized because the default in *Mplus* is to run 30 random starting values for a given rotation and display one solution. To ensure identification of all possible unique solutions (i.e., re-representations of the single solution on display), the number of random starting values was increased to 1000 and up to 10 of the best unique solutions were displayed (i.e., using the *restarts=1000 10* command, as recommended by Mansolf & Reise, 2016). The same procedure was applied to all EFA analyses as the geomin rotation criterion is also known to produce multiple optimal solutions (Asparouhov & Muthén, 2009).

A related challenge in applying JB bifactor rotations is specific factor collapse, a hallmark symptom of local minima (Mansolf & Reise, 2016). Factor collapse occurs when a substantial amount of variance is absorbed by the general factor from one or more specific factors, leading to inflated general factor loadings and specific factor loadings that are either too small, negative, or vanished altogether. Paradoxically, solutions with one or more collapsed factors often provide rotation criterion function values that are just as low as a true bifactor solutions. This happens for two reasons, which are both due to only the specific factors being rotated explicitly in JB rotations. First, when variance is shifted from the specific factors to the general factor, the rotation criteria

will be lowest when the general factor explains as much variance as possible. Second, because both JB rotation criteria only penalize certain specific factors for row complexity (i.e., cross-loadings), the rotation criteria can be minimized when one factor loading is large and others are very small, or when all specific factor loadings are very small. However, it should be noted that factor collapse does not always signal that a solution is inaccurate; factor collapse also occurs when pure indicators of a general factor are present (i.e., when indicators are incorrectly thought to form a separate specific factor).

Confirmatory bifactor S-1 analyses. Lastly, inspection of confirmatory and exploratory bifactor results guided the application of three confirmatory bifactor S-1 models (Eid et al., 2017) in which the general factor was re-defined as a reference factor based on a specific group of diagnoses (i.e., rather than a general factor common to all diagnoses in the model; see Figure 4). Latent variables had a mean of 0 and variances were freely estimated. Diagnostic indicators with the strongest loadings on their respective factors in the CFA and EFA bifactor models were chosen to set the metric of each latent variable (i.e., unstandardized factor loadings were fixed to 1; c.f., Eid et al., 2017; Burns et al., 2019). For the first bifactor S-1 model, the distress diagnoses were chosen to define the general reference factor, with MDD setting the metric of the general reference factor, PD+AG the fear factor, and alcohol dependence the externalizing factor. For the second bifactor S-1 model, fear disorders defined the general reference factor, with PD+AG setting the metric for the general reference factor, dysthymia the distress factor, and alcohol dependence the externalizing factor. For the third and final bifactor S-1 model, externalizing disorders defined the general reference factor, with drug dependence setting the metric for the general reference factor, MDD the distress factor, and PD+AG the fear factor. In all bifactor S-1 models, the specific factors were allowed to correlate (e.g., fear and externalizing in the first model). These partial correlations

were indicative of the shared specific variance in the two non-reference domains that was not shared with the general reference factor.

Factor Score Correlations. Factor scores were estimated using maximum a posteriori (MAP) estimation to examine the associations between latent variables in the bifactor S-1, correlated factor, and traditional bifactor confirmatory factor models (using WLSMV). Factor scores were saved and then treated as observed variables in Pearson Product Moment correlation analyses.

Results

All models fit the data well according to model fit indices and the information criteria (see Table 1). Goodness-of-fit comparisons are noted for both WLSMV and MLR results. Standardized factor loadings were generally similar across estimators so factor loading patterns for WLSMV are presented for all CFAs and EFAs. Diverging results for MLR were only observed for bifactor models and are elaborated on later.

Traditional Confirmatory Factor Models

For the two- and three-factor correlated factors models (see Table 2), all standardized factor loadings were positive and substantial, as were the interfactor correlations. As expected, the WLSMV higher-order models (see Table 3) showed identical fit and first-order factor loadings compared to the corresponding correlated factors models, with strong first-order factor loadings on the second-order factors. Approximate fit indices and the information criteria for WLSMV and MLR estimators showed improved fit for correlated factor and higher-order models with a greater number of factors (i.e., a preference for the distress-fears-externalizing model compared with the internalizing-externalizing model; $\Delta\text{TLI} = 0.21$; $\Delta\text{BIC} = -826.873$).

Standardized loadings for the bifactor models were less consistently robust (see Tables 4 and 5 for the orthogonal and oblique bifactor models, respectively). In all bifactor models, the general factor was most strongly indicated by internalizing disorders—particularly MDD, Dysthymia, GAD, and PD+AG—which showed attenuated loadings on corresponding specific factors. Only the four-factor bifactor model with orthogonal specific factors contained all positive and robust factor loadings. GAD was a particularly weak indicator of the distress specific factor ($\lambda = .19$ to $\lambda = .21$ between the two estimators), especially once the specific factors of distress, fear, and externalizing were allowed to correlate ($\lambda = .07$ to $\lambda = .10$ between the two estimators). The factor correlations for externalizing with the fear and distress factors remained positive and significant across both estimators ($r = .22$ to $r = .33$), while the correlations between distress and fear became negative ($r = -.51$ to $r = -.13$). For the three-factor solutions using WLSMV, bifactor models with oblique and orthogonal specific factors both produced a bipolar factor for internalizing disorders in which the distress disorders loaded negatively or near zero ($\lambda = .04$ to $\lambda = -.33$). This pattern was reversed for the bifactor model with orthogonal specific factors using MLR, in which the only significant indicators for internalizing were MDD and Dysthymia. Factor correlations between internalizing and externalizing in the bifactor model with oblique specific factors were near zero for WLSMV ($r = .06$), but positive and significant using MLR ($r = .21$). Approximate fit indices generated by WLSMV were highly similar across all bifactor models and did not meaningfully differ from the correlated factor and higher-order models. However, the information criteria (AIC, BIC, and SSBIC) favored all bifactor models over the correlated factor and higher-order models (ΔBIC ranged from -97 to -185), as well as the three-factor rather than the four-factor bifactor models (ΔBIC ranged from -15 to -87), despite these favored models being less interpretable.

Exploratory Models

As shown in Table 1, the extraction of more factors led to better fitting EFAs using WLSMV. Although, the four-factor models showed evidence of overfitting the data. When using MLR, BIC favored the three-factor models over the two- and four-factor models (Δ BIC ranged from -28 to -931).

Results from the SLT of the higher-order CFA model are shown in Table 6, and are for descriptive purposes only. Standardized factor loadings and interfactor correlations for the oblique and orthogonal exploratory models using geomin, cf-quartimax, and the JB bifactor rotation criteria are displayed in Table 7 (two-factor solutions), Table 8 (three-factor solutions), and Table 9 (four-factor solutions). These solutions were those generated by *Mplus*'s default functions (i.e., 30 random starts and one solution on display). To illustrate the local minima phenomenon, interpretations for all unique solutions and their optimization values are tabulated in Tables 10, 11, and 12. Bolded **Xs** signify solutions that appeared when a single solution was displayed, whereas unbolded **X*s** signify additional unique solutions that appeared after requesting that up to 10 solutions be displayed and using 1000 random starts. Consistent with prior research (Mansolf & Reise, 2016), the most interpretable solution was not always the product of the lowest function value for a given rotation (e.g., oblique four-factor bi-cf-quartimax rotation). The number of local minima, and thus the number of possible interpretations, increased as a function of extracting greater numbers of factors and use of orthogonal rotation, especially for the geomin and bi-geomin rotation criteria, as described below.

Basic exploratory factor models. In the oblique two-factor solutions, there was one unique optimization value for the cf-quartimax and geomin rotation criteria. Results were highly similar and showed independent clusters structure, with large standardized factor loadings and

moderate to strong interfactor correlations. Factors corresponded to the correlated two-factor CFA: internalizing and externalizing. In the oblique three-factor solutions, there was one unique optimization value for the cf-quartimax rotation and two for geomin. The lowest criterion function values for both rotations produced the same robust pattern of results that aligned with the correlated three-factor CFA: distress, fear, and externalizing. Because GAD significantly cross-loaded on the distress and fear factors in both models, they were best characterized as independent cluster basis structures. The oblique four-factor solutions both resulted from a single criterion function value and produced similar, but problematic, interpretations that were suggestive of overfactoring: distress, fear, externalizing, and a junk factor defined by theoretically nonsensical loadings for specific phobia and nicotine.

The orthogonal EFA rotations (geomin and cf-quartimax) produced a greater variety of factor pattern in comparison to the oblique EFAs. As a result, there was no convergence on a single interpretation across orthogonal rotations. The only similarity was that cross-loadings were upwardly biased due to interfactor correlations being constrained to zero. In the orthogonal two-factor solutions, there was one unique solution for the cf-quartimax rotation and three for the geomin rotation. The cf-quartimax rotation produced an independent clusters structure characterized by internalizing and externalizing. In stark contrast, the geomin rotation produced a pseudo-bifactor structure, with a general factor that was strongly indicated by distress disorders and an externalizing factor. This pattern of results continued to emerge when three- and four-factors were extracted. In both instances, a single solution was found for the cf-quartimax rotation, whereas five and three unique solutions, respectively, were found for the geomin rotation. In the three-factor solution, the cf-quartimax rotation produced an independent cluster basis structure, with common factors reflecting distress, fear, and externalizing, and cross-loadings for GAD,

social phobia, and PD+AG. The geomin rotation produced a general factor that was mostly defined by distress disorders, along with fear and externalizing factors. Similar to the oblique EFAs, orthogonal four-factor solutions provided evidence of overextraction through the emergence of a junk factor.

In sum, there were multiple indications of problematic extraction and rotation. First, all four-factor solutions were suggestive of overfactoring. This is an important observation given that numerous published bifactor models of psychopathology follow this structure (Forbes et al., 2021; Greene & Eaton, 2017; Lahey et al., 2012). Second, the orthogonal geomin criterion was highly susceptible to local minima that resulted in various interpretations. Cf-quartimax reached a global minimum in all cases and consistently produced independent cluster basis structures across oblique and orthogonal rotations, which is likely due to this rotation's low tolerance for large cross-loadings. Because geomin does not penalize for cross-loadings explicitly, the variance once captured by interfactor correlations was re-expressed through numerous large cross-loadings in orthogonal models, leading to the emergence of general and specific factors. Lastly, agreement between the two rotations was only observed for the optimal two-and three-factor oblique models, which provided the clearest substantive interpretations.

Exploratory bifactor models. Similar to the basic EFA results, the JB bifactor rotation criteria showed more agreement in the oblique case (see Tables 7-9). In the two- and three-factor solutions, there was one unique optimization value for both the bi-cf-quartimax and bi-geomin rotations. Results showed interfactor correlations near zero and matching factor interpretations: two-factor models included general and externalizing factors; three-factor models contained a general factor and two specific factors for externalizing and fear. Three-factor solutions were independent cluster pure structures in which the internalizing factor partially collapsed onto the

general factor, resulting in a general factor that was primarily defined by distress disorders, much like the orthogonal geomin solutions. In the four-factor solutions, there were two unique solutions for the bi-cf-quartimax rotation and four for bi-geomin. The smallest optimization values for both rotations yielded results with moderate interfactor correlations ($r = .44$ to $r = .58$) but different factor interpretations. In the bi-geomin rotation, the externalizing factor fully collapsed onto the general factor, producing two specific factors for fear and distress, and one junk factor. This is noteworthy because most general factors are primarily defined by internalizing as opposed to externalizing. The bi-cf-quartimax rotation produced a general factor that was strongly indicated by all disorders, a specific factor for distress, and two collapsed factors for fear and externalizing. Although, the second unique solution for bi-cf-quartimax did result in an independent cluster structure: a general factor and three specific factors for distress, fear, and externalizing. This demonstrates that the lowest criterion function value does not always correspond to the most interpretable solution.

Results for the orthogonal models were generally aligned with those described for the oblique models. In the two-factor solutions, there was one unique optimization value for the bi-cf-quartimax and bi-geomin rotations. Factor structure interpretations were identical to their oblique counterparts: a general factor and a specific factor for externalizing. For three-factor models, one unique solution was found for bi-cf-quartimax and two for bi-geomin. Again, partial factor collapse was observed for both rotations' smallest optimization values, yielding independent cluster pure structures characterized by a general factor that was primarily defined by distress disorders and two specific factors for externalizing and fear. The number of local minima increased for both JB rotations once four factors were extracted. Three unique solutions were found for bi-cf-quartimax and five for bi-geomin. The smallest optimization value for the bi-cf-quartimax

rotation produced the only fully interpretable independent clusters structure: a general factor and three specific factors for distress, fear, and externalizing. In the bi-geomin rotation, the specific factor of distress fully collapsed onto the general factor, leaving two specific factors for fear and externalizing and one junk factor

To summarize, the JB rotations suffered from comparable extraction and rotation problems as the basic EFA rotations. The bi-geomin rotation was unable to generate a full four-factor bifactor model and, like geomin, was prone to multiple local optima. In contrast, the bi-cf-quartimax rotation continued to reach a global minimum at two- and three-factor levels, and also identified an independent cluster structure at the four-factor level. Here, the bi-cf-quartimax rotation's superior performance is related to the orthogonal cf-quartimax rotation's generation of approximate independent clusters because only the specific factors are explicitly rotated in exploratory bifactor analysis.

Confirmatory Bifactor S-1 Models.

Table 13 shows the standardized parameter estimates for the three bifactor S-1 models using WLSMV. Distress disorders defined the general reference factor in the first model (left panel), fear disorders in the second model (middle panel), and externalizing disorders in the third model (right panel). As shown in Table 1, traditional fit indices for WLSMV did not meaningfully differ, but BIC favored the bifactor S-1 model with fear as the reference domain as opposed to the models with distress ($\Delta\text{BIC} = -146$) and externalizing ($\Delta\text{BIC} = -204$) as the reference domains, and even the optimal orthogonal bifactor CFA model ($\Delta\text{BIC} = -67$). All factor loadings were positive, substantial, and highly stable across WLSMV and MLR estimators. Specific factor loadings were higher and more homogenous compared to those for the traditional bifactor models presented in Tables 4 and 5.

For the bifactor S-1 model with distress as the reference domain, there was a low interfactor correlation between the specific factors of fear and externalizing ($r = .19, p < .001$). This showed that these two factors had little variance in common once variance shared the general distress reference factor was removed (less than 5%). Distress disorders loaded highly on the general reference factor ($\lambda = .78$ to $\lambda = .89$), an indication of their substantial reliability as measures of the general factor. The externalizing disorders had lower loadings on the general distress reference factor ($M = .42$) than on the specific externalizing factor ($M = .64$), while fear disorders had similar loadings on both the general ($M = .56$) and specific factors ($M = .55$). This demonstrated that externalizing disorders had more unique variance accounted for by its specific factor, whereas fear disorders' variance was more evenly associated with the general distress reference factor and the specific fear factor.

With fear as the reference domain, the interfactor correlation between the specific factors of distress and externalizing was higher ($r = .32, p < .001$), but still indicative of little common variance after accounting for variance shared with the general fear reference factor (slightly more than 10%). Fear disorders loaded highly on the general reference factor ($\lambda = .70$ to $\lambda = .88$), showing that they also had substantial reliability as measures of the general factor. Again, externalizing disorders had lower loadings on the general fear reference factor ($M = .39$) than on the specific externalizing factor ($M = .66$), demonstrating that externalizing disorders had more unique variance accounted for by its specific factor. Distress disorders had higher loadings on the general fear reference factor ($M = .61$) than on their specific factor ($M = .58$), indicating that more distress disorder variance was associated with the general fear reference factor than specific distress factor.

When externalizing was chosen as the reference domain, there was a strong interfactor correlation between the distress and fear specific factors ($r = .62, p < .001$). This denoted a large amount of remaining internalizing variance (38%) once the shared variance from the general externalizing factor was removed. Externalizing disorders were shown to have high reliability as indicators of the general factor ($\lambda = .70$ to $\lambda = .87$), while the general factor loadings for distress ($M = .45$) and fear ($M = .39$) disorders were much weaker. The high specific factor loadings for distress ($M = .71$) and fear ($M = .68$) disorders suggested that greater amounts of unique variance was associated with the specific factors compared to the general externalizing reference factor.

Factor Score Associations

Building on previous evaluations of the relations between the correlated factors, bifactor S-1 models, and traditional bifactor models (Eid, 2020; Kim et al., 2016), we examined degrees of similarity between the latent factors scores generated by each of these confirmatory factor models. Factor score correlations are presented in Table 14, with bolded r s $\geq .90$ to highlight notable patterns of correspondence. The general factor in the bifactor model with orthogonal specific factors was nearly equivalent to the distress and fear factors (r s = .98 and .96, respectively) in the correlated factors model, whereas the specific factors showed much weaker associations with the corresponding domains of distress, fear, and externalizing in the correlated factor model (r s = .69, .61, and .82, respectively). Because the bifactor S-1 model's general reference domain is isomorphic with the corresponding domain in a correlated factor model (Eid, 2020), these factor scores were correlated a unity (e.g., $r = 1.00$ for the general distress reference factor and the distress factor in the correlated factors model). Striking similarities were also observed between the latent factors in the bifactor model with orthogonal specific factors and the bifactor S-1 models with distress as reference domain. The degree of correspondence was nearly perfect between these two

model's general factors ($r = .98$) and the specific factors of fear and externalizing ($r_s = .96$ and $.99$, respectively).

Discussion

Several studies have demonstrated the replicability of correlated factor models of psychopathology across exploratory and confirmatory methods (Blanco et al., 2013; Eaton et al., 2012; Eaton et al., 2011; Forbush & Watson, 2013; Greene & Eaton, 2016). However, bifactor models of psychopathology have largely been examined with CFA, despite the availability of several exploratory bifactor methods. Research from other fields suggests that researchers make better choices when EFA plays a substantial role in the development and testing of structural models (Conway & Huffcutt, 2003; Goldberg & Velicer, 2006; Haig, 2005; Schmitt, 2011; Schmitt et al., 2018). The present study thus sought to evaluate the benefits of using EFA and CFA in tandem. This was done by comparing the replicability and substantive interpretability of the correlated factor, higher-order, and several bifactor models of psychopathology across exploratory and confirmatory factor analytic contexts. We paid special attention to exploratory bifactor models as their use in psychology, and quantitative nosology more specifically, is less established than traditional EFA and CFA. These results were then used to inform the specification and evaluation of the bifactor S-1 model (Eid et al., 2017). By investigating previously unexplored versions of the bifactor model of psychopathology in the NESARC dataset, our results build on existing research using these data and highlight unique challenges for their use in modeling the latent structure of psychopathology more generally.

Limitations of Goodness of Fit Indices

As expected, all models in this study fit the data well by technical standards. Among confirmatory models, fit indices routinely favored the bifactor model over the more parsimonious

higher-order and correlated factor models, especially the relative fit indices (i.e., AIC, BIC, SSBIC). Simulation studies have shown that bifactor models are associated with better model fit statistics even when the data were generated by less complex alternatives (e.g., a correlated factor model; Greene et al., 2019) due to its inherent flexibility (Bonifay & Cai, 2017), resulting in greater accommodation of unmodeled complexities (e.g., negligible cross loadings and correlated residuals; Greene et al., 2019; Morgan et al., 2015; Murray & Johnson, 2013) and noise or error (Bonifay & Cai, 2017; Reise et al., 2016). In applied studies, the bifactor model's flexibility tends to translate into idiosyncratic results that neither generalize over time (e.g., substantial shifts in factor loadings across waves of data due to large standard errors, despite meeting the strictest criteria for longitudinal measurement invariance; Forbes et al., 2021) nor between samples (e.g., shifting definitions of the general and specific factors; Caspi et al., 2014; Lahey et al., 2014; see Watts, Lane, et al., 2020, for review). The current study illustrates the propensity for excessively complex models to overfit the data by accommodating noise or error as all four-factor EFAs showed a perfect fit to the data, despite these factor structures being the least interpretable.

The present study's exploratory model results further illustrate the dangers of relying on model fit due to the issue of factor indeterminacy. That is, while the model fit statistics were identical for each group of two-, three-, and four factor EFAs, there was a striking variety of junk versus interpretable factor solutions. This shows that multiple equivalent factor structures with drastically different interpretations can result from a single run of EFA or EBFA. The present study also revealed the highly protean nature of the bifactor CFA results, which rarely extended to bifactor EFA solutions, despite nearly identical model fit statistics. Thus, idiosyncratic results are also possible when either the same method (e.g., a specific factor rotation criterion) or different methods (i.e., EFA and CFA) are used to estimate the same model in the same dataset. Taken

together, these methodological issues present clear barriers to relying on model fit as an index for the verisimilitude of any complex model of psychopathology in these data.

Using Exploratory Methods to Interrogate Confirmatory Models

Before turning to the benefits of using exploratory methods to better understand confirmatory structures, we will first revisit the reason why correlated factor models began to be followed up by general factor models. Some researchers have posited a general factor of psychopathology on the basis of the sizable interfactor correlations in correlated factor models. However, concerns about discriminant validity generally follow when correlated factor models' interfactor correlations rise to the order of $\geq .75$ (Farrell, 2010). None of the interfactor correlations in this study exceeded that threshold ($r = .50$ to $r = .72$ across WLSMV and MLR estimators), indicating that all primary factors represented sufficiently distinct constructs. Also, there tend to be high correlations between distress and fear factors ($r = .72$), which has been interpreted as evidence for a general factor of psychopathology, but it is also possible that these two dimensions form a superordinate dimension reflecting internalizing as opposed to general psychopathology (c.f., Forbes, 2020; Kim & Eaton, 2015).

Another, less discussed, reason for large interfactor correlations is unmodeled complexity, such as when meaningful cross-loadings are constrained to zero in CFA (Marsh et al., 2014; Morin et al., 2016; Schmitt & Sass, 2011). Tests of the possible presence of meaningful cross-loadings were conducted with EFA using oblique geomin and cf-quartimax rotations. Both rotations produced factor structure patterns that replicated CFA results, with the only difference being a significant cross-loading for GAD on the distress and fear factors. This suggests that the elevated interfactor correlations between distress and fear are partially due to the GAD indicator's construct-relevant multidimensionality (Morin et al., 2016), and should not be interpreted as

evidence that an additional factor is needed. Thus, all correlated factor models were highly invariant in meaning and were not found to be overly restrictive.

Related to discriminant validity is dimensionality, which involves the determination of how many factors to extract. While there are numerous strategies for deciding on the number of factors, the practice of doing so remains highly subjective because there is no single best method for doing so in EFA or CFA (Preacher & MacCallum, 2003). This means that judgements about the optimal number factors should be based on the interpretability of resulting solutions. Most structural researchers begin with confirmatory approaches by using past research, theory, or their combination, to justify decisions about their data's dimensionality. Because the number of latent factors in psychopathology data is reasonably known, the use of *a priori* knowledge tends to not be problematic. A trend that does appear problematic, however, is the continued selection of “optimal” (i.e., best-fitting) models despite estimation problems (e.g., negative factor variances; Caspi et al., 2014; Conway et al., 2016). Such is the case for the continued application of bifactor models of psychopathology, which regularly feature theoretically and statistically problematic results, such as weak specific factors (Greene & Eaton, 2017; Lahey et al., 2012; Forbes et al., 2021), those that vanish altogether (Caspi et al., 2014; Martel et al., 2017), and/or negative loadings for specific factor domains (Castellanos-Ryan et al., 2016).

Recently, this topic of dimensionality has been framed in terms model-based statistics (e.g., coefficient omega; Rodriguez et al., 2016a, 2016b) which describe the strength, reliability and expected replicability of latent variables (Brunner et al., 2012). For example, a recent study found that these data were not unidimensional (i.e., a single factor model lost important information), and that the primary factors in the correlated factors model captured these data's

multidimensionality far more reliably than the specific factors in the bifactor model, which did not show good reliability or validity (Forbes et al., 2021).

Given this slew of concerning evidence that the bifactor model of psychopathology may be inappropriate for these data, or at least not in the one way it has always been applied (i.e., orthogonal four-factor model using CFA, Forbes et al., 2021; Greene & Eaton, 2017; Lahey et al., 2012; Figure 2), we re-assessed these data with a series of additional confirmatory and exploratory bifactor models involving different numbers of factors. This approach was based on recommendations that proceeding in an integrative fashion might be helpful for finding out where and why model misspecifications might be occurring (Hayashi et al., 2007; Preacher & MacCallum, 2003; Schmitt et al., 2018). Also of interest was the extent to which the meaning of bifactor structures might shift depending on the methods used to estimate them. As discussed by Goldberg & Velicer (2006), such replicability in an exploratory context can be viewed as “more independently tested than if the data are fitted to a specified model” using confirmatory techniques (see also Macdonald, 1999).

Overall, the bifactor structures evaluated herein were found to take many forms and therefore many meanings, with the four-factor structures being the most variable. The four-factor models resembled a hall of mirrors, with the “general” factor’s meaning shifting across each unique solution. These general factors typically reflected fear (four solutions) and distress (two solutions), and in one instance, externalizing—the gestalt a glaring reminder of the intractable factor indeterminacy problem (see Table 12). The two most consistent aspects of these results were: (1) full or partial collapse of internalizing disorders onto the general factor and (2) evidence of overextraction in the four-factor EBFAs. Confirmatory and exploratory bifactor models both contained inadmissible factor loadings for the specific factor of internalizing at the three-factor

level (i.e., partial factor collapse), and the JB rotations produced mixed results at the four-factor level (e.g., full factor collapse for distress for one rotation). The frequent collapse of internalizing disorders onto the general factor suggests there was little reliable variance in these specific factors that was independent of the “general internalizing” factor, leading to overextraction in four-factor solutions (i.e., reliable appearance of at least one junk factor). These findings highlight the importance of carefully inspecting EBFA results before conducting bifactor confirmatory analysis (Reise, 2012), and clarify why the bifactor CFA model tends to produce weak distress and fear factors (e.g., Forbes et al., 2021).

Here, we will pause for a moment over these results to wonder what might have occurred if previous studies (e.g., Forbes et al., 2021; Greene & Eaton, 2017; Lahey et al., 2012) had included this same set of EBFAs before specifying the bifactor CFA that is typical of structural work using NESARC data. If all the analyses presented herein were reported in those articles, would there be enough evidence for a four-factor confirmatory bifactor model? The JB rotations yielded various four-factor solutions with very different implications for a four-factor confirmatory model, and only two of the 14 unique EBFA solutions replicated the bifactor CFA model. The remaining 12 unique solutions were uninterpretable and only the bi-cf-quartimax rotation produced two fully interpretable solutions, one of which was a local minimum. It seems likely that in the face of these results, those studies would not have pursued further analyses focused on the bifactor CFA. However, it is noteworthy that the JB rotation criteria were integrated into *Mplus* after the landmark article on the general factor of psychopathology was written (i.e., Lahey et al., 2012), so it was not an option to compare these specific models at that time. So, the only way to “find” a general factor of psychopathology using exploratory techniques would have been to use an orthogonal geomin rotation, a highly dubious choice. This highlights the role that technological

developments have in shaping all published work containing advanced statistical methods, which in turn impacts the progression of future research and knowledge.

Viewed another way, the emergence of a pseudo-bifactor structure from a non-bifactor rotation criterion offers an opportunity for understanding how different rotation criteria impact factor structure interpretation (Schmitt & Sass, 2011). As shown in the two top-left panels in Tables 7, 8, and 9, when the geomin and cf-quartimax rotation criteria were used to rotate factors to orthogonal dimensions, cross-loadings were upwardly biased as the relationship between factors was reflected in the larger cross-loadings. However, results for the two rotation criteria differed considerably in terms of their cross-loading magnitudes: the cf-quartimax rotation produced independent cluster basis structures with a few meaningful cross-loadings, while geomin's high tolerance for cross-loadings yielded a comparatively large increase in "meaningful" large cross-loadings that closely resembled the bifactor structures produced by the JB rotation criteria. Thus, the cf-quartimax rotation performed more consistently across oblique and orthogonal rotations, producing relatively independent cluster structures with cross-loadings that were aligned with theoretical expectations (i.e., cross-loadings for internalizing disorders on distress and fear factors). These findings broadly accord with Thurstone's (1947) notion of simple structure, which does not promote perfect independent clusters (though they may be easy to interpret), but rather structures that reflect the reality that variables commonly measure multiple factors (Goldberg & Velicer, 2006; Morin et al., 2016; Schmitt & Sass, 2011; Zhang & Preacher, 2015). The geomin rotation's production of a pseudo-bifactor structure, pervasive factor collapse, and evidence of overextraction (overfitting) in the four-factor solutions are all aligned with Markon's (2019) recent gesture towards the idea that there might be important relationships between bifactor and exploratory models. Indeed, this pattern of results shows how the overlapping specification

principles underlying both model types give rise to “[s]imilarities in overfitting patterns between exploratory and hierarchical models, approaches to hierarchical structure through bifactor rotations, and patterns of anomalous estimates that are sometimes obtained with hierarchical models” (p. 67). This is largely consistent with Bonifay and Cai’s (2017) finding that the confirmatory bifactor model had as high, or even higher, fitting propensity than exploratory factor analyses in some cases. All told, both the bifactor model and exploratory models tend to exhibit a high degree of fitting propensity.

Issues to be Aware of When Using Exploratory Factor Analysis

The user-friendly interface of programs like *Mplus* belie the intricacies of implementing exploratory factor analysis, leading to an unfortunate overreliance on default options that may produce unstable results (Browne, 2001; Dombrowski et al., 2019). This is compounded by the convention of turning to prior studies’ methods without a clear conceptual understanding of how rotation criteria differ (Sass & Schmitt, 2010). Indeed, the popularity of a rotation criterion is often conflated with its appropriateness, an impractical approach in comparison to careful consideration of different rotation methods (Hattori et al., 2017). These issues are exacerbated in the context of conducting exploratory bifactor analysis, which is even more interactive than traditional EFA (Mansolf and Reise, 2016). This is because initial EBFA solutions are not to be immediately trusted (Abad et al., 2017; Mansolf & Reise, 2016) and, in the absence of any justifiable reason to prefer one over the other, multiple mathematically equivalent solutions may need to be critically examined in order for the most interpretable one to be selected (Asparouhov & Muthén, 2009).

Following recommendations by Mansolf and Reise (2016), the present study increased the number of start values to 1,000 and up to 10 of the best unique solutions were displayed for each EFA and EBFA. As shown in Tables 10 through 12, no more than five local minima were found

for any given rotation criterion. The number of local minima steadily increased as a function of increasing numbers of factors, orthogonal rotation, with geomin and bi-geomin rotation criteria being most problematic as observed by others (Asparouhov & Muthén, 2009; Dombrowski et al., 2019; Hattori et al., 2017; Mansolf & Reise, 2016). At the three-factor level, the JB rotations produced solutions with the same interpretation: a general factor defined by distress disorders due to a partially collapsed internalizing factor and a specific factor for externalizing. This high rate of convergence suggested these instances of factor collapse were not erroneous, but indicative of pure indicators for the general factor (Robertson, 2019).

At the four-factor level, interpretations varied widely for the unique solutions produced by the JB rotations, leading to mixed results. Each of the solutions found for the bi-geomin rotation included one junk factor and/or one collapsed factor, leading to the conclusion that this rotation did not work well for four-factors. The bi-cf-quartimax did result in two bifactor solutions with independent clusters structure (one oblique and one orthogonal), but one of these solutions would not have been found without inspecting the local minima (i.e., the global minimum did not yield the most interpretable solution). Because bi-cf-quartimax performs best for simpler factor structures, or those that only deviate from an independent cluster structure due to pure indications, the implication is that these data are not very complex (Abad et al., 2017). This accords well the results for the oblique and orthogonal EFA results using cf-quartimax. In contrast, the bi-geomin rotation is expected to be more accurate for complex bifactor structures that combine cross-loadings and pure indicators (Abad et al., 2017), or at least include cross-loadings that are greater in number and magnitude than those observed here.

These findings reiterate the sizable influence that different rotation methods have on factor structure and their subsequent interpretation. It is suggested that researchers give more thought to

issues of factor structure complexity when choosing rotation criteria (Sass & Schmitt, 2010; Schmitt & Sass, 2011), rather than focusing on the choice between oblique or orthogonal rotations. As demonstrated in the literature, rotation criteria are frequently selected based on prior research with little justification for their use (Blanco et al., 2013; Eaton et al., 2011; Greene & Eaton, 2016; Keyes et al., 2013; Kim & Eaton, 2015; Sharp et al., 2015), with oblique geomin and orthogonal bi-geomin being the most common. Because these particular rotations were the most prone to local minima, previous studies might have missed opportunities to inspect multiple solutions; in the future, comprehensive evaluations of additional unique solutions are likely to increase the accuracy of conclusions. Overall, researchers are urged to make greater use of EFA methods, especially JB rotations when desiring to directly implement a bifactor model within an EFA framework, while remaining cognizant of these methods' limitations.

Application of Confirmatory Bifactor S-1 Models

In recent years, a large number of studies have found that when general factor models are applied to these data, the general factor is defined by internalizing disorder variance (Forbes et al., 2021; Fried et al., 2021; Greene & Eaton, 2017; Kim & Eaton, 2015; Lahey et al., 2012). Kim and Eaton (2015) found that backwards latent factors of internalizing and distress were strongly correlated with the bifactor model's general factor ($r_s = .92$ and $.87$, respectively). It has also been shown that a simple sum of distress diagnoses is highly correlated with the bifactor model's general factor (i.e., $r = .94$ in SEM and $r = .83$ with factor scores; Fried et al., 2021). For the current study's confirmatory models, factor score correlations approached unity between the optimal bifactor CFA model's general factor and the correlated factors model's distress ($r = .98$) and fear ($r = .96$) factors. These associations between the correlated factor, traditional bifactor, and bifactor S-1 models demonstrate that the general factor scores generated by both versions of

bifactor model consisted of internalizing disorder variance, regardless of whether the internalizing disorders collapsed onto general factor (i.e., in the case of bifactor CFAs and EBFAs) or were specified as pure indicators (i.e., in the case of the bifactor S-1 models). These findings are informative for understanding instances of specific factor collapse onto the general factor in past studies (e.g., Caspi et al., 2014), as well as in the present study's confirmatory and exploratory bifactor models.

While instances of factor collapse can be erroneous in some cases, “true” factor collapse occurs when pure indicators of the general factor are present (i.e., $\lambda > .80$; Robertson, 2019). Identification of pure indicators is dependent on how each indicator's variance is distributed between the general and specific factors. That is, because a bifactor model's indicators load on two factors by definition, extremely high loadings on either the general or the specific factor produces a corresponding decrease for one of the factors. In all four of the three-factor EBFA solutions presented in Table 8, the distress factors collapsed onto the general factors, with MDD and Dysthymia displaying general factor loadings that ranged from $\lambda = .81$ to $\lambda = .84$ and negative loadings on the specific internalizing factor. An identical pattern of results was also observed for the two three-factor bifactor CFA models presented in Tables 4 and 5, with MDD and Dysthymia loading strongly on the general factor (i.e., $\lambda = .81$ and $\lambda = .88$, respectively), but negatively on the specific internalizing factor. The misspecification of these pure indicators within traditional confirmatory bifactor models created a general factor that was no longer “general” and a specific internalizing factor that was stripped of unique reliable variance. As noted by Burns et al. (2019), negative factor loading patterns are unexpected and contradictory when all indicators have strong positive correlations (i.e., negative loadings suggest a negative

correlation between a factor and the indicator), suggesting this classic bifactor modeling approach may be inappropriate in most cases (Eid, 2020; Eid et al., 2017).

In an effort to better understand these results, a comparison was made between the problematic confirmatory bifactor models and the *bifactor S-1 model* (see Figure 4; Eid et al., 2017). The three bifactor S-1 models are shown in Table 13, which include pure indicators of the general factor and can be contrasted against the traditional bifactor models with collapsed factors. While the primary interest was in evaluating the bifactor S-1 model with distress disorders as the reference domain, all bifactor S-1 models produced general and specific factors with more consistent and robust loading patterns compared to the traditional bifactor models in Tables 4 and 5. In each of the bifactor S-1 models, with distress, fear, and externalizing disorders as the reference domains, all three sets of disorders loaded highly on the general reference factor, and all specific residual factors retained substantial amounts of unique variance that was independent of general reference factors. This suggests that when pure indicators are identified using EBFA, or when factor collapse is observed using CFA, a bifactor S-1 model ought to be considered. Beyond the improved factor pattern, an additional benefit of the bifactor S-1 model is that the general reference factor carries an unambiguous meaning, because it is defined *a priori* by a specific group of diagnostic indicators. The specific factors in the bifactor S-1 model are also defined *a priori* and interpreted as residual factors that can be contrasted against the reference domain that defines the general factor (Burns et al., 2019). An unfortunate, and poorly recognized, feature of traditional bifactor factors is that they are only identified as latent variables (i.e., there are no observed scores; Eid et al., 2017). As a consequence, constructs associated with traditional bifactors are ambiguous and cannot be interpreted with the same clarity as those in bifactor S-1 models.

Eternal Recurrences

Several methodological mishaps have been discussed so far, including 1) overreliance on model fit, 2) neglect of exploratory techniques, and 3) leaving signs of model misspecification unchecked. Another poor practice is what Fried (2020) has described as a muddling of the models we apply to data with the theories we hope to test. Nowhere is this more evident than in the literature on the *p*-factor and general factors of psychopathology (for a review see Smith et al., 2020), where general factors and the theories they purport to test appear as one (Watts, Lane, et al., 2020). This type of confusion has an uncomfortable parallel to a bad habit of thought possessed by the inventor of factor analysis: for Charles Spearman, factor analysis was the Two-Factor Theory of Intelligence (Bartholomew, 1995). Spearman's obsessive focus on the general factor of intelligence translated into him being much less interested in the development of a new multivariate technique, which appeared to be very slow during his tenure.² Reflection on this piece of history raises the question of whether current *p*-factor enthusiasts might be in danger of repeating similar historical mistakes.

Wading through the *p*-factor literature reveals three main sources of confusion for how common factor models are interpreted within the structural psychopathology literature. These three highly related issues are that: 1) latent factors are little more than the sum of their parts, statistically, 2) they are not invariant in meaning, and 3) the impulse to reify these latent variables largely stems from the field's primary use of confirmatory factor analysis and the reflective latent variable model in particular. Each of these issues will now be discussed in turn.

The substantive meaning of the *p*-factor is likely to be debated ad nauseam until structural researchers fully embrace the statistical truth about general factors, which Cattell (1952) described

² In Bartholomew's (1995) tracing of the origins of factor analysis, he notes that "[t]he exact nature of factor analysis only gradually emerges in Spearman's writing and never gets very much beyond what we would call the one-factor model," which led him to "become stuck in a methodological cul-de-sac."

nearly 70 years ago: scores on the general factor are “essentially the sum of the scores.” In a recent study using these data (Fried et al., 2021), the correlation between the p -factor and the sum of all diagnostic indicators approached unity ($r = .99$ in an SEM context, and $r = .93$ when using factor scores from the first wave of NESARC). In this way, the statistical definition of the p -factor has a very clear meaning: it is simply a re-expression of the total number of diagnoses that a person experiences. This was also true for the domain-specific factors in the correlated factors, higher-order, and bifactor models, with the implication being that latent variables based on these diagnostic data are best interpreted as rough indices for more or less specific types of diagnostic comorbidity, not necessarily general or specific liabilities. Moreover, count variables of diagnoses likely reflect a proxy for severity or impairment, as opposed to some clear mechanism (Helle et al., 2020). To test the idea that a general factor represents liability for psychopathology, models should not be estimated on symptoms and diagnoses, but on broad influences, such as economic and early adversity, attachment styles, and mentalization (Fried et al., 2021). In pursuing such tests, etiological variables could be appropriately modeled as general reference domains/indicators, as demonstrated using the bifactor S-1 model (Burns et al., 2020; Eid, 2020; Eid et al., 2017; Willoughby, 2020).

Second, because general factors in orthogonal bifactor models are essentially the sum of their indicators, they are not invariant in meaning (Cattell, 1952). The meaning of the p -factor will only be invariant across studies to the extent that the observed variables we choose to model are invariant across studies (Bornovalova et al., 2020; Fried et al., 2021; Watts, Poore, et al., 2019). All current competing definitions of the p -factor suffer from this cardinal weakness of general factor modeling. Therefore, the current menu of definitions for the p -factor are but narrow reflections of individual researcher’s lines of inquiry, which poses considerable barriers to

synthesizing results across studies. This reality is highlighted by one of Cattell's (1952) forgotten insights: "what is general or group or specific, in terms of a correlation matrix, depends intimately on what has been chosen to go into the matrix...the distinction between group and general factors therefore loses any meaning—except in a particular matrix and in the particular sense used by bifactors—and it is better to call both of these older concepts *common factors of greater or less coverage*." So, while an overwhelming portion of the literature has tended to focus on the extent to which the latent structure of psychopathology can be characterized as both general and domain-specific (Afzali et al., 2018; Blanco et al., 2013; Caspi & Moffitt, 2018; Castellanos-Ryan et al., 2016; Del Giudice, 2016; Forbes et al., 2021; Hankin et al., 2017; Laceulle et al., 2015; Lahey et al., 2016; Martel et al., 2017; Murray et al., 2016; Olino et al., 2014; Patalay et al., 2015; Sharp et al., 2015; Snyder et al., 2016), Cattell (1952) would point out that classifying latent factors as "general" or "specific" is "artificial." This artificiality can clearly be seen in the current study's EBFA factor structures, where the general factor came in many flavors; sometimes it was defined by internalizing, distress, or fear, and sometimes externalizing. Nevertheless, researchers are usually more protected from the urge to reify factors (i.e., as reflective of some general or specific liability) when conducting EFA because factors are derived from the data and given names after they are extracted (Bollen, 2002). This makes it easier to see latent variables as hypothetical rather than real entities. Determining factors prior to the analysis, as in CFA, seems to increase the likelihood of regarding factors as real, leading to interpretations that stretch far beyond the data and the model.

Third, there is an apparent mismatch between the reflective variable model and the statistical definition of general factors. If the *p*-factor is statistically defined as a summary index of diagnostic comorbidity or severity (Fried et al., 2021), using a reflective latent variable makes

little sense. Researchers choose a reflective model when there is a belief that latent factors are proxies of some common cause that leads indicators to covary (Bollen, 1989). It is unlikely that structural researchers would claim that diagnostic comorbidity underlies, explains, or directly influences the observed covariance among diagnostic indicators. This is because variation in diagnostic comorbidity *is* constructed by variation in the diagnostic indicators, much like variation in socioeconomic status *is* constructed by income, education, and so forth (Bollen, 1989; Fried, 2020). In these instances, the indicators are causal and can be assumed to give rise to the latent constructs of diagnostic comorbidity and socioeconomic status, which are best modeled using a formative latent variable model. As discussed by Bollen (1989) and Fried (2020), cause indicators like these are often neglected despite their appropriateness and usefulness in many cases. Watts and colleagues (2020) proposed a similar argument regarding conceptualizations of the *p*-factor as reflecting impairment (Oltmanns et al., 2018; Smith et al., 2020) because impairment is one consequence of experiencing psychopathology and because they concluded that there was no clear, replicable *p*-factor across the published literature.

However, common clinical experience suggests that bolstering individual ranges of functioning is no less important than reducing diagnostic symptoms (Barber & Sharpless, 2015; McWilliams, 2011). For instance, increased functioning in the in the areas identified by the DSM-5 Levels of Personality Functioning — identity, self-direction, empathy, and intimacy (Huprich et al., 2018) — often translates into an increased ability to manage daily stressors, which reduces the likelihood of experiencing emotional distress and impairment (i.e., being diagnosed with a mental disorder). Although, these more humanistic relations between functioning and psychopathology are obscured in our current framework due to the neglect of adaptive poles of functioning (e.g., agency and communion; Bender, 2019; Meehan et al., 2019; Widiger, 2010; Widiger et al., 2019).

Indeed, beginning with Freud's credo that the goal of treatment is to improve one's ability to "love and work" (Erikson, 1963), the ultimate aim of all clinical interventions remains focused on improving life functioning (Smith et al., 2020). This is true regardless of a psychotherapy practitioner's theoretical orientation, and it is true of psychiatry.

Tracing these lines of argument leads to the conclusion that it is important not to confuse interfactor correlations, or any other nominally valid correlation between personality, psychopathology and behavioral or biological variables, for a sufficient theory (Mischel, 2004; Srivastava, 2020; Turkheimer, 1998). It is also critical to not confuse the usefulness or appropriateness of a model for the mysterious laws of nature. The usefulness of a model is dictated by its ability to characterize a specific research question within a particular context and particular correlation matrix, which are all intimately linked to individual researchers' wishes and priorities (Cattell, 1952; Srivastava, 2020). As of now, the available range of observed variables that we choose to prioritize and include in our models typically yields a maximum of four spectra (i.e., distress, fear, externalizing, and thought disorder). Structural models might be too abstract and low-dimensional to "carve nature at its joints"—it is the structure of data that we model, not nature (Wiernik et al., 2020). To fully embrace the richness, complexity, and the contextual and dynamic elements of human vulnerabilities, it is essential to scale up measurement and assess a broader range of mainstays in the clinical corpus (e.g. temperament, attachment, defense, etc.; McWilliams, 2011), collect various types of data (e.g., behavioral, audio, and text data in clinical settings and via wearable devices; Bryan et al., 2018; Imel et al., 2015; Wang et al., 2020), and to develop interdisciplinary collaborations (e.g., with clinicians, computer scientists, sociologists, etc; Cai et al., 2020). As noted by others (Cai et al., 2020; Smith et al., 2020), greater consensus about phenotypic structure can also be helped through greater systematization of measurement

across studies. Future efforts to develop measures of broad constructs, like the p -factor, must also begin with a general construct in mind, which will help limit post-hoc “discoveries” of general factors.

Limitations

There are several limitations of the present study, some of which are unique to the NESARC dataset, despite the high statistical power achieved due to its very large sample size. Like many examinations of the structure of psychopathology using large-scale, epidemiological data, this relied on a single dataset with binary diagnostic indicators due to the skip-out structure of the AUDADIS-IV. This precluded the construction of dimensional symptom counts, which are demonstrably more reliable than categorical diagnoses.

As discussed earlier, there were a limited number of diagnostic indicators, which presents two significant challenges for modelling the latent structure of psychopathology. First, there is an underrepresentation of other key dimensions of psychopathology, including temperament and personality (e.g., negative emotionality, detachment, antagonism; Kotov et al., 2011; Tackett, 2013, Wright & Simms, 2015), thought disorder (e.g., schizophrenia, mania; Caspi et al., 2014, Keyes et al., 2013), somatoform (e.g., pain, hypochondriasis; Kotov et al., 2011), and neurodevelopmental (e.g., autism spectrum; Kim et al., 2018) dimensions. Increasing coverage of such dimensions also helps reduce the likelihood of model identification problems (e.g., overextraction), increase replication (e.g., increasing the number indicators can reduce factor indeterminacy in EFA; Bollen, 2002), and is beneficial for statistically differentiating between the models evaluated herein. With only three first-order factors to indicate the second-order general psychopathology factor, the higher-order model is just-identified and, therefore, is a direct reparametrization of the interfactor correlations in the correlated factor model. As for the higher-

order and bifactor models, the general factors in both models are highly similar (Forbes et al., 2021).

Another limitation is that this study only evaluated the JB rotation criteria for EBFA. Several other exploratory bifactor methods are available (see Abad et al., 2017; Giordano & Waller, 2019), and researchers are urged to consider their relative performance in similar structural modeling scenarios. Although not illustrated here, it has been recommended that the Schmid-Leiman with iterative target rotation (SLiD; Garcia-Garzon et al., 2019) should be used when pure indicators of the general factor are present given evidence that it outperforms other rotation methods under this condition (Garcia-Garzon et al., 2020; Robertson, 2019).

Lastly, tests of predictive validity were not included in the present study. However, a recent investigation using the NESARC dataset showed that measures of adaptive functioning were limited in their specificity to different domains of psychopathology within the traditional confirmatory models evaluated herein (i.e., correlated factors, bifactor, and higher-order models all performed well; Forbes et al., 2021). Additional studies are needed to compare the bifactor S-1 model to these predominant models, to assess potential differences in their associations with important outcomes. Future research examining these models' abilities to tease apart differential associations with external criteria would also benefit from improving upon some of the current study's limitations, including use of continuous indicators, more indicators per factor, and greater multivariate normality (less skewed variables); all of these features contribute to greater precision of parameter estimates (i.e., narrow confidence intervals), which should not be conflated with achieving adequate power given a large sample size (Schmitt, 2011).

Conclusions

This study builds on the prior work showing that unsound statistical practices and myopic approaches to model building can distort results, cloud judgement, and impede theory development (Fabrigar et al., 1999; MacCallum et al., 1992; Preacher & MacCallum, 2003; Schmitt et al., 2018). As emphasized throughout, the process of conducting factor analysis is subjective, which has significant ramifications on the resulting models and the interpretability of results. Through elaborating on various misbegotten methodologies in the applied literature, we demonstrated the benefits of viewing EFA and CFA as complementary methodological functions, and introduced issues that quantitative nosologists ought to be aware of when incorporating exploratory bifactor analysis into their research. We also illustrated the usefulness of considering and reporting on multiple factor structures from different exploratory rotation criteria and confirmatory specifications (Sass & Schmitt, 2010). This allows readers to draw their own conclusions about competing structural representations of a broad swath of psychological constructs.

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Table 1. Model fit indices.

Model	Fit Indices						
	WLSMV				MLR		
	k	RMSEA	CFI	TLI	AIC	BIC	Adjusted BIC
Correlated Factors CFA							
Two Factors	23	.019	.977	.970	196632.728	196832.164	196759.07
Three Factors	25	.011	.993	.991	195788.513	196005.291	195925.840
Higher-order CFA							
Three Factors (Gen & 2SFs)	23	.019	.977	.970	196632.735	196832.171	196759.077
Four Factors (Gen & 3SFs)	25	.011	.993	.991	195791.557	196008.335	195928.884
Bifactor CFA (Orthogonal)							
Three Factors (Gen & 2SFs)	33	.006	.998	.997	195533.994	195820.141	195715.267
Four Factors (Gen & 3SFs) ^a	33	.010	.995	.992	195621.225	195907.372	195802.497
Bifactor CFA (Correlated SFs)							
Three Factors (Gen & 2SFs) ^b	34	.006	.998	.997	195529.740	195824.558	195716.505
Four Factors (Gen & 3SFs) ^b	36	.005	.999	.998	195527.445	195839.605	195725.197
Exploratory Factor Analyses							
Two Factors	21	.024	.971	.953	196518.856	196796.332	196694.636
Three Factors	30	.006	.999	.997	195509.659	195865.175	195734.876
Four Factors	38	.002	1.000	1.000	195468.467	195893.352	195737.629
Bifactor S-1 Models							
Distress as Reference Domain	31	.011	.994	.990	195718.111	195986.915	195888.397
Fear as Reference Domain	31	.007	.998	.996	195572.055	195840.859	195840.859
EXT as Reference Domain	29	.011	.993	.989	195793.662	196045.125	195952.963

Note: Bolded fit indices reflect the best fitting model in each group of models. Gen=general factor; 2SF=two specific factors; 3SF=three specific factors; EXT = externalizing; WLSMV=weighted least squares with adjusted means and variances estimation; MLR=robust maximum likelihood estimation; k=number of estimated parameters; RMSEA=root mean square error of approximation, CFI=comparative fit index; TLI=Tucker-Lewis index; AIC=Akaike information criterion; BIC=Bayesian information criterion; SABIC=sample-size adjusted BIC; a=with MLR estimation, the maximum number of integration points was 13 for orthogonal bifactor CFA models with three correlated specific factors; b= with MLR estimation, the maximum number of integration points was 10 for both oblique bifactor CFA models.

Table 2. Factor loadings for confirmatory correlated factor models.

Indicators	2F CF CFA		3F CF CFA		
	INT	EXT	Distress	Fear	EXT
Major Depressive Disorder	.86	-	.89	-	-
Dysthymia	.83	-	.84	-	-
Generalized Anxiety Disorder	.77	-	.78	-	-
Social Phobia	.68	-	-	.78	-
Specific Phobia	.60	-	-	.69	-
Panic Disorder/Agoraphobia	.79	-	-	.88	-
Antisocial Personality Disorder	-	.70	-	-	.70
Alcohol Dependence	-	.75	-	-	.75
Other Drug Dependence	-	.87	-	-	.87
Nicotine Dependence	-	.71	-	-	.71
Marijuana Dependence	-	.83	-	-	.83
Interfactor Correlations					
INT with EXT	.56		Fear with Distress	.72	
			EXT w Distress	.54	
			EXT w Fear	.50	

Note: Factor loadings $\geq .60$ are bolded for ease of interpretation, all were significant at $p < .001$. 2F CF=two correlated factors; 3F CF=three correlated factors; CFA=confirmatory factor analysis; INT=internalizing; EXT=externalizing.

Table 3. Factor loadings for confirmatory higher-order factor models.

Indicators	3F Higher-Order CFA			4F Higher-Order CFA			
	Gen	INT	EXT	Gen	Distress	Fear	EXT
Major Depressive Disorder	-	.86	-	-	.89	-	-
Dysthymia	-	.83	-	-	.84	-	-
Generalized Anxiety Disorder	-	.77	-	-	.78	-	-
Social Phobia	-	.68	-	-	-	.78	-
Specific Phobia	-	.60	-	-	-	.69	-
Panic Disorder/Agoraphobia	-	.79	-	-	-	.88	-
Antisocial Personality Disorder	-	-	.70	-	-	-	.70
Alcohol Dependence	-	-	.75	-	-	-	.75
Other Drug Dependence	-	-	.87	-	-	-	.87
Nicotine Dependence	-	-	.71	-	-	-	.71
Marijuana Dependence	-	-	.83	-	-	-	.83
Internalizing	.75			Distress	.88		
Externalizing	.75			Fear	.82		
				Externalizing	.62		

Note: Factor loadings $\geq .60$ are bolded for ease of interpretation, all parameter estimates were significant at $p < .001$.
3F=general factor with two lower-order factors; 4F=general factor with three lower-order factors; CFA=confirmatory factor analysis; Gen=general factor of psychopathology; INT=internalizing; EXT=externalizing.

Table 4. Factor loadings for confirmatory bifactor factor models with orthogonal factors.

Indicators	3F Bifactor CFA			4F Bifactor CFA			
	Gen	INT	EXT	Gen	Distress	Fear	EXT
Major Depressive Disorder	.86	-.27	-	.78	.45	-	-
Dysthymia	.81	-.33	-	.71	.51	-	-
Generalized Anxiety Disorder	.77	-.03	-	.75	.21	-	-
Social Phobia	.68	.31	-	.65	-	.37	-
Specific Phobia	.61	.39	-	.56	-	.42	-
Panic Disorder/Agoraphobia	.77	.45	-	.70	-	.59	-
Antisocial Personality Disorder	.43	-	.53	.46	-	-	.50
Alcohol Dependence	.38	-	.69	.42	-	-	.67
Other Drug Dependence	.51	-	.69	.55	-	-	.65
Nicotine Dependence	.41	-	.56	.44	-	-	.53
Marijuana Dependence	.48	-	.67	.53	-	-	.64

Note: Factor loadings $\geq .60$ are bolded for ease of interpretation. Factor loadings that were not significant at $p \leq .001$ are italicized. 3F=general factor with two specific factors; 4F= general factor with three specific factors; CFA=confirmatory factor analysis; Gen=general factor of psychopathology; INT=internalizing; EXT=externalizing.

Table 5. Factor loadings for confirmatory bifactor factor models with oblique factors.

Indicators	3F Bifactor CFA			4F Bifactor CFA			
	Gen	INT	EXT	Gen	Distress	Fear	EXT
Major Depressive Disorder	.88	<i>-.19</i>	-	.82	.39	-	-
Dysthymia	.83	<i>-.26</i>	-	.75	<i>.42</i>	-	-
Generalized Anxiety Disorder	.77	<i>.04</i>	-	.80	<i>.07</i>	-	-
Social Phobia	.65	<i>.37</i>	-	.68	-	.31	-
Specific Phobia	<i>.57</i>	<i>.44</i>	-	<i>.60</i>	-	<i>.41</i>	-
Panic Disorder/Agoraphobia	.72	<i>.52</i>	-	.76	-	<i>.46</i>	-
Antisocial Personality Disorder	<i>.42</i>	-	<i>.53</i>	<i>.36</i>	-	-	<i>.58</i>
Alcohol Dependence	<i>.38</i>	-	.69	<i>.30</i>	-	-	.73
Other Drug Dependence	<i>.51</i>	-	.69	<i>.43</i>	-	-	.74
Nicotine Dependence	<i>.41</i>	-	<i>.56</i>	<i>.34</i>	-	-	.60
Marijuana Dependence	<i>.48</i>	-	.67	<i>.41</i>	-	-	.72
Interfactor Correlations							
INT with EXT	<i>.06</i>			Fear with Distress	<i>-.51</i>		
				EXT w Distress	<i>.32</i>		
				EXT w Fear	<i>.22</i>		

Note: Factor loadings $\geq .60$ are bolded for ease of interpretation. Factor loadings and interfactor correlations that were not significant at $p \leq .001$ are italicized. 3F=general factor with two specific factors; 4F=general factor with three specific factors; CFA=confirmatory factor analysis; Gen=general factor of psychopathology; INT=internalizing; EXT=externalizing.

Table 6. Schmid-Leiman transformation based on factor loadings from a four-factor higher-order CFA.

Indicators	SLT from 4F H-O CFA			
	Gen	Distress	Fear	EXT
Major Depressive Disorder	.79	.41	-	-
Dysthymia	.75	.39	-	-
Generalized Anxiety Disorder	.69	.36	-	-
Social Phobia	.63	-	.46	-
Specific Phobia	.56	-	.41	-
Panic Disorder/Agoraphobia	.71	-	.52	-
Antisocial Personality Disorder	.42	-	-	.56
Alcohol Dependence	.45	-	-	.60
Other Drug Dependence	.52	-	-	.69
Nicotine Dependence	.42	-	-	.56
Marijuana Dependence	.50	-	-	.67

Note: Factor loadings $\geq .60$ are bolded for ease of interpretation; 4F=general factor with three lower-order factors; SLT=schmid leiman transformation; CFA=confirmatory factor analysis; Gen=general factor of psychopathology; EXT=externalizing; 3F=general factor with two lower-order factors; SLT=schmid leiman transformation; p=general factor of psychopathology; INT=internalizing; EXT=externalizing.

Table 7. Two-factor solutions for exploratory factor analyses.

Orthogonal Rotation Criteria								
Indicators	Geomin		CF-Quartimax		Bi-Geomin		Bi-CF-Quartimax	
	F1	F2	F1	F2	F1	F2	F1	F2
MDD	.85	.04	.82	.23	.79	-.30	.85	.00
Dysthymia	.83	.02	.80	.21	.76	-.34	.83	-.02
GAD	.78	-.03	.77	.15	.69	-.37	.78	-.07
Social Ph	.68	.02	.66	.17	.62	-.28	.68	-.02
Specific Ph	.59	.06	.56	.19	.55	-.20	.59	.03
PD/AG	.80	-.01	.78	.18	.72	-.35	.80	-.05
ASPD	.41	.54	.28	.62	.60	.31	.44	.52
Alcohol Dep	.36	.70	.19	.76	.63	.48	.40	.68
Other Drug Dep	.49	.70	.32	.79	.74	.42	.52	.68
Nicotine Dep	.39	.57	.25	.64	.59	.35	.41	.55
Marijuana Dep	.46	.68	.30	.77	.71	.42	.50	.66
Oblique Rotation Criteria								
Indicators	Geomin		CF-Quartimax		Bi-Geomin		Bi-CF-Quartimax	
	F1	F2	F1	F2	F1	F2	F1	F2
MDD	.83	.03	.83	.04	.79	-.33	.85	.00
Dysthymia	.83	.00	.83	.01	.76	-.34	.83	-.02
GAD	.81	-.06	.81	-.05	.69	-.37	.78	-.07
Social Phobia	.68	.01	.68	.01	.62	-.28	.68	-.02
Specific Phobia	.56	.05	.55	.06	.55	-.20	.59	.03
PD/AG	.82	-.03	.81	-.02	.72	-.35	.80	-.05
ASPD	.04	.66	.06	.65	.60	.31	.44	.52
Alcohol Dep	-.11	.85	-.09	.83	.63	.48	.40	.68
Other Drug Dep	.01	.85	.04	.83	.74	.42	.52	.68
Nicotine Dep	.00	.69	.02	.68	.59	.35	.41	.55
Marijuana Dep	.00	.83	.03	.81	.71	.42	.50	.66
Interfactor Correlations								
	F2	.58		.55		.00		.00

Note: Dark grey shading reflects strong factor loadings ($\lambda \geq .60$). Medium grey shading reflects moderate factor loadings ($.59 \leq \lambda \leq .30$). Light grey shading reflects unremarkable factor loadings. Standard errors could not be computed for oblique and orthogonal Bi-CF-Quartimax solutions. Large and statistically significant ($p < .05$) interfactor correlations are bolded. MDD=Major Depressive Disorder; GAD=Generalized Anxiety Disorder; PD/AG=Panic Disorder with Agoraphobia; ASPD=Antisocial Personality Disorder; Dep=Dependence.

Table 8. Three-factor solutions for exploratory factor analyses.

Orthogonal Rotation Criteria												
Indicators	Geomin			CF-Quartimax			Bi-Geomin			Bi-CF-Quartimax		
	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3
MDD	.86	.00	-.24	.82	.30	.20	.86	.00	-.25	.86	.00	-.24
Dysthymia	.81	.01	-.31	.82	.28	.11	.81	.00	-.33	.82	.00	-.31
GAD	.78	-.07	.01	.65	.21	.39	.78	-.07	.00	.78	-.07	.01
Social Ph	.67	.00	.33	.38	.23	.60	.67	.00	.34	.67	.00	.33
Specific Ph	.59	.04	.40	.27	.24	.62	.59	.03	.40	.59	.03	.40
PD/AG	.76	-.01	.48	.38	.25	.78	.76	-.02	.48	.75	-.02	.49
ASPD	.43	.53	.00	.19	.64	.11	.43	.53	.00	.43	.53	.00
Alcohol Dep	.39	.69	.00	.11	.78	.06	.39	.68	.00	.39	.68	.00
Other Drug Dep	.51	.68	-.04	.24	.82	.09	.52	.68	-.04	.52	.68	-.04
Nicotine Dep	.41	.56	.00	.16	.66	.10	.41	.55	.00	.41	.55	.01
Marijuana Dep	.49	.67	.03	.18	.79	.14	.49	.66	.03	.49	.66	.03
Oblique Rotation Criteria												
Indicators	Geomin			CF-Quartimax			Bi-Geomin			Bi-CF-Quartimax		
	F1	F2	F3	F1	F2	F3	F1	F2	F3	F1	F2	F3
MDD	.83	.08	.03	.85	.04	.03	.86	.00	-.26	.86	-.01	-.25
Dysthymia	.87	-.03	.03	.90	-.07	.03	.81	.00	-.33	.81	.00	-.32
GAD	.55	.36	-.06	.56	.33	-.06	.78	-.07	-.01	.78	-.07	.00
Social Ph	.11	.67	.02	.10	.67	.02	.67	.00	.32	.67	.00	.33
Specific Ph	-.03	.71	.06	-.05	.72	.06	.60	.03	.39	.59	.03	.40
PD/AG	.02	.89	.00	.00	.89	.01	.76	-.02	.47	.76	-.02	.48
ASPD	.04	.04	.64	.04	.03	.64	.43	.53	.00	.44	.53	.00
Alcohol Dep	-.06	-.02	.82	-.06	-.03	.83	.39	.68	.00	.40	.68	.00
Other Drug Dep	.08	-.01	.82	.07	-.03	.83	.52	.68	-.04	.52	.68	-.04
Nicotine Dep	.01	.03	.67	.01	.02	.67	.41	.55	.00	.41	.55	.01
Marijuana Dep	-.01	.07	.80	-.02	.06	.81	.49	.66	.03	.50	.66	.03
Interfactor Correlations												
F2	.60	-	-	.63	-	-	.00	-	-	-.01	-	-
F3	.50	.44	-	.52	.46	-	.00	-.01	-	.00	-.01	-

Note: Dark grey shading reflects strong factor loadings ($\lambda \geq .60$). Medium grey shading reflects moderate factor loadings ($.59 \leq \lambda \leq .30$). Light grey shading reflects unremarkable factor loadings. Standard errors could not be computed for oblique and orthogonal Bi-CF-Quartimax solutions. Large and statistically significant ($p < .05$) interfactor correlations are bolded. Dark grey MDD=Major Depressive Disorder; GAD=Generalized Anxiety Disorder; PD/AG=Panic Disorder with Agoraphobia; ASPD=Antisocial Personality Disorder; Dep=Dependence

Table 9. Four-factor solutions for exploratory factor analyses.

Orthogonal Rotation Criteria																
Indicators	Geomin				CF-Quartimax				Bi-Geomin				Bi-CF-Quartimax			
	F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4
MDD	.86	.01	-.25	.10	.83	.29	.18	.08	.85	-.01	-.29	.11	.70	.57	.03	.06
Dysthymia	.82	.02	-.30	-.03	.82	.29	.11	-.05	.80	.00	-.34	-.02	.70	.51	.00	-.07
GAD	.78	-.05	.01	.02	.65	.21	.38	-.02	.78	-.07	-.03	.02	.69	.32	-.09	.18
Social Ph	.67	.03	.34	-.08	.38	.25	.60	-.12	.69	-.01	.30	-.09	.69	-.02	-.09	.31
Specific Ph	.58	.02	.44	.26	.26	.21	.66	.22	.60	-.01	.42	.24	.50	.05	.03	.59
PD/AG	.75	.01	.47	-.02	.39	.26	.75	-.07	.77	-.03	.43	-.05	.76	-.04	-.11	.45
ASPD	.42	.54	.01	-.02	.19	.65	.11	-.02	.44	.52	.00	-.03	.51	-.02	.45	-.03
Alcohol Dep	.37	.68	.00	.11	.12	.77	.06	.11	.40	.67	-.01	.09	.46	.00	.64	.01
Other Drug Dep	.50	.69	-.03	.00	.24	.82	.08	.00	.53	.67	-.05	-.02	.61	.01	.60	-.06
Nicotine Dep	.38	.56	-.02	.23	.17	.65	.08	.23	.40	.55	-.02	.22	.39	.11	.58	.11
Marijuana Dep	.49	.70	.06	-.18	.18	.82	.14	-.18	.52	.67	.03	-.20	.67	-.15	.52	-.12
Oblique Rotation Criteria																
Indicators	Geomin				CF-Quartimax				Bi-Geomin				Bi-CF-Quartimax			
	F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4
MDD	.86	.05	.02	.07	.88	.03	.02	.07	.69	.57	.02	.06	.65	.63	.06	-.08
Dysthymia	.87	-.03	.04	-.06	.89	-.06	.04	-.06	.68	.55	-.03	-.07	.59	.64	-.03	.09
GAD	.56	.34	-.05	.00	.58	.32	-.04	-.03	.44	.48	.29	.00	.62	.39	-.17	-.06
Social Ph	.10	.66	.04	-.07	.10	.65	.05	-.13	.05	.47	.57	-.07	.65	.04	-.39	.02
Specific Ph	-.04	.77	.00	.28	-.03	.77	.01	.20	-.01	.41	.60	.28	.64	-.07	-.08	-.39
PD/AG	.04	.85	.02	-.01	.04	.84	.03	-.09	.01	.51	.72	-.01	.75	-.02	-.42	-.08
ASPD	.04	.04	.65	-.03	.04	.04	.64	-.02	-.03	.68	-.02	-.03	.61	.004	.12	.22
Alcohol Dep	-.04	-.03	.81	.10	-.03	-.02	.80	.11	-.08	.76	-.11	.10	.65	-.06	.33	.14
Other Drug Dep	.08	-.02	.82	-.01	.08	-.02	.82	.00	-.01	.85	-.09	-.01	.74	.02	.22	.27
Nicotine Dep	.05	.00	.66	.23	.06	.01	.65	.23	.01	.68	-.10	.22	.61	.01	.41	-.05
Marijuana Dep	-.03	.06	.84	-.19	-.04	.06	.84	-.18	-.13	.84	.02	-.19	.74	-.06	-.01	.46
Interfactor Correlations																
F2	.60	-	-	-	.61	-	-	-	.00	-	-	-	.00	-	-	-
F3	.50	.45	-	-	.50	.43	-	-	.44	.00	-	-	.00	-.19	-	-
F4	-.04	-.12	.00	-	-.07	-.04	.00	-	-.01	.00	-.01	-	.00	-.10	.58	-

Note: Dark grey shading reflects strong factor loadings ($\lambda \geq .60$). Medium grey shading reflects moderate factor loadings ($.59 \leq \lambda \leq .30$). Light grey shading reflects unremarkable factor loadings. Standard errors could not be computed for oblique and orthogonal Bi-CF-Quartimax solutions. Large and statistically significant ($p < .05$) interfactor correlations are bolded. MDD=Major Depressive Disorder; GAD=Generalized Anxiety Disorder; PD/AG=Panic Disorder with Agoraphobia; ASPD=Antisocial Personality Disorder; Dep=Dependence.

Table 10. Interpretations of all 10 unique two-factor solutions when using 1000 random starts for each rotation.

Rotation Criteria	INT / EXT	Gen / EXT	Gen/ INT
Orthogonal			
Geomin	X(f _Q =.16)	X(f _G =1.49)	X*(f _G =1.76, 1.77)
CF-Quartimax			
Bi-Geomin		X(f _{BG} =1.40)	
Bi-CF-Quartimax		X(f _{BQ} =.00)	
Oblique			
Geomin	X(f _G =.30)	X(f _{BG} =1.40)	
CF-Quartimax	X(f _Q =.01)		
Bi-Geomin			
Bi-CF-Quartimax	X(f _{BQ} =.00)		

Note: Interpretations in bolded text with bolded X's reflect those that appeared when a single solution was displayed for each rotation criterion. X*s reflect interpretations associated with additional local minima when multiple solutions were displayed. f_Q=cf-quartimax criterion function value; f_G=geomin criterion function value; f_{BQ}= bi-cf-quartimax criterion function value; f_{BG}=bi-geomin criterion function value; INT=internalizing; EXT=externalizing; Gen=general factor of psychopathology.

Table 11. Interpretations of all 14 unique three-factor solutions when using 1000 random starts for each rotation.

Rotation Criteria	Distress / Fear / EXT	Gen / Fear / EXT	Gen/ Distress / EXT	INT / EXT / Fear	Gen / INT / Distress	Gen / INT / Fear	INT / Distress + EXT / Fear + EXT
Orthogonal							
Geomin		X(f_G=.48)	X*(f _G =.66)		X*(f _G =.91)	X*(f _G =.93)	X*(f _G =.82)
CF-Quartimax	X(f_Q=.31)						
Bi-Geomin		X(f_{BG}=.19)	X*(f _{BG} =.27)				
Bi-CF-Quartimax		X(f_{BQ}=.00)					
Oblique							
Geomin	X(f_G=.21)			X*(f _G =.30)			
CF-Quartimax	X(f_Q=.03)						
Bi-Geomin		X(f_{BG}=.19)					
Bi-CF-Quartimax		X(f_{BQ}=.00)					

Note: Interpretations in bolded text and bolded **X**'s reflect those that appeared when a single solution was displayed for each rotation criterion. X*s reflect interpretations associated with additional local minima when multiple solutions were displayed. f_Q=cf-quartimax criterion function value; f_G=geomin criterion function value; f_{BQ}= bi-cf-quartimax criterion function value; f_{BG}=bi-geomin criterion function value; INT=internalizing; EXT=externalizing; Gen=general factor of psychopathology.

Table 12. Interpretations of all 16 unique four-factor solutions when using 1000 random starts for each rotation.

Rotation Criteria	Gen / Distress / Fear / EXT	Distress / Fear / EXT / ?	Gen/ Fear / EXT / ?	Gen/ Distress / Fear / ?	Gen/ Distress/ ? / ?	Gen/ Distress / EXT / ?	Gen/ EXT / ? / ?	Gen/ INT / Distress / ?	Gen/ INT / Fear / ?	INT / Distress+EXT/ Fear+EXT / ?	Gen / Distress / EXT / Soc Ph+ APan
Orthogonal											
Geomin	X*(f _G =.43)		X(f_G=.40)			X*(f _G =.41)					
CF-Quartimax		X(f_Q=.36)									
Bi-Geomin			X(f_{BG}=.68)			X*(f _{BG} =.70)		X*(f _{BG} =.73)	X*(f _{BG} =.75)	X*(f _{BG} =.80)	
Bi-CF-Quartimax	X(f_{BQ}=.02)					X*(f _{BQ} =.02)					X*(f _{BQ} =.02)
Oblique											
Geomin		X(f_G=.42)									
CF-Quartimax		X(f_Q=.08)									
Bi-Geomin				X(f_{BG}=.38)	X*(f _{BG} =.38)	X*(f _{BG} =.40)	X*(f _{BG} =.40)				
Bi-CF-Quartimax	X*(f _{BQ} =.01)				X(f_{BQ}=.01)						

Note: Interpretations in bolded text and bolded X's reflect those that appeared when a single solution was displayed for each rotation criterion. X*s reflect interpretations associated with additional local minima when multiple solutions were displayed. f_Q=cf-quartimax criterion function value; f_G=geomin criterion function value; f_{BQ}= bi-cf-quartimax criterion function value; f_{BG}=bi-geomin criterion function value; INT=internalizing; EXT=externalizing; Gen=general factor of psychopathology; Soc Ph=Social Phobia; APan=Panic Disorder with Agoraphobia.

Table 13. Factor loadings for confirmatory bifactor s-1 models with correlated specific factors.

Bifactor S-1 with Distress as Reference Domain				Bifactor S-1 with Fear as Reference Domain				Bifactor S-1 with Externalizing as Reference Domain			
Indicators	General	Fear	EXT	Indicators	General	Distress	EXT	Indicators	General	Distress	Fear
Major Depressive Disorder	.89	-	-	Panic Disorder/Agoraphobia	.88	-	-	Other Drug Dependence	.87	-	-
Dysthymia	.84	-	-	Social Phobia	.78	-	-	Antisocial Personality Disorder	.70	-	-
Generalized Anxiety Disorder	.78	-	-	Specific Phobia	.70	-	-	Alcohol Dependence	.75	-	-
Social Phobia	.58	.47	-	Major Depressive Disorder	.62	.66	-	Nicotine Dependence	.70	-	-
Specific Phobia	.49	.52	-	Dysthymia	.55	.67	-	Marijuana Dependence	.83	-	-
Panic Disorder/Agoraphobia	.62	.65	-	Generalized Anxiety Disorder	.66	.39	-	Major Depressive Disorder	.49	.74	-
Antisocial Personality Disorder	.41	-	.54	Antisocial Personality Disorder	.38	-	.57	Dysthymia	.40	.71	-
Alcohol Dependence	.36	-	.70	Alcohol Dependence	.32	-	.71	Generalized Anxiety Disorder	.46	.68	-
Other Drug Dependence	.49	-	.70	Other Drug Dependence	.45	-	.73	Panic Disorder/Agoraphobia	.41	-	.79
Nicotine Dependence	.39	-	.57	Nicotine Dependence	.36	-	.59	Social Phobia	.39	-	.67
Marijuana Dependence	.46	-	.69	Marijuana Dependence	.44	-	.70	Specific Phobia	.36	-	.58
Interfactor Correlations											
EXT with Fear		.19		EXT with Distress		.32		Fear with Distress		.62	

Note: Factor loadings $\geq .60$ are bolded for ease of interpretation; CFA=confirmatory factor analysis; p=general factor of psychopathology; EXT=externalizing.

Table 14. Factor Score Correlations Across Models

Model	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
Correlated Factor Model																
1. Distress Factor	1.0															
2. Fear Factor	.91	1.0														
3. Externalizing Factor	.74	.73	1.0													
Orthogonal Bifactor Model																
4. General Factor	.98	.96	.81	1.0												
5. Distress Factor	.69	.37	.21	.52	1.0											
6. Fear Factor	.24	.61	.15	.37	-.29	1.0										
7. Externalizing Factor	.24	.25	.82	.32	-.17	-.11	1.0									
Bifactor S-1 with Distress as Reference																
8. General Distress Reference Factor	1.0	.91	.74	.98	.69	.24	.23	1.0								
9. Fear Factor	.30	.67	.36	.45	-.36	.96	.15	.30	1.0							
10. Externalizing Factor	.27	.34	.85	.38	-.23	.03	.99	.27	.28	1.0						
Bifactor S-1 with Fear as Reference																
11. General Fear Reference Factor	.89	1.0	.72	.96	.33	.62	.23	.90	.68	.32	1.0					
12. Distress Factor	.80	.48	.52	.68	.93	-.33	.16	.80	-.30	.11	.45	1.0				
13. Externalizing Factor	.44	.36	.90	.49	.08	-.19	.97	.43	.06	.94	.34	.41	1.0			
Bifactor S-1 with Externalizing as Reference																
14. General Externalizing Reference Factor	.74	.74	1.0	.81	.22	.15	.82	.74	.36	.84	.72	.52	.90	1.0		
15. Distress Factor	.86	.73	.29	.78	.80	.23	-.29	.86	.15	-.26	.73	.74	-.06	.30	1.0	
16. Fear Factor	.73	.86	.29	.75	.37	.74	-.26	.73	.67	-.16	.87	.30	-.16	.29	.82	1.0

Figure Captions

Figure 1. A flowchart adapted from Schmitt et al. (2018) of exploratory and confirmatory approaches for investigating factor structure. Researchers are encouraged to examine model-based reliability indices to test for multidimensionality and to assess factor strength. The dashed lines/boxes and bolded text reflect the flow of procedures for the present study's investigation of the bifactor model in the NESARC dataset. CFA=confirmatory factor analysis; EFA=exploratory factor analysis; ESEM=exploratory structural equation modeling.

Figure 2. The confirmatory factor structures compared in this study. The correlated factor, higher-order, and bifactor models of psychopathology. Dashed bi-directional arrows linking the bifactor's specific factors represent interfactor correlations that were removed for orthogonal bifactor analyses. CFA=confirmatory factor analysis.

Figure 3. Graphical depiction of the exploratory factor models evaluated in the present study. EFA=exploratory factor analysis; EBFA=exploratory bifactor factor analysis.

Figure 4. Bifactor S-1 model with the distress as the reference domain.

Figure 1.

Correlated Factor CFA Models

Higher-Order CFA Models

Bifactor CFA Models

Figure 2.

Oblique EFA Model

Orthogonal EBFA Model

Figure 3.

Figure 4.